Financing Intermediate Goods and Misallocation: Evidence from China's Firm-Level Data

Wenya Wang*

October 8, 2019

Click for Latest Version

Abstract

This paper quantifies the role of intermediate goods frictions in accounting for misallocation. In China's NBS firm-level data, intermediate goods allocation across firms are found distorted at a magnitude similar to capital misallocation. For explanations, I find evidence of (i) pre-pay frictions that firms buy intermediate goods long before collecting cash from receivables; (ii) financial frictions that its misallocation is larger in more financially vulnerable industries. I build the two frictions into a standard firm investment model with adjustment costs and borrowing constraints on capital. Counterfactuals suggest that financial frictions on intermediate goods account for a similar magnitude of misallocation compared to financial frictions on capital. The conventional static measure of misallocation that uses value added production functions overstates misallocation when there are intermediate goods frictions.

JEL Codes: E32, E44, F41, G32, L60, O33, O47

*School of Finance, Shanghai University of Finance and Economics, 322 Tongde Building, 100 Wudong Road, Shanghai, 200433, P.R. China (email: wang.wenya@mail.shufe.edu.cn). I am greatly indebted to my supervisor Jim MacGee for his invaluable research guidance and support. I deeply thank Igor Livshits, David Rivers, Simona Cociuba, Xiaodong Zhu, Loren Brandt, Michael Song, Johannes Van Biesebroeck and Sophie Osotimehin for their insightful discussions. I thank conference participants in NAESM (Davis), SAET (Taipei), Wuhan University CERW Workshop, Midwest Macro Worshop (LSU) and AESM (Hong Kong). Lastly, I thank SUFE finance fin-lab for their assistance in computation. All errors are mine.

1 Introduction

Operating a firm requires constant payments for material and intermediate goods, a big part of which incurs before firms receive cash from product sales. In real world, the process could be as lengthy as half a year in many countries. A strand of corporate finance literature hence discusses an optimal level of working capital to cover these payments (Jose, Lancaster, and Stevens, 1996). When there are financial frictions, empirical studies show that constrained firms may give up fixed capital investment for working capital needs (Fazzari and Petersen, 1993).

Such a feature of firm-level productions has not been studied in the literature of misallocation. In their seminal work Hsieh and Klenow (2009), firm-level marginal revenue products of capital and labor are more dispersed within finely defined industries in China and India than in the United States. In a competitive static framework without distortions, marginal revenue products of an input equal to its market price and thus equalize across firms. The theory-data gap and related output loss is defined as misallocation, and suggests existence of market frictions and policy distortions.[1] To understand what frictions or distortions they are, the literature mostly focuses on capital and labor.[2] Despite that intermediate goods have the largest revenue share in production across countries (Jones, 2011), little is known on whether its firm-level usage is distorted, and if there is, whether the narrative of working capital constraint is one of the explanations.

This paper fills up the gap and studies how financial constraints on intermediate goods shape misallocation. I use Chinese Above-Scale Industrial Enterprise Survey (AIES) 1998-2007 for my research purpose. The paper first empirically documents intermediate goods misallocation in China's data. For an average 2-digit Chinese Industrial Classification code (CIC) industry, industry-level gross output increases by 4.98%, and value added by 20.61%, if marginal revenue products of intermediate goods are equalized across firms. This magnitude is about the same compared to gains when one reallocates capital alone, and twice as large the gains when one reallocates labor alone. Robustness checks show that intermediate goods misallocation is not mainly driven by output market distortions, China-specific estimates of intermediate goods share and unobserved heterogeneity in its composition, quantity and price.

I then find suggestive evidence of pre-pay and working capital constraints on intermediate goods in the data. Like in other countries, firms in China have a long operating cycle of 160 days, i.e. firms pay production materials 160 days before they collect cash from account receivables. Given this time window, financial frictions could hinder firms from using optimal levels of inter-

[1] Throughout the paper, I call the approach following Hsieh and Klenow (2009) that uses value added production functions as *value added approach*.

[2] One exception is Boehm and Oberfield (2018).

mediate goods, and hence create dispersion of marginal revenue products. This effect is arguably stronger when industries are financially vulnerable in its nature of production, captured by asset tangibility and external finance dependence measures developed by Braun (2003). Consistent with this narrative, I find that an industry with asset tangibility 1 standard deviation above the mean is 0.22 standard deviation lower in dispersions of marginal revenue products of intermediate goods. Similarly, an industry with external finance dependence 1 standard deviation below the mean is 0.12 standard deviation lower in dispersions of marginal revenue products of intermediate goods. More financially vulnerable industries also have higher dispersions in marginal revenue products of capital.

My empirical findings motivate the following question: how much can pre-pay and borrowing constraints on intermediate goods quantitatively account for misallocation in China's manufacturing sector? To answer the question, I incorporate the two intermediate goods frictions, as well as borrowing constraints on capital, into a standard firm investment model of Cooper and Haltiwanger (2006). Similar to their model, firms maximize net present value of future dividends, given a transitory stochastic productivity process and capital adjustment costs.

Unlike the standard firm investment model, this paper models intermediate goods frictions and borrowing constraints on capital. Specifically, firms order and prepay for a fraction of intermediate goods one period ahead (pre-pay). Firms also face a fixed cost and a convex adjustment cost when choosing next period capital. Payments of intermediate goods and capital investment are financed by retained earnings, and borrowings if needed. Firm-level borrowing is subject to a endogenous constraint that depends on default risk and net worth. After realization of stochastic productivities at the beginning of a period, firms choose to continue or exit under limited liability. Default happens when firms exit and liquidation of net worth is less than debt.

To quantify how much the model can account for measured misallocation in data, I calibrate the model to match key moments in firm-level debt, productivity, and market share distribution over age groups in AIES. My calibration explicitly takes account the fact that AIES has a minimum sales threshold of 5 million yuan for private-owned firms during this period, and only includes top 20% of manufacturing firms in terms of sales in China.[3]

Reallocation exercises in simulated firm-level data suggests that the benchmark model well captures the amount of output gains in data, if intermediate goods were reallocated *alone* and if they were reallocated with capital, and labor *simultaneously.* In the top 20% subsample of simulated firms, gross output would increase by 5.37% and value added by 13.97%, if only marginal revenue products of intermediate goods were equalized. These numbers are comparable to 4.98% and

[3]This number is based on firm counts in AIES 2004 and First Economic Census 2004.

20.61% for an average 2-digit industry in the data. If marginal products of capital, labor and intermediate goods were all equalized, the model delivers 21.84% gross output and 58.87% value added gains. Throughout the paper, I call the percentage of potential gross output gains as gross output misallocation, and value added gains as value added misallocation. Hence, the model accounts for 100% of gross output misallocation and 65% of value added misallocation in the data.

Further counterfactual experiments remove subsets of frictions in order to quantify misallocation accounted by each of the four frictions: prepay and borrowing constraints on intermediate goods, borrowing and adjustment costs on capital. In a model without these frictions and with only one-period time-to-build on capital, gross output misallocation is 13.11% and value added misallocation is 43.69%. The dynamic nature of capital in an economy where firm-level productivities evolve stochastically contributes the most misallocation, which is consistent with Asker, Collard-Wexler, and De Loecker (2014).

Intermediate goods frictions and capital frictions account for about half-half of the differences between the benchmark model and the model left with time-to-build on capital alone. Pre-pay and borrowing constraints on intermediate goods, primarily the latter, account for 62% of the remaining 10.41% gross output misallocation. These numbers are 52% for capital frictions, primarily from borrowing constraints on capital. This paper hence contributes to the discussion on financial frictions and misallocation (see Midrigan and Xu, 2014, Moll, 2014 and Buera and Shin, 2013), and argues that the effect of financial frictions on misallocation doubles when it distorts both capital and intermediate goods.

How do value added misallocation measures in this gross output approach compare to the ones in Hsieh and Klenow (2009)? I find that the conventional approach using value added production function may overstate misallocation. Value added misallocation quantified by value added gains through capital, labor and intermediate goods reallocations are about 30 $\sim$ 45% of the numbers obtained by capital and labor reallocation using a value added production function. The percentage gaps are similar in model and data, and decrease when elasticity of substitution across output varieties increases. Such a gap is from an overestimated dispersion of $TFPR$ contaminated by intermediate goods distortions under the value added approach.

To illustrate mechanisms of intermediate goods frictions, I compare the benchmark model with the model that has capital frictions alone. When firms in the latter model are hit by intermediate goods frictions shock for *one period*, financing needs increase as they pre-pay partly for next period intermediate goods. Next period capital stock decreases for both incumbents and entrants consequently, compared to their counterparts without intermediate goods frictions. Further, more entrants exit because continuation and borrowing for intermediate goods are too expensive to be optimal. The negative effect is long-lasting since lower capital stock decreases profit and collaterals for future borrowings. When firms are instead imposed of intermediate goods frictions *permanently*, recurrent financing for intermediate goods reinforce its negative effects on firm dynamics intertemporally. As a result, capital stock of incumbents are further lower at steady state than their counterparts without intermediate goods frictions. Under strong cleansing effects, entrants catch up in average capital stock, but at a much slower rate than their counterparts without intermediate goods frictions.

The endogenous borrowing constraint also delivers several results that are consistent with the discussions of size-dependent distortions.[4] First, firms constrained in intermediate goods have higher $TFPQ$, lower capital stock and pay higher interest rates in both model and AIES. Second, model induced borrowing limits vary and depend on state variables of productivities, capital stock and current debt. Young and more productive firms face tighter constraints and hence higher shadow prices of borrowings. These findings contribute to the discussion that more misallocation in data could be accounted, if distortions are positively correlated with firm-level productivities in Restuccia and Rogerson (2008).

The impact of intermediate goods frictions on measured misallocation is of general interests and not specific to China. Jones (2011) documents that intermediate goods revenue share is more than 50% in most countries, while the working capital management literature (e.g. Jose et al., 1996) documents a similar time length between intermediate goods purchases and collection of sales across countries. Further, financial markets are underdeveloped in most developing countries, for instance, India and Mexico (e.g. Ghate and Kletzer, 2012; Pratap and Urrutia, 2012), and in developed countries in 19th century (Ziebarth, 2013).

This paper is related to a large and still growing body of literature on misallocation.[5] One strand studies misallocation in China specifically, which the paper firstly contributes to. Hsieh and Klenow (2009) first find large firm-level distortions and substantial misallocation in China's data. Brandt, Van Biesebroeck, and Zhang (2012) further document limited input reallocation across firms in China despite a high TFP growth over 1998-2007. Explanations for misallocation include preferred lending to state-owned firms (Brandt, Tombe, and Zhu, 2013), trade and migration costs (Tombe and Zhu, 2019), entry costs (Brandt, Kambourov, Storesletten et al., 2018), and financial frictions (Bai, Lu, and Tian, 2018), to name a few.

This paper also contributes to a general theme that takes *direct approach* and investigates ex-

[4]See Guner, Ventura, and Xu (2008) and Restuccia and Rogerson (2008)

[5]See three surveys, Restuccia and Rogerson (2013), Hopenhayn (2014) and Buera, Kaboski, and Shin (2015), for a comprehensive review of the literature.

act frictions and distortions that rationalize the misallocation in firm-level datasets of many countries. Examples include information friction (David, Hopenhayn, and Venkateswaran, 2016; David and Venkateswaran, 2019), heterogenous and non-isolelastic production functions (Haltiwanger, Kulick, and Syverson, 2018; Uras and Wang, 2018) and heterogenous makrups (Peters, 2013). One of the mostly studied topics is capital misallocation and its causes. Some argue the importance of the dynamic nature of capital and the adjustment costs (Bartlesman, Haltiwanger, and Scarpetta, 2013; Asker et al., 2014). Others focus on financial frictions that make constrained firms choose a suboptimal level of capital stock. However, a counter-argument lies in the dynamic process when firms self-finance and gradually grow out of constraints, which implies a small misallocation in the steady state. This self-financing does not undo misallocation if (1) productivity is less persistent (Caselli and Gennaioli, 2013; Moll, 2014); (2) firms cannot save (Amaral and Quintin, 2010); (3) transition dynamics start from a pre-misallocated economy (Buera and Shin, 2013); (4) entrepreneurs slowly accumulate wealth before paying entry costs (Midrigan and Xu, 2014); and (5) the borrowing constraint is endogenous, and size-dependent (Bai et al., 2018; Gopinath, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez, 2107). This paper adds a new angle to the discussion and finds that the self-financing channel slows down when there are recurrent financing needs for intermediate goods, and hence a larger misallocation.

This paper also contributes to the work that links intermediate goods to TFP. Works include an input-output amplifier of distortions via intermediate goods (Jones, 2011; Bartelme and Gorodnichenko, 2015), working capital constraints on intermediate goods and TFP in crisis of emerging economies (Mendoza and Yue, 2012; Pratap and Urrutia, 2012), and legal enforcement frictions on intermediate goods (Boehm and Oberfield, 2018). This paper complements with these studies by applying working capital constraints of intermediate goods onto discussions of misallocation.

The rest of this paper is structured as follows. Section 2 illustrates distortions of intermediate goods allocation in the AIES data. Section 3 presents the model. Section 4 calibrates the model, computes the misallocation in the model and in the data, and implements decomposition exercises of misallocation contributed by each friction. Section 5 concludes.

2 Intermediate Goods Misallocation in Data

This section describes China's NBS firm-level data first. I then document intermediate goods misallocation with a magnitude as sizable as capital misallocation. Lastly, inspired by the working capital literature, I find suggestive evidence of pre-pay friction and borrowing constraints on intermediate goods.

2.1 Data

This paper is based on China Above-scale Industrial Enterprise Survey (AIES) collected by National Bureau of Statistics from 1998 to 2007. The dataset has been extensively used in the literature, such as Hsieh and Klenow (2009), Brandt et al. (2012) and Bai et al. (2018) among many others. Observations in AIES are firms with unique registration identities at State Administration for Industry and Commerce of China. The dataset combines annual firm-level balance sheets, income and cash flow statements for all state-owned manufacturing firms, and private-owned ones with sales above 5 million yuan before 2007.[6] During this period, number of manufacturing firms in the dataset increased from 147,690 in 1998 to 304,599 in 2007.

Variables of interest include gross output, book value of capital, employment, wage bill, intermediate goods cost, opening years, inventory, account receivables, interest expenses, total liability, ownership and industries. Industries in this dataset are classified according to 1994 version of 4-digit China Industrial Classification (CIC) codes before 2002, and 2003 version of CIC codes since 2003. Concordances and all the following analysis are done under broader industries of 2-digits. Nominal values of output and inputs are deflated to constant 1998 yuan at industry-level. The original data are cross-sectional for every year, and I match firms over years to construct a 10-year unbalanced panel to understand firm dynamics.[7] Codes of matching firm across time and industry-level deflators are borrowed from Brandt et al. (2012).

On average, 80% of intermediate goods used by Chinese firms are materials and intermediate input, and 20% electricity and fuel (World Bank Enterprise Survey, 2012). They take a 74% revenue share of aggregate gross output for all firms in China, regardless of ownerships. Most industries have the share within the 0.6-0.8 interval . This number is slightly higher than 68% in Jones (2011) that uses input-output table for the entire economy, and higher than the average 50% share for OECD countries.

2.2 Misallocation of Intermediate Goods

This subsection presents evidence of misallocation of intermediate goods in China's AIES data. I first lay out the conceptual framework of misallocation in spirit of Hsieh and Klenow (2009), and secondly introduce its measurement in firm-level data.

Conceptual Framework Consider a standard monopolistic competition economy. Aggregate out-

[6] In 2007, the threshold of 5 million yuan sales became a requirement for state-owned firms to enter AIES. In 2011, the threshold increased to 20 million yuan, for both state-owned and private-owned firms.

[7] See Data Appendix for details about how I match firms over years.

put Y is produced as a Cobb-Douglas production function of industry-level output

$$Y = \Pi_{s=1}^{S} Y_s^{\theta_s} \tag{1}$$

where θ_s represents expenditure shares of output from each industry s, and $\sum_{s=1}^{S} \theta_s = 1$. Aggregate output are consumed for household consumption C and used for intermediate input in further productions M, i.e. $Y = C + M$.

Output in industry s, Y_s, is produced under monopolistic competition with elasticity of substitution σ

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

Firm i in industry s produces gross output quantity

$$Y_{is} = exp(\tilde{z}_{is}) K_{is}^{\tilde{\alpha}_k^s} L_{is}^{\tilde{\alpha}_l^s} M_{is}^{1-\tilde{\alpha}_k^s-\tilde{\alpha}_l^s} \tag{3}$$

and revenue

$$\begin{aligned} P_{is} Y_{is} &= P_s Y_s^{-\frac{1}{\sigma}} exp(\tilde{z}_{is})^{\frac{\sigma-1}{\sigma}} K_{is}^{\alpha_k^s} L_{is}^{\alpha_l^s} M_{is}^{\alpha_m^s} \\ &= exp(z_{is}) K_{is}^{\alpha_k^s} L_{is}^{\alpha_l^s} M_{is}^{\alpha_m^s} \end{aligned} \tag{4}$$

where $\tilde{z}_{is}$ is log quantity productivity, z_{is} is log revenue productivity, K_{is}, L_{is}, M_{is} are firm-level capital, labor and intermediate goods input. Note industry-specific revenue shares of each input $\alpha_k^s = \tilde{\alpha}_k^s \frac{\sigma-1}{\sigma}$, $\alpha_l^s = \tilde{\alpha}_l^s \frac{\sigma-1}{\sigma}$, and $\alpha_m^s = (1 - \tilde{\alpha}_k^s - \tilde{\alpha}_l^s) \frac{\sigma-1}{\sigma}$.

Firms face distortions in product market $\tau_{y,is}$, intermediate goods market $\tau_{m,is}$, labor market $\tau_{l,is}$ and capital market $\tau_{k,is}$. First order conditions imply

$$MRPK_{is} := \alpha_k^s \frac{P_{is} Y_{is}}{K_{is}} = \frac{1 + \tau_{k,is}}{1 - \tau_{y,is}} R \tag{5}$$

$$MRPL_{is} := \quad \alpha_l^s \frac{P_{is} Y_{is}}{L_{is}} = \frac{1 + \tau_{l,is}}{1 - \tau_{y,is}} w \tag{6}$$

$$MRPM_{is} := \quad (1 - \alpha_k^s - \alpha_l^s) \frac{P_{is} Y_{is}}{M_{is}} = \frac{1 + \tau_{m,is}}{1 - \tau_{y,is}} P \tag{7}$$

where P_{is} is firm i's output price in industry s, and w and R are labor and capital rental prices. Intermediate goods price is P, which is also the price for aggregate output.

Note that firm-level $TFPR_{is}$ and $TFPQ_{is}$ are

$$TFPR_{is} = log(P_{is} Y_{is}) - \tilde{\alpha}_l^s log(L_{is}) - \tilde{\alpha}_k^s log(K_{is}) - (1 - \tilde{\alpha}_k^s - \tilde{\alpha}_l^s) log(M_{is}) \tag{8}$$

$$TFPQ_{is} = log(Y_{is}) - \tilde{\alpha}_l^s log(L_{is}) - \tilde{\alpha}_k^s log(K_{is}) - (1 - \tilde{\alpha}_k^s - \tilde{\alpha}_l^s) log(M_{is}) \tag{9}$$

respectively. Also note that $TFPR_{is}$ could be written as

$$TFPR_{is} = (\frac{MRPM_{is}}{1 - \tilde{\alpha}_k^s - \tilde{\alpha}_l^s})^{(1-\tilde{\alpha}_k^s-\tilde{\alpha}_l^s)} (\frac{MRPK_{is}}{\tilde{\alpha}_k^s})^{\tilde{\alpha}_k^s} (\frac{MRPL_{is}}{\tilde{\alpha}_l^s})^{\tilde{\alpha}_l^s} \tag{10}$$

Misallocation Measure Following the literature, I quantify misallocation through dispersions of marginal revenue products of each input, as well as the potential gross output gain by reallocating each input. The latter one-input-reallocation exercise is designed to distinguish the contribution of misallocation for each input, and consequently highlights the importance of intermediate goods.

To compute $TFPR_{is}$ and $TFPQ_{is}$, I use sales for $P_{is}Y_{is}$, wage payment for effective units of labor L_{is}, capital stock for K_{is}, and intermediate input for M_{is}. Each variable is in real 1998 yuan. As in most firm-level datasets, AIES does not report price and quantity of output and inputs. Thus, the following calculations relies on the Cobb-Douglas assumption of firm-level production function and a second assumption that firms within industries face the same intermediate goods price.

My benchmark procedure trims the top and the bottom 1% of $TFPR$ and $TFPQ$ distributions across industries for each year.[8] I set α_m^s and α_l^s as the median intermediate goods and labor shares within 2-digit industries in the AIES data. Capital shares are set as 0.85 minus the sum of intermediate goods and labor shares, implying an elasticity of substitution $\sigma = 6.67$.[9]

Figure 1 plots dispersions of marginal revenue products for intermediate goods, capital and labor across firms across industries in pooled 1998-2007 data. One can see substantial dispersion of $MRPM_{is}$ in panel (a), although it is smaller than those of capital and labor in panel (b) and (c). Such a dispersion is not driven by existence of state-owned firms. One drawback of measuring $MRPM_{is}$ by equation (7) is, however, its inability to distinguish intermediate goods distortions $\tau_{m,is}$ separately from output distortions $\tau_{y,is}$.[10] To check how severe the problem is, I compare the relative dispersion of marginal revenue products of intermediates to labor, $\frac{MRPM_{is}}{MRPL_{is}}$, to the relative dispersion of marginal revenue products of capital to labor, $\frac{MRPK_{is}}{MRPL_{is}}$. The relative marginal product measures cancel out $\tau_{y,is}$ in numerator and denominator. Panel (d) of Figure 1 shows that the two relative marginal products, $\frac{MRPM_{is}}{MRPL_{is}}$ and $\frac{MRPK_{is}}{MRPL_{is}}$, show a similar dispersion. If product market distortions were the main cause of dispersion in $MPRM_{is}$, one should expect a much smaller dispersion in $\frac{MRPM_{is}}{MRPL_{is}}$. However, this is not the case in data.

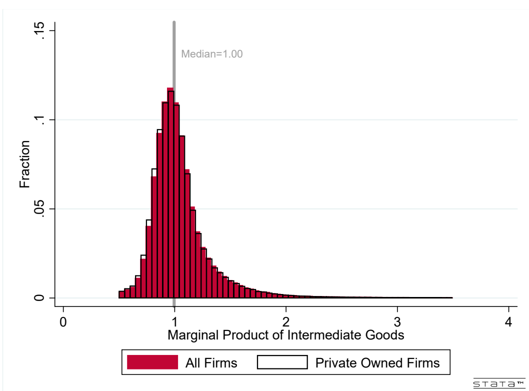
[8]An early circulated version of this paper only trims the TFPQ distribution, and hence has larger misallocation.

[9]The return-to-scale parameter is thus 0.85 in the revenue production function, consistent with later calibration results.

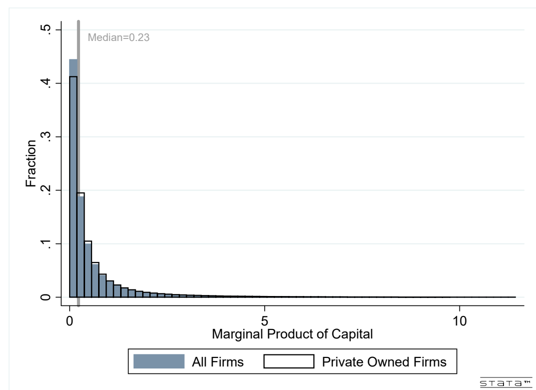
[10]For example, studies such as De Loecker and Warzynski (2012) and many following papers estimate firm-level product markups from first order conditions with respect to intermediate goods, which essentially considers dispersions in panel (a) of Figure 1 as dispersions of firm-level markups $\tau_{y,is}$.

Figure 1: Marginal Products Histograms, 1998-2007 Pooled

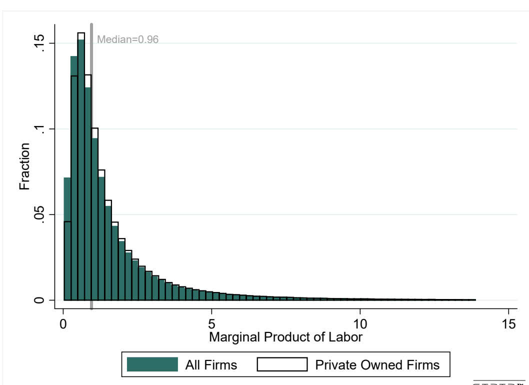
(a) Intermediate goods



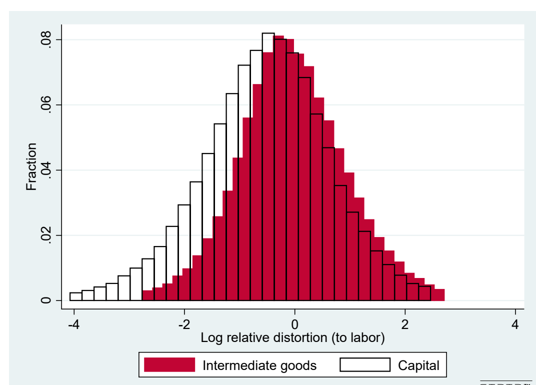
(b) Capital



(c) Labor



(d) Intermediate goods relative to capital



Given dispersions of marginal products, I quantify intermediate goods misallocation by potential output gains if it is removed. In particular, I reallocate one input at a time to equalize its marginal products across firms within 2-digit industries, holding the other two inputs as observed in the data.[11] Table 1 shows that there could be 2.57% to 6.88% of gross output gains for reallocating each input alone. Because of its largest revenue share, reallocating intermediate goods result in 4.98% gross output gain on average, similar to a gain of 4.26% from capital reallocation. In value added terms, reallocating either intermediate goods and capital increases industry-level value added by about 21.61% and 17.88% for an average 2-digit industry. The magnitudes for intermediate goods are about twice of the output gains when I reallocate labor alone.

Table 1: Output Gains by Reallocating One Input, Benchmark

	Gross Output Gains			Value Added Gains		
Year	Intermediates	Capital	Labor	Intermediates	Capital	Labor
1998	5.41%	4.48%	2.75%	25.60%	21.21%	13.04%
1999	4.36%	4.38%	2.72%	19.86%	19.95%	12.38%
2000	4.31%	4.24%	2.75%	18.27%	17.98%	11.65%
2001	3.65%	4.24%	2.67%	15.81%	18.40%	11.58%
2002	3.82%	4.30%	2.66%	17.12%	19.30%	11.92%
2003	3.68%	4.14%	2.68%	15.39%	17.33%	11.22%
2004	5.67%	4.25%	2.60%	23.01%	17.27%	10.56%
2005	5.50%	4.06%	2.57%	21.36%	15.77%	9.97%
2006	6.48%	4.22%	2.73%	24.19%	15.75%	10.17%
2007	6.88%	4.29%	2.79%	25.46%	15.86%	10.34%
Average	4.98%	4.26%	2.69%	20.61%	17.88%	11.28%

Notes: Top and bottom 1% of $TFPR$ and $TFPQ$ are trimmed across industries for each year. Reallocation gains are at 2-digit industry levels, weighted by industry-level gross output shares.

I use several alternative procedures to test the robustness of results above. Procedure *Private* keeps only privately owned firms for each year. Procedure *Trim2.5* trims the top and the bottom 2.5% of $TFPR$ and $TFPQ$ distributions. Procedure $U.S.shares$ use industry-level intermediate goods and labor share computed from NBER-CES productivity database.

[11] See Appendix for mathematical details on one-input reallocation.

The procedure *GE* warrants more discussions. Conceptually it takes the general equilibrium effect of reallocation in intermediate goods into account. The idea is that when inefficiency in intermediates allocation is eliminated, gross outputs for all industries increase, which would increase the supply of industrial products and consequently intermediate goods supply. The result is a lower intermediates price, and more equilibrium usage of intermediates in production. I approach this idea by setting the revenue shares of intermediate goods *before* and *after* reallocation unchanged at industry level, implied by the Cobb-Douglas production function.[12] Numerically, this is to find an industry-specific multiplier $\lambda_s > 1$ such that reallocation of λ_s-fold of industry-level intermediate goods result in an unchanged intermediate goods revenue share for each industry.

Lastly, the procedure *Example Industries* check if the unobserved heterogeneity in composition, quantity and price of intermediate goods accounts for the misallocation entirely. I focus on several industries that feature (1) arguably Leontif production with a technological recipe of intermediate inputs; (2) homogeneous manufacturing process across firms; (3) competitive and standard upstream input, not relation-specific (Rauch, 1999; Boehm and Oberfield, 2018). These industries are ice making (industry code 1495), cement (industry code 3111), and flat glasses (industry code 3141). [13]

Table 2 presents gross output and value added gains under alternative samples and parametrizations, averaged over 1998-2007. A few messages arise here. First, misallocation in each input does not change much when the sample include private firms alone. Therefore, ownership differences is unlikely to account for the large part of misallocation.

Second, intermediate goods misallocation drops if I trim the top and the bottom 2.5% of TFPR and TFPQ distributions, or decrease intermediate goods revenue share in procedure *US shares*. If the upward bias of intermediate goods share in China is a concern, the *US Shares* procedure gives a lower bound of intermediate goods misallocation, which is 2.68% in gross output and 10.94% in value added. However, a high intermediate goods share is not unique to China, as Korea and Japan have similar shares when they were world manufacturing factories (Jones, 2011). Hence, if there were any frictions on intermediate goods, these numbers would be the most conservative

[12] A more rigorous investigation requires a general equilibrium framework that considers the structure on input-output (Jones, 2011), as well as households labor and saving decisions that shall affect aggregate labor and capital. This investigation is beyond the scope of this paper and left for future research.

[13] For the flat-glass industry, 63% production lines in China are made by float method according to an industrial report by Tianfeng Securities in 2018. In the data, the production method is revealed in its product names of ”flat glass”, ”flat glass by float method”, and ”flat glass by vertical drawing method”. I restrict my subsample to those who report flat glass by float method.

Table 2: Output Gains by Reallocating One Input, 1998-2007 Average, Robustness

	Gross Output Gains			Value Added Gains		
Procedure	Intermediates	Capital	Labor	Intermediates	Capital	Labor
Private	4.20%	3.49%	2.42%	17.35%	14.63%	10.06%
4-digit Industry	4.50%	3.67%	2.35%	18.64%	15.40%	9.84%
Trim 2.5	3.74%	3.81%	2.57%	16.02%	16.54%	11.14%
US Shares	2.68%	9.22%	7.88%	10.94%	37.91%	32.30%
GE	4.98%	4.26%	2.69%	20.61%	17.88%	11.28%
Example Industries:						
1.Ice Making (before 2002)	29.58%	9.67%	5.22%	106.66%	34.77%	19.81%
2.Cement	2.32%	5.46%	2.12%	7.60%	17.50%	6.13%
3.Float Glass	3.28%	1.92%	1.17%	17.87%	10.97%	6.26%

estimates of intermediate goods misallocation .

Third, when I include general equilibrium effect, potential gross output and value added gains keep unchanged surprisingly. As total intermediate goods increase, efficient fraction of intermediate goods used by each firm depends on z_{is}, K_{is} and L_{is} and hence are the same as in partial equilibrium framework, although efficient levels increase by λ times. Therefore, magnitudes of $MRPK_{is}$ and $MRPL_{is}$ relative to their industrial means do not change. In other words, dispersions of $TFPR_{is}$ do not change and consequently misallocation measures stay the same.

Fourth, in cement and float glass industries, there are a similar level of intermediate goods misallocation, compared to an average 2-digit industry. In ice making industry, the misallocation is even larger in both gross output and value added terms.

To summarize, I find the existence of intermediate goods misallocation that is comparable to the magnitude of widely-studied capital misallocation. The misallocation is unlikely to be attributed to (1) existence of inefficient state-owned firms in China; (2) output market distortion; (3) biased estimates of intermediate goods revenue share in China; (4) unobserved heterogeneity in intermediate goods composition, quantity and price.

2.3 Intermediate Goods Frictions

The goal of this subsection is to provide two potential explanations of the intermediate goods misallocation in data: pre-pay and borrowing constraints.

Pre-pay for Intermediate Goods By focusing on value added output, existing literature of misallocation essentially models intermediate goods as statically chosen after the realizations of firm-level productivity *and* at the same time when sales revenue are received. In reality, however, production takes time from purchasing intermediate goods to production, and from sales of products to collection of cash from account receivables. For example, Chinese firms in WBES 2012 report that they buy most important material at least 36 days before production. Another example is based on a survey on CFOs of large public America firms, which claims that "days on sales outstanding" averaged about 39.7 days in 2006 and increased in 2008 economic downturn (*Economist*).

An ideal measure of pre-pay is to directly ask firm owners how long the time window is. But it is also a common practice to quantify the time-length using firms' operating cycle in the trade credit and working capital management literature (e.g. Jose et al., 1996; Petersen and Rajan, 1997). The definition is

$$OC_{is} := DI_{is} + DR_{is} \tag{11}$$

$$:= \frac{\text{Inventory}_{is}}{\text{Sales}_{is}} \times 365 + \frac{\text{Account Receivables}_{is}}{\text{Sales}_{is}} \times 365 \tag{12}$$

where DI_{is} and DR_{is} are Days on Inventory and Days on Receivable for firm i in industry s, standardized into numbers of calendar days. Inventory$_{is}$, Account Receivables$_{is}$ and Sales$_{is}$ are from the AIES data. According to World Bank Enterprise Survey China data (2012), materials, semi-finished products and finished products each take up a third of the inventory value. Thus, operating cycles roughly counts number of days it takes for firms to receive sales revenues starting from the time firms purchase intermediate goods.

Table 3 reports the mean and the median of OC_{is}, DI_{is} and DR_{is} for Chinese firms over 1998-2007. For each year, I calculate the mean and the median of the three measures across firms and industries. Numbers reported in Table 3 are averages of means and medians across years, respectively. An average firm in China pays intermediate goods 161 days before receiving sales revenue. Time-length from intermediates purchases to sale of products is on average 86 days, and it takes another 75 days until sales revenue are received. A median firm has a shorter operating cycle of 108 days, with DI and DR again taking half-half of the cycle.

Operating cycle are influenced by several factors. For instance, state-owned firms have a longer operating cycle, 40 days more on average, perhaps due to loose management by the lack of profit-maximizing motives. Further, average operating cycle declines over years universally across industries in China, possibly due to improvements of transportation infrastructures and management practices over time (Li and Li, 2013; Gao, 2017).[14] While these are interesting for further

[14]Most declines of operating cycles come from shortening days on inventory. See Table A2-A4 in Appendix for more

Table 3: Operating Cycle, Days on Inventory and Days on Receivable

	OC	*DI*	*DR*
Mean	161.20	86.39	74.81
Median	107.89	46.94	42.92

Notes: Numbers are average over 1998-2007 across firms.

investigation, my model in this paper takes the operating cycle exogenous to understand its first-order effect.

Financial Frictions on Intermediate Goods With uncertainty in productivity shocks and the pre-pay, intermediate goods levels could be suboptimal if firms are financially constrained. This is similar to the classical argument that constrained firms underinvest in capital.

To empirically test this theory, I investigate whether marginal revenue products of intermediate goods are more dispersed for more financially vulnerable industries. The idea is similar to Manova (2013) that explores how financial frictions affect firm production and export in some industries more than others. Specifically, I estimate

$$\begin{aligned} disp(MRPM_{st}) = \beta_0 + \beta_1 AssetTang_s + \beta_2 ExtFin_s + \beta_3 MedAge_{st} + \beta_4 SOEShare_{st} \\ + \beta_5 ExporterShare_{st} + \delta_t + \epsilon_{st} \end{aligned} \tag{13}$$

with the main interests on coefficients β_1 and β_2. Here, industry-level measures of financial vulnerability, asset tangibility $AssetTang_s$, and external finance dependence $ExtFin_s$, are from Braun (2003) based on Compustat data 1986-1995.[15] The former measures the share of net property, plant and equipment in total book-value assets, and the latter is the share of capital expenditures not financed by cash from operations. Arguably, the U.S. based measures capture the nature of production for every industry and consequently are not reversely caused by intermediate goods usage in AIES data. $MedAge_{st}$ is the industry-level median firm ages. I also control for fractions of state owned firms, $SOEShare_{st}$ and of exporting firms, $ExporterShare_{st}$, as well as year fixed effects δ_t.

For dispersions of $MRPM$, I use four alternative measures, 95-5, 90-10, 75-25 percentile differences standardized by median and standard deviation of $MRPM_{st}$, $SD(MRPM_i^{st})$, that trims off its top and bottom 1% for each industry s each year t. I also run regressions using dispersion of marginal revenue products of capital as dependent variable for comparison.

details about time trends and industry-level trends of these measures.

[15] See Appendix for $AssetTang_s$ and $ExtFin_s$ measures for each 2-digit CIC industry.

Table 4 presents summary statistics of various $disp(MRPM_{st})$ measures across industries and time in the upper panel, and regression results in the lower panel. Several messages arise here. First, a higher intermediate goods misallocation does exist in more financially vulnerable industries with low asset tangibility and high external finance dependence. Specifically, if asset tangibility increases by 1 standard deviation across industries, i.e. 11.04%, 95-5 percentile difference of marginal revenue products decreases by 0.054, which is about 27% of its standard deviation across industries and time, 0.2019. Similarly, 90-10 difference decreases by 24%, 75-25 difference by 10% and $SD(MRPM_i^{st})$ by 22% of their corresponding standard deviations across inustry and time.[16] Meanwhile, if external finance dependence decreases by 1 standard deviation across industries, i.e. 33.18%, 95-5 percentile difference of marginal revenue products decreases by 18%, 90-10 difference by 13%, and 75-25 difference by 3% and $SD(MRPM_i^{st})$ by 12% of their standard deviations across industry and time.[17] The impacts of asset tangibility are more statistically significant.

Second, financially vulnerable industries have not only more intermediate goods misallocation, but also more capital misallocation. The effect is statistically more significant when one uses external finance dependence as vulnerable measures. The insignificance of $AssetTang$ might be explained by the dual roles of capital in borrowings. On one hand, industries with higher asset tangibility provide more collateral to lenders, which implies a negative coefficient of $AssetTang$. On the other hand, higher asset tangibilities also suggest more importance of capital in production, and thus more likely to hinder small and constrained firms. The latter channel implies a positive coefficient.

Third, consistent with existing studies, industries with more old firms, and more exporting firms have lower misallocation of capital. Their effects on intermediate goods misallocation are however not significant. Further, industries that have more SOE firms feature greater misallocation of intermediate goods and capital. Although the coefficient of $SOEShare$ in the 90-10 regression for capital is negative, the effect is not statistically significant.

To summarize, this section presents misallocation of intermediate goods in the AIES data. Removing distortions in intermediate goods alone generates sizable gross output and value added gains that are comparable with that of capital. While capital misallocation has been extensively studied, intermediate goods misallocation has been rarely investigated. This section fills up this gap by providing suggestive evidence of intermediate goods misallocation.

This section also suggests two types of distortions in intermediate goods. First, firms pre-pay

[16]Consider such a tangibility increase as shifting from industry 23 ”printing and publishing” to industry 31 ”nonmetal mineral products”. The former has 30.07% asset tangible, and the latter has 42.00%.

[17]Consider such a drop of dependence roughly shifting from industry 17 ”manufacture of textile” to industry 39 ”electronic equipment and machinery”. The former has an external dependence measure of 40.45%, while the latter has 76.75%.

intermediate goods long before production and before they receive sales revenue. This creates a working capital need and potentially causes the second friction of financial constraint. Empirical evidence indicates that misallocation of intermediates is more severe in more financial vulnerable industries, consistent with the financial friction narrative.

Table 4: Industry-Level Financial Vulnerabilities and Dispersions of Marginal Product of Intermediates

	(p95-p5)/p50		(p90-p10)/p50		(p75-p25)/p50		Standard Deviation	
	Intermediates	Capital	Intermediates	Capital	Intermediates	Capital	Intermediates	Capital
Mean	0.7218	9.2543	0.4456	5.0620	0.1972	1.8487	0.1388	1.7195
SD	0.2019	2.0894	0.1171	0.9476	0.0588	0.2552	0.0393	0.3418
				Regressions				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AssetTang	-0.4898***	-1.4567	-0.2530***	-0.2055	-0.0507*	-0.0771	-0.0778***	-0.1302
	(0.0000)	(0.2547)	(0.0000)	(0.7129)	(0.0184)	(0.6027)	(0.0000)	(0.5269)
ExtFin	0.1096***	0.7005	0.0456**	0.3687*	0.0048	0.1340**	0.0142**	0.1298*
	(0.0005)	(0.0808)	(0.0044)	(0.0358)	(0.4749)	(0.0041)	(0.0062)	(0.0448)
MedAge	0.0134	-0.3393***	0.0055	-0.1324**	-0.0006	-0.0699***	0.0018	-0.0542***
	(0.0806)	(0.0007)	(0.1641)	(0.0024)	(0.7109)	(0.0000)	(0.1579)	(0.0008)
SOEShare	0.8436***	1.0881	0.6726***	-0.5115	0.4659***	0.7391**	0.2377***	0.0498
	(0.0000)	(0.6244)	(0.0000)	(0.5987)	(0.0000)	(0.0044)	(0.0000)	(0.8894)
ExporterShare	0.0739	-2.8178*	0.0398	-1.1787*	0.0801***	0.0469	0.0267	-0.3955*
	(0.4087)	(0.0151)	(0.3842)	(0.0201)	(0.0000)	(0.7257)	(0.0735)	(0.0340)
Constant	0.3266***	13.6209***	0.0953	7.3775***	-0.0664**	2.1394***	0.0089	2.4732***
	(0.0008)	(0.0000)	(0.0529)	(0.0000)	(0.0015)	(0.0000)	(0.5772)	(0.0000)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	270	270	270	270	270	270	270	270
R-sq	0.5349	0.2775	0.6405	0.3298	0.7464	0.3523	0.6642	0.3014
adj. R-sq	0.509	0.238	0.621	0.293	0.733	0.317	0.646	0.263
p-values in parentheses								
="* p<0.05	** p<0.01	*** p<0.001"						

Notes: $(p95-p5)/p50$, $(p90-p10)/p50$ and $(p75-p25)/p50$ are 95-5, 90-10, 75-25 percentile differences of marginal revenue products of intermediate goods and capital, standardized by medians within an industry. The fourth dispersion measure, standard deviation, is computed after the trimming of top and bottom 1% of marginal revenue products within industries. Mean and SD of these dispersion measures are across industries over 1998-2007. Regression results are also across industries over 1998-2007.

3 Model

If there are borrowing constraints on both intermediate goods and capital, firms may face trade-off in investing which using limited funds, documented empirically in Fazzari and Petersen (1993). Such an interaction of frictions on different inputs could interact with each other and change magnitude of misallocation.

Therefore, this paper incorporates pre-pay and borrowing constraints on intermediate goods into a standard firm investment model of Cooper and Haltiwanger (2006), to quantify their roles in accounting for misallocation separately from capital frictions. Capital are borrowing constrained and subject to adjustment costs in the model.

The model has two types of agents: firms and financial intermediaries. Firms organize production and maximize net present value of dividends, given financial and real frictions on both intermediate goods and capital. Firms endogenously exit when its net present value of continuation is smaller than exit value. Under limited liability, default happens when the liquidation value after exit does cover debt repayment. Financial intermediaries choose a break-even interest rate that reflects this default probability. The equilibrium in loanable funds market leads to an endogenous borrowing constraint that shapes firm dynamics.

3.1 Firms

The infinite-horizon economy is populated with a mass M_t of heterogeneous firms at time t that grows over time. A firm is a decreasing-return-to-scale technology that produces gross output with inputs of intermediate goods, capital and labor, given an exogenous and stochastic productivity.[18]

Production Firm i produces gross output in a Cobb-Douglas production function

$$p_{it}y_{it} = exp(z_{it})k_{it}^{\alpha_k}l_{it}^{\alpha_l}m_{it}^{\alpha_m} \tag{14}$$

where $p_{it}y_{it}$ is gross output revenue, z_{it} is log revenue productivity, and k_{it}, l_{it}, and m_{it} are capital, labor and intermediate goods with their respective revenue shares α_k, α_l, and α_m. Decreasing return to scale arises because of monopolistic competition, i.e. $\alpha_k + \alpha_l + \alpha_m < 1$.

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

[18]From now on, firms are modeled as revenue producer in a representative industry. I will convert output gains into quantity in later model simulated data by using the same conceptual framework as in Section 2.

$\epsilon_{it+1} \sim N(0, \sigma_\epsilon^2)$:

$$\mu_{it+1} = \rho\mu_{it} + \epsilon_{it+1} \tag{15}$$

I include a permanent component since productivities in the data are more persistent than an AR(1) process.

Given productivity z_{it}, capital k_{it} and intermediate goods m_{it}, firms choose labor input l_{it} to maximize its gross output net of labor payment, π_{it}:

$$\pi_{it} = \max_{l_{it}} p_{it} y_t(z_{it}, k_{it}, m_{it}, l_{it}) - w l_{it} \tag{16}$$

where p_{it} is output price and w is wage. The separability of labor inputs from other input choices is because labor is adjustable intra period without any frictions.

Pre-pay for Intermediate Goods Firms pre-pay for intermediate goods m_{it+1} one period in advance, when choosing next period capital k_{it+1}. For m_{it+1} intermediate goods, firms pay ω fraction, ωm_{it+1} at time t, and the remaining $(1-\omega)m_{it+1}$ at time $t+1$. In this environment, firms need working capital to pay intermediate goods before sales revenue is collected. If the realization of next period productivity z_{it+1} is relatively low, the pre-paid level m_{it+1} could be too high. In this case, firms can choose $\tilde{m}_{it+1} < m_{it+1}$ to maximize profit at time $t+1$ by selling off the extra intermediate good $m_{it+1} - \tilde{m}_{it+1}$. However, if the pre-paid intermediate goods level m_{t+1} is too low to be optimal in a high productivity realization z_{it+1}, firms cannot adjust the intermediates goods beyond m_{it+1}. In other words, firms choose $\tilde{m}_{it+1} \leq m_{it+1}$ to maximize the profit Π_{it+1} after payment for intermediate goods

$$\Pi_{it+1} = \max_{\tilde{m}_{it+1} \leq m_{it+1}} \pi_{t+1}(z_{it+1}, k_{it+1}, \tilde{m}_{it+1}) - (1-\omega)m_{it+1} + (m_{it+1} - \tilde{m}_{it+1}) \tag{17}$$

Firms adjust capital stock given fixed and convex adjustment cost. If $k_{it+1} \neq k_{it}$, adjustment cost $C(k_{it}, k_{it+1}) = \xi k_{it} + \frac{\theta(k_{it} - k_{it+1})^2}{2k_{it}}$. If on the other hand, firms choose $k_{it+1} = k_{it}$, adjustment cost $C(k_{it}, k_{it+1}) = 0$.

Borrowing Constraints Firms save and borrow at financial intermediaries. The saving interest rate is $r_1 = \frac{1}{q_t^1} - 1$. When firms borrow, they issue one-period corporate bonds. As detailed later in the section of financial intermediaries, the price of corporate bonds, $q_{it}^2(z_{it}, b_{it+1}, k_{it+1}, m_{it+1})$, depends on firms' fundamentals: current productivity z_{it}, future debt b_{it+1}, future capital stock k_{it+1} and future intermediate goods m_{it+1}. The price of bonds q_{it}^2 decreases with the expected default probability, implying a higher interest rate for borrowing. In the special case with zero probability of default, debt price $q_{it}^2 = \frac{1}{1+r_2}$ where r_2 is default-free prime borrowing rate.

The default-free borrowing rate r_2 exceeds the saving rate r_1 by assuming per-dollar intermediation costs c_I. With this positive spread $r_2 - r_1$, firms never find it optimal to save and borrow simultaneously. I thus use $b_{it+1} > 0$ to represent borrowing and $b_{it+1} < 0$ to represent saving.

Since firms cannot issue new equity, dividend by the end of each period d_{it} is nonnegative after payments for next period intermediate goods ωm_{it+1}, capital investment $k_{it+1} - (1-\delta)k_{it} + C(k_{it}, k_{it+1})$, repayment of debt or saving b_{it}, new borrowings or adding savings $q_{it}(z_{it}, b_{it+1}, k_{it+1}, m_{it+1})b_{it+1}$ and operation cost c_o

$$\begin{aligned} d_{it} = \Pi_{it}(z_{it}, k_{it}, m_{it}) - (k_{it+1} - (1-\delta)k_{it}) - C(k_{it}, k_{it+1}) - \omega m_{it+1} - \\ b_{it} + q_{it}(z_{it}, b_{it+1}, k_{it+1}, m_{it+1})b_{it+1} - c_o \geq 0 \end{aligned} \tag{18}$$

Note that the above constraint is endogenous, since amount of borrowings depends on state variables of productivities, current capital stock and debt levels.

Value of Continuation For simplicity, the rest of the model is in a recursive form that abstracts away the subscript i.

At the beginning of each period, firms choose to continue operation or exit. If a firm continues, given state variables (z, b, k, m) and the bond price schedules $q'(z, b', k', m')$, firms' problem is to maximize its value of continuation

$$\begin{aligned} V^c(z, b, k, m) = \max_{b', k', m'} \Pi(z, k, m) + (1-\delta)k - \omega m' - k' - C(k, k') - b + q'(z, b', k', m')b' \\ - c_o + \beta E_{z'|z} V(z', b', k', m') \qquad (19) \\ s.t. \quad \Pi(z, k, m) + (1-\delta)k - \omega m' - k' - C(k, k') - b + q'(z, b', k', m')b' - c_o \geq 0 \\ q'b' \leq E_{z'|z} V^0(z', k') \qquad (20) \end{aligned}$$

where β is the discounting factor and cannot exceeds $\frac{1}{1+r_2}$, because otherwise firms borrow indefinitely. If $\beta < \frac{1}{1+r_2}$, firms only borrow when investment on capital and intermediate goods has a return greater than $\frac{1}{\beta} - 1$. To make sure that firms borrow whenever the return is greater than the prime borrowing rate, I set $\beta = \frac{1}{1+r_2}$.

The constraint (20) imposes a state-dependent upper limit of borrowing for $q'b'$, $E_{z'|z} V^0(z', k')$. $E_{z'|z} V^0(z', k')$ is the expected value of firms when there is only capital adjustment cost without financial frictions. The rationale is that the amount of borrowing cannot exceed the net present value of future dividends the firm creates given productivity z. This constraint stops firms from playing Ponzi-game.

Solutions to problem (19) are policy functions

$$\text{Demand of debt/saving: } b'^d = b'^d(z, b, k, m; q') \tag{21}$$

$$\text{Next period capital: } k' = k'(z, b, k, m; q') \tag{22}$$

$$\text{Next intermediate goods: } m' = m'(z, b, k, m; q') \tag{23}$$

The indicator function $\mathbb{T}(z, b, k, m; b', k', m')$ describes the transition of current state (z, b, k, m) to the choice of future state (b', k', m'), and is defined as

$$\mathbb{T}(z, b, k, m; b', k', m') = \begin{cases} 1 & \text{if (21), (22), and (23) hold for firm } (z, b, k, m) \\ 0 & \text{otherwise} \end{cases} \tag{24}$$

Exit and Default At the end of production in the current period, net worth of a firm equals cash $\Pi(z, k, m) - b\mathbb{1}(b \leq 0)$ plus depreciated capital $(1-\delta)k$ minus debt $b\mathbb{1}(b > 0)$. Once a firm decides to exit, $(1-\gamma_2)$ fraction of cash $\Pi(z, k, m) - b\mathbb{1}(b < 0)$, and $(1-\gamma_1)$ fraction of capital $(1-\delta)k$ evaporates, $\gamma_2 < \gamma_1$. In other words, exit costs some resource. Under limited liability, value of exit

$$V^x(z, b, k, m) = \max\{\gamma_2\Pi(z, k, m) - b[\mathbb{1}(b \leq 0)\gamma_2 + \mathbb{1}(b > 0)] + \gamma_1(1-\delta)k, 0\} \tag{25}$$

Endogenous exit $\chi(z, b, k, m) = 1$ happens when $V^x(z, b, k, m) > V^c(z, b, k, m)$. Therefore, the value function $V(z, b, k, m)$ prior exit is $\max\{V^x(z, b, k, m), V^c(z, b, k, m)\}$.

Default only happens when firms exit, while debts are rolled over when firms choose to continue.[19] However, firms may exit without default, if firms save $b \leq 0$, or if the liquidation value of capital and cash $\gamma_2\Pi(z, k, m) + \gamma_1(1-\delta)k$ exceeds debt repayment b. The only case when an exiting firm defaults is that the liquidation value is smaller than the debt. Loss for lenders in this case is

$$b - \gamma_2\Pi(z, k, m) - \gamma_1(1-\delta)k \tag{26}$$

3.2 Entrants and Firm Size Distribution

In each period t, there are $\mu_{ent}M_t$ mass of entrants. Each entrant draws an initial permanent productivity $\bar{z}$ from $N(0, \sigma_z^2)$ distribution, and a transitory μ_0 from $N(0, \sigma_\mu^2)$ distribution. They also draw an initial wealth $b_0 < 0$ independently from a Pareto distribution with the density

[19]See, for instance, Bai et al. (2018) for default when firms continue.

function $g(-b_0)$:

$$g(-b_0) = \begin{cases} \frac{\alpha a_{\min}^{\alpha}}{(-b_0)^{\alpha+1}} & if - b_0 \geq a_{\min}, \\ 0 & if - b_0 < a_{\min}. \end{cases} \tag{27}$$

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 goods out of scratch, according to their initial productivity $z_0 = \bar{z} + \mu_0$ and wealth b_0. In other words, firms have zero initial capital stock and intermediate goods, $k_0 = 0, m_0 = 0$. Their choices of debt or saving $b'_{ent}(z_0, -b_0, 0, 0)$, capital $k'_{ent}(z_0, -b_0, 0, 0)$, and intermediate goods $m'_{ent}(z_0, -b_0, 0, 0)$ for the first production period are given by maximizing the value function $V_{ent}(z_0, b_0, 0, 0)$

$$V_{ent}(z_0, b_0, 0, 0) = \max_{b',k',m'} -\omega m' - k' - b_0 + q'(z, b', k', m')b' - c_o + \beta E_{z'|z_0} V(z', b', k', m') \tag{28}$$

$$s.t. - \omega m' - k' - b_0 + q'(z, b', k', m')b' - c_o \geq 0 \tag{29}$$

$$q'b' \leq E_{z'|z} V^0(z', k') \tag{30}$$

where the next period z' evolves in the same AR(1) process as incumbents in Equation (15), and V is the value function of incumbents.[20] Note that there is no adjustment costs with zero initial capital stock.

As before, the indicator function $\mathbb{T}_{ent}(z, b, 0, 0; b', k', m') = 1$ if policy functions with state $(z, b, 0, 0)$ give next period choices b', k', m', and 0 otherwise. Constraint of (29) implies an initial misallocation on entrants. A high productivity entrant with a low draw of wealth find it hard to finance the first period capital stock and intermediate goods without retained earnings from past.

3.3 Financial Intermediaries

There exists a continuum of risk-neutral competitive intermediaries that take deposits and lend. In this paper, intermediaries are not restricted to financial institutions. One can view the competitive lender as a representation that includes intermediate goods suppliers and other lenders as well.

[20] Unlike most literature in entry, exit and industrial dynamics, e.g. Hopenhayn (1992), Cooley and Quadrini (2001), Bento and Restuccia (2015), this paper does not model endogenous entry. In general equilibrium, price channels affect the value of entry and pin down the equilibrium mass of entrants through equating value of entry to entry costs. Since this paper adopts a partial equilibrium framework, there are no such price channels. The approach here is to take an equilibrium mass of entrants over distributions of productivity and wealth as given, which are later parametrized to match the data.

What is implicitly assumed is that the competitive lender can see all borrowing, including trade credit in the form of account payables for example.

Thus, given a debt price function $q'(z,b',k',m')$, 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:

$$\max_{b'}(1 - E_{z'|z}\chi'(z',b',k',m'))b' + E_{z'|z}\{\chi'(z',b',k',m')(b' - \gamma_2\Pi(z',k',m') \\ - \gamma_1(1-\delta)k')\} - (1 + r_1 + c_I)q'b' \tag{31}$$

The first term here presents debt repayment b'^s with the probability that firms continue and debt is rolled over. The second term gives an expected loss when the borrower defaults.

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 $m'_{ent}(z_0,-b_0,0,0;q')$, an exit 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 distribution 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 $m'(z,b,k,m;q')$ solve the problem of firms in (19), and the exit rule $\chi(z,b,k,m)$ solves the exiting problem.

2. given the debt price function $q'(z,b',k',m')$, the supply function of funds $b^s(z,k',m';q')$ solves lenders' problem (31).

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

$$\mathbb{T}(z,b,k,m;b',k',m')b'^d(z,b,k,m;q') = b'^s(z,k',m';q') \text{ for incumbents} \tag{32}$$

and

$$\mathbb{T}_{ent}(z,b_0,0,0;b',k',m')b'^d_{ent}(z,b,0,0;q') = b'^s(z,k',m';q') \text{ for entrants} \tag{33}$$

4. distribution and mass of firms f' and M' evolve recursively as in (34) and (35), respectively, given an initial mass M_0, an initial firm distribution f_0, mass of entrants μ_{ent}, an exit rule

$\chi(z,b,k,m)$ and policy functions of incumbents and entrants:

$$f'(z',b',k',m') = \chi'(z',b',k',m')\{\int_z \int_b \int_k \int_m f(z,b,k,m)\mathbb{T}(z,b,k,m;b',k',m')\pi(z'|z)dzdbdkdm$$
$$+ \mu_{ent} \int_z \int_b \phi(z)g(-b)\mathbb{T}_{ent}(z,b,0,0;b',k',m')dzdb\} \tag{34}$$

$$M' = M(1 - \int_{z'} \int_{b'} \int_{k'} \int_{m'} \chi(z',b',k',m')f(z',b',k',m')dz'db'dk'dm' + \mu_{ent}) \tag{35}$$

with a growth rate $\mu_{ent} - \int_{z'} \int_{b'} \int_{k'} \int_{m'} \chi(z',b',k',m')f(z',b',k',m')dz'db'dk'dm'$. A stationary distribution is defined as $f'(z,b,k,m) = f(z,b,k,m)$ for any state (z,b,k,m).

4 Quantitative Analysis

I calibrate the model to AIES and simulate the model to compare measured misallocation in model and data. I then implement several counterfactual experiments to quantify misallocation caused by each friction. The benchmark model with intermediate goods frictions is shown to account for a larger percentage of misallocation in data than a model without. Section 4.1 describes how I parametrize the model. Using model simulated data, section 4.2 quantifies and compares measured misallocation in model and data. Section 4.3 decomposes misallocation generated by each friction. Section 4.4 discusses economic mechanisms through which intermediate goods frictions cause misallocation.

4.1 Parametrization

I first introduce how I map the model to data, given that AIES is a selective sample and only covers the largest 20% manufacturing firms in sales over 1998-2007. According to Economic Census 2004, average nominal sales and capital stock of Chinese manufacturing firms are 6.64 and 2.84 million yuan, far below the average, 39.63 and 16.47 million yuan, in AIES in the same year. Entry and exit in this dataset is also biased by the left-truncation of sales. Using the opening year variable, I find that more than 30% of entrants over 5-year horizons in AIES are incumbent firms. They produce less than 5 million yuan at the beginning of 5-year periods (98-03 and 02-07), and more than 5 million in five years. These firms have a non-negligible market share, close to 15% at the end year of 5-year periods.[21]

[21] See Table A3-A4 in Appendix for more details.

Given these facts, I simulate firms from model implied stationary distributions and obtain the top 20% subsample in sales, which I treat as the AIES model analog in the following analysis. Using Simulated Method of Moments (SMM), moments of productivity, size and dispersions of marginal products in the top 20% sample are matched to the data. Calibrated parameters help to generate a stationary firm size distribution in productivity, capital, intermediate goods and debt or savings. Combined with wealth and productivity distributions of entrants, one could simulate a 5-year unbalanced panel of firms that looks like AIES.

In terms of parameters, I first parametrize capital adjustment costs as in Cooper and Haltiwanger (2006) with a fixed cost parameter $\xi = 0.039$ and a convex adjustment cost parameter $\theta = 0.049$. Capital deprecation rate δ equals to 0.09. Firms' discount factor β is set to 0.94, which implies an average prime borrowing interest rate $r_2 = \frac{1}{\beta} - 1 = 0.06$ according to People's Bank of China (PBOC) annual reports over 1998-2007. Similarly, saving interest rate r_1 equals to 0.03 to match the average deposit rate in PBOC reports.

Given these assigned parameters, the remaining parameters are calibrated. In the gross output production function, the labor share α_l is set 0.05, which is the wage bill fraction of gross output revenue. The intermediate goods share α_m is set to 0.7, between the number 74% and 68% reported in Jones (2011). Since the capital share is unobservable, I 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 the manufacturing sector, which are equivalently the top 50% firms in AIES. The idea is that as η increases, gross output is more concentrated on top producers in the sales distribution. This gives $\eta = 0.85$ and consequently $\alpha_k = 0.10$.

The population exit rate differs from the exit rate in AIES, and is largely determined by the operating cost c_o. The level is set to match the population exit rate 8% during 2008-2012, according to a survival analysis report of firms by State Administration for Industry and Commerce of China. The annual growth rate in the manufacturing population during this period is approximately 9%, according to censuses 2004 and 2008. To match this growth rate, the relative mass of entrants μ_{ent} is set 17%. The threshold sale $y_c = 584.15$ such that 20% of firms are above this level in the simulated gross output distribution.

Capital and cash recovery rates, γ_1 and γ_2 are crucial to determine how binding the borrowing constraint is. I calibrate γ_2 to match the standard deviation of marginal revenue products of intermediate goods. Jointly, γ_1 is calibrated to match the correlation between debt level and capital stock. The idea is that when γ_1 increases, borrowings using capital stock as a superior form of collateral increases, and hence increases the correlation. This gives $\gamma_1 = 0.50, \gamma_2 = 0.10$. These numbers are slightly higher than average asset recovery rates of non-performing loans in the book

Capitalizing China (Fan and Morck, 2013, p. 85) that reports 30% for capital recovery rate, and 6.9% for cash.

The productivity process parameters are calibrated to match the productivity moments in the top 20% sample to those in AIES. I discretize the permanent productivity $\bar{z}_i$ into 5 grids, and the transitory productivity μ_{it} into 15 grids, using Tauchen (1986) method. The persistence of transitory productivity ρ and its standard deviation are chosen to match the one-period persistence and cross-sectional dispersion of productivities in AIES. Mean and standard deviation of permanent productivity are jointly calibrated to match average and 5-year period persistence of productivities in AIES.

Entrants draw productivities from the unconditional distribution $\phi(z)$, and wealth from the Pareto wealth distribution with a shape parameter α and a minimum wealth a_{min}. The productivity distribution of entrants is the same as that of incumbents. The shape parameter α and minimum wealth a_{min} determines the distribution of first-period output for entrants after entry. The fraction of intermediate goods paid a period ahead ω impacts how fast a firm grows after birth, and therefore the relative market share over different ages. Thus, the three parameters α, a_{min} and ω are jointly pinned down to match facts that 37.04% fraction of AIES entrants are older than 5, that 9.52% of new born firms ever year have sales greater than y_c, and that new born firms over the 5-year period are 63.01% in size relative to incumbents in sales.

Table 5 lists all calibrated parameters and their values, and Table 6 shows the differences of targeted moments in model and data. The model overall well replicates these moments in data, especially on exit rates, dispersion of marginal products in intermediate goods, productivity patterns and the 5-year period statistics. Yet there are several moments that the model hardly fit, such as correlation between debt and capital, the 5-year persistence of productivities, and fraction of growing incumbents that enter into the top 20% subsample by the end of 5-year horizons.

4.2 Misallocation: Model vs Data

This subsection computes and compares measured misallocations in model simulated firm-level data and in AIES data. I first discuss similarities of intermediate goods misallocation between model and data. I then quantify how much measured gross output and value added misallocation in AIES could be accounted by the model, when all three inputs, intermediate goods, capital and labor are reallocated.

Intermediate Goods Misallocation My calibration targets the cross-sectional dispersion of marginal revenue products of intermediate goods in AIES. Thus, it is unsurprising to see that in-

Table 5: 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	α_l	0.05
Capital Adjustment Cost			Intermediate goods share	α_m	0.70
Fixed cost	ξ	0.039	Fraction of intermediate goods in advance	ω	40%
Convex cost	θ	0.049	Threshold sales	y_c	584.15
Interest Rates			Operating cost	c_o	0.30
Saving rate	r_1	0.03	*Recovery Rates*		
Prime borrowing rate	r_2	0.06	Capital	γ_1	0.50
			Cash	γ_2	0.10
			Transitory Productivity		
			Persistence	ρ	0.80
			Standard deviation	σ_ϵ	0.18
			Permanent Productivity		
			Mean	$\mu_{\bar{z}}$	0.90
			Standard deviation	$\sigma_{\bar{z}}$	0.40
			Initial Wealth Distribution of Entrants		
			Mass of entrants	μ_{ent}	0.17
			Pareto Shape	α	50.00
			Minimum Wealth	a_{min}	8.00

Table 6: Targeted Moments

Moments	Data	Model
All Firms		
Market share by firms of top 10% sales	84.50%	87.50%
Exit rate	8.00%	8.38%
Frac. of firms above threshold	20.00%	20.00%
Above threshold sales		
SD $MRPM$	0.2720	0.2653
Corr(debt, capital)	0.7834	0.4764
Corr(productivity, productivity lag 1)	0.6086	0.6620
Corr(productivity, productivity lag 5)	0.3898	0.1984
Average productivity	1.9770	1.9680
SD productivity	0.4253	0.3625
5-year unbalanced & Above threshold sales		
Fraction of new born firms above threshold	6.99%	5.56%
Fraction of end year entrants: incumbents	37.04%	56.03%
Relative size of new born firms	63.01%	73.80%

Notes: Correlation between debt and capital is only for firms that borrow.

termediate goods misallocation in model is quantitatively close to misallocation in AIES in Table 7.

Specifically, recall the exercise in Table 1 of Section 2.2 that reallocates intermediate goods alone to compute gross output and value added gains, holding capital and labor fixed. The same exercise in the model simulated data (top 20% firms) gives an gross output gain of 5.37%, and an value added gain of 13.97%. These are about the same magnitude of intermediate goods misallocation in AIES. Table 7 further suggests that there is perhaps more intermediate goods misallocation in China's manufacturing sector than the magnitude quantified in AIES. Compared to the top 20% subsample, gross output and value added gains for all firms increase by 2.19% and 0.84% additionally, when marginal revenue products of intermediate goods are equalized.

Firms with $MRPM_i$ greater than 1 in the model either have a unexpected high productivity because of pre-pay, or are financially constrained and under-invest in intermediate goods. In the latter case, if the model captures the data well, one would expect that firms with $MRPM_i > 1$ in

Table 7: Output Gains by Reallocation of Intermediate Goods Alone, Simulated and Actual

	Gross Output	Value Added
AIES	4.98%	20.61%
Top 20%, simulated	5.37%	13.97%
All, simulated	6.21%	16.16%

Table 8: Average Productivity, Capital and Interest Rates, Constrained and Unconstrained

	AIES		Top 20%, Simulated		All, Simulated	
	Constrained	Unconstrained	Constrained	Unconstrained	Constrained	Unconstrained
Log TFPQ	2.14	1.89	1.89	1.58	1.15	1.21
Capital Stock	23,153.83	24,373.31	1720.03	2715.37	308.05	1187.64
Interest Rate	6.43%	4.02%	6.20%	6.19%	267.66%	8.94%

Notes: Constrained firms have $MRPM_i > 1$, and unconstrained ones have $MRPM_i \leq 1$. Statistics in AIES are calculated first for each year, and average over 1998-2007. Capital stock in AIES are in thousand yuan.

model and data are similar. Table 8 thus compares capital stocks, productivities and interest rates for firms with $MPRM_{it} > 1$ (constrained) and $MRPM_{it} \leq 1$ (unconstrained), in model and data. To remove the impact of state-owned firms, I restrict to the private-owned sector in AIES. And to meaningfully discuss financial constraints, I restrict my model simulated data to the subsample of firms with debt, excluding firms that save.

The model resembles AIES in several aspects. Constrained firms, on average, have higher productivity $TFPQ$, lower capital stock, and pay higher interest rates than unconstrained firms both in AIES data and in model simulated top 20% subsample. For $TFPQ$, constrained firms are 25% and 31% more productive than unconstrained firms in data and model, respectively. The model delivers this phenomenon of size-dependent distortions because of a higher demand in intermediate goods for more productive yet financially constrained firms. Firms who are below the cutoff are less productive, and might be constrained exactly because their inability to generate cash flows from production. Hence, for the entire simulated sample, constrained firms are actually 6% less productive than unconstrained ones. But this does not revoke size-dependent distortions. Correlation between marginal revenue products of intermediate goods and productivity is 0.02 in the whole sample, although much smaller than 0.58 in top 20% subsample.

For capital stock, constrained firms are 5% and 36% smaller than unconstrained firms in AIES

Table 9: Measured Gross Output and Value Added Misallocation, Data vs Model

	AIES	Top 20%, Simulated	All, Simulated
Gross output	21.64%	21.84%	23.06%
Value added	89.86%	58.87%	62.17%

Notes: Numbers from AIES are averaged over 1998-2007.

data and in the top 20% subsample, respectively.[22] Accordingly, constrained firms pay interests rates 2.41% and 0.01% higher in AIES and in top 20% subsample. The phenomenon of lower capital and higher interest rates are more pronounced in the entire sample.

Reallocation Gains of All Inputs Given the above results of intermediate goods misallocation, the next question is how much the model could account for measured gross output and value added misallocation in AIES.

I quantify gross output misallocation by the percentage of total gross output gain when capital, labor and intermediate goods are reallocated to equalize their marginal products across firms, holding the total amount of capital, labor and intermediate goods constant. Value added misallocation is quantified by the percentage of value added gain in the above process. In AIES, the reallocation is done within 2-digit industries as in Section 2.2.

Table 9 suggests that the model well accounts for measured misallocation in data. In AIES, gross output for an average 2-digit industry increases by 21.64%, and value added by 89.86% if there were no dispersions of marginal revenue products for all inputs. These numbers in the model simulated top 20% subsample are 26.65% and 60.29%. Thus, the model accounts for about 100% gross output misallocation, and 65% of value added misallocation in data. The difference between these two percentages are that I impose 0.7 to be the undistorted intermediate goods revenue share, and constrained firms use intermediate goods with an actual share smaller than 0.7. In the data, there are firms with distorted intermediate goods revenue share both above and below 0.7.

Table 9 also suggests that quantifying misallocation in AIES gives a downward bias of the amount of misallocation for China's manufacturing sector. In the model, if firms below and above cutoff sales are both included, gross output and value added would increase by 23.06%

[22] In the AIES data, the relative magnitude of capital stock for constrained firms vary over years. In 2007, constrained firms are 23% smaller compared to unconstrained ones. In 1998, the result is flipped and constrained firms are 9% larger.

and 62.17%, respectively, after reallocation of all three inputs. Such a fact is sensible since firms below cutoff sales are more financially constrained, as illustrated by their lower capital stock and higher interest rates in Table 8. In fact, standard deviation of $MRPM_i$ for all firms is 1.9819, much higher than the calibration target 0.2953 among top 20% firms.

To summarize, this section compares misallocation measures in model and data. Results show that the model well captures intermediate goods misallocation quantitatively, the phenomenon of size-dependent distortions on intermediate goods, and the overall misallocation compared to output levels when dispersions in marginal revenue products of capital, labor and intermediate goods are eliminated.

4.3 Decomposing Misallocation

There are four frictions in the benchmark model: borrowing constraints on capital and intermediate goods, pre-pay on intermediate goods and capital adjustment costs. How much does each friction account for the measured misallocation? More importantly, do frictions on intermediate goods help to account for more misallocation, on top of a standard investment model with capital frictions? To answer these questions, I implement several counterfactual experiments that remove subsets of frictions.

The left panel of Table 10 illustrates what frictions are removed for each experiment. Experiment 1 removes borrowing constraints on intermediate goods. Experiment 3 removes borrowing constraints on capital and Experiment 4 removes capital adjustment costs. Since I embed borrowing constraints on intermediate goods through pre-pay, it is infeasible to remove pre-pay friction alone. Experiment 2 then removes borrowing constraints and pre-pay on intermediate goods. Experiment 5 removes borrowing constraints and adjustment costs on capital. Experiment 6 removes all frictions, and is left with only time-to-build friction on capital. Thus, comparing amount of misallocation in each experiment to the benchmark model gives the magnitude of misallocation caused by the removed friction(s).

Because of the partial equilibrium framework, levels of output, intermediate goods, capital, and labor are not comparable across experiments. Thus instead, I quantify gross output and value added misallocation by computing reallocation gains among simulated firms, which are re-generated using calibrated parameters for each experiment. The idea is to see how much static misallocation there would be if firms lived in the counterfactual economy hypothetically.

Table 10 presents the misallocation results on its right panel. Note that across experiments, total intermediate goods usage as shares of total gross output varies. In Experiment 2 and 6 without intermediate goods frictions, the share is the model-specified 70%. But when there are intermediate goods frictions in the Benchmark model and Experiment 3 to 5, the share drops to an distorted level less than 70%. Such a difference matters for value added misallocation since it equals to $1/(1 - \text{Actual Intermediate Goods Revenue Share})$ times gross output misallocation. Therefore, when I isolate misallocation caused by certain frictions, I discuss the distorted α_m case and undistorted α_m case. One can think the former as purely static misallocation, and the latter that adds extra gains by increasing total intermediate goods to an undistorted level as 70% of gross output revenue.

I start discussions of misallocation generated by certain friction(s) in the subsample of top 20% firms. Comparison between Benchmark and Experiment 6 implies that one-period time-to-build on capital combined with stochastic productivities drives the most of gross output, about 60%, and value added misallocation, about 74% in the Benchmark model. These numbers are unexpectedly high given the rich specification of frictions, but generally consistent with findings in Asker et al. (2014) that the dynamic nature of capital, rather than levels of adjustment costs, account for cross-country differences in firm-level $TFPR$ dispersions. [23]

If I compute the misallocation caused by each friction, Table 11 suggests that a similar level of importance for borrowing constraints on intermediate goods compared to borrowing constraints on capital. Differencing Benchmark and Experiment 1 implies that an additional 5.12% potential gross output gain when borrowing constraints on intermediate goods exist. The corresponding additional value added gains with undistorted α_m is 17.08%. These numbers are 4.89%, and 16.29% for borrowing constraints on capital. When I use the actual distorted α_m, value added misallocation generated by borrowing constraints on intermediate goods drops to 5.84%, because intermediate goods revenue share increase from 63% in Benchmark to 68% in Experiment 1. The value added misallocation by borrowing constraints on capital using distorted α_m does not drop much, because there are both intermediate goods frictions with an distorted α_m 64% in Experiment 3, close to that in Benchmark.

When I group frictions by the input they affect, Table 11 suggests that frictions on each input generate about a similar magnitude of misallocation compared to borrowing constraints on that input. If I further focus on all simulated firms instead, the magnitude of misallocation for gross output and value added from four frictions are larger in row (1) of Table 11. Qualitatively and

[23] In a related paper David and Venkateswaran (2019), firms receive a noisy signal of productivity shocks for next period, and are hence partially informed of next period productivity, in addition to the information of current z_{it}. Firms make capital investment according to the signal. Because of this semi-static nature of capital, their estimate of misallocation induced by pre-determined capital is smaller than this paper.

quantitatively, the importance of borrowing constraints on intermediate goods and capital still hold among all simulated firms.

Results above are different from several existing studies. First, Table 11 implies that the importance of financial frictions could be quantitatively doubled in accounting for misallocation in firm-level data. Thus, the conflict between the persistent misallocation in developing economies and the argument that self-finance could undo misallocation could be alleviated when intermediate goods are included.[24] Second, note my estimate of value added misallocation caused by borrowing constraints on capital is greater than studies like Midrigan and Xu (2014). In those papers, borrowing for capital happens after the realization of current period productivities. Here, I model time-to-build on capital and hence borrowing for investment happens before productivities realize. The latter creates uncertainties and hence lowers level of debt intermediaries are willing to lend in the setup of endogenous borrowing constraints.

To conclude this section, the decomposition exercise first finds that time-to-build on capital contributes the most to gross output and value added misallocations. Second, financial frictions on intermediate goods generate an amount of misallocation that is comparable to financial frictions on capital.

Table 10: Simulated Gains by Equalizing Marginal Products, Benchmark and Counterfactuals

	B.C. on M	Pre-pay on M	B.C. on K	Adj. Cost on K	Gains, Top 20% Gross Output	Gains, Top 20% Value Added	Gains, All Gross Output	Gains, All Value Added
Data					21.64%	89.86%	-	-
Model								
Benchmark					21.84%	58.87%	23.06%	62.17%
Exp 1	×				16.72%	53.03%	17.06%	54.15%
Exp 2	×	×			16.47%	54.88%	16.47%	54.88%
Exp 3			×		16.95%	46.68%	18.45%	50.86%
Exp 4				×	20.83%	57.15%	22.73%	62.38%
Exp 5			×	×	17.31%	47.48%	18.48%	50.75%
Exp 6	×	×	×	×	13.11%	43.69%	13.25%	44.18%

Notes: B.C. on M means borrowing constraints on intermediate goods. B.C. on K means borrowing constraints on capital. Pre-pay on M means pre-pay friction on intermediate goods. Adj. costs on K means capital adjustment costs. Cross in each cell of the left panel specifies which friction is removed from the Benchmark model.

[24]See Moll (2014) for discussions on the self-finance argument.

Table 11: Contribution of Each Friction to Misallocation

	Gains, Top 20%			Gains, All		
	Gross Output	Value Added (Undistorted α_m)	Value Added (Distorted α_m)	Gross Output	Value added (Undistorted α_m)	Value added (Distorted α_m)
All Frictions (1)	8.73%	29.11%	15.18%	9.81%	32.70%	17.99%
Single Friction						
B.C. on M (2)	5.12%	17.08%	5.84%	6.00%	20.01%	8.02%
B.C. on K (3)	4.89%	16.29%	12.19%	4.61%	15.37%	11.31%
Adj. Cost on K (4)	1.01%	3.38%	1.72%	0.33%	1.11%	-0.22%
By input						
Intermediate Goods Frictions (5)	5.38%	17.92%	3.98%	6.60%	21.99%	7.28%
Capital Frictions (6)	4.53%	15.11%	11.39%	4.58%	15.27%	11.42%

Notes: B.C. on M means borrowing constraints on intermediate goods. B.C. on K means borrowing constraints on capital. Adj. costs on K means capital adjustment costs. Undistorted α_m means that aggregate intermediate goods as percentage of aggregate gross output is undistorted by frictions and 70%. Distorted α_m takes the actual aggregate intermediate goods revenue share in the simulated data.

4.4 Discussions

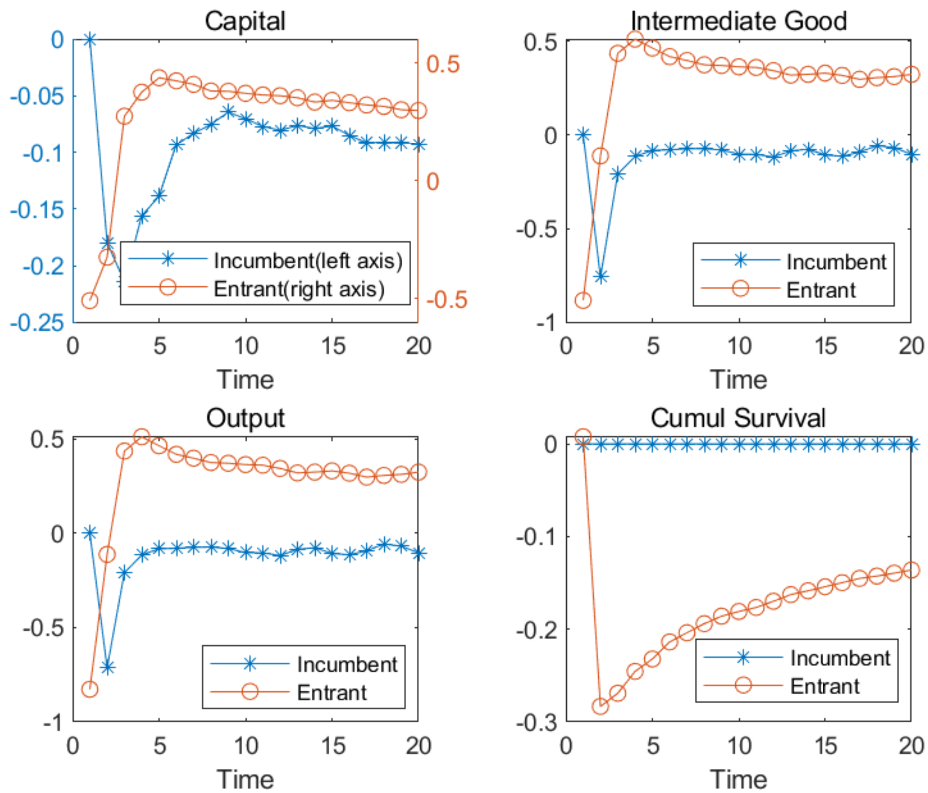
This subsection discusses economic mechanisms in the benchmark model, and how I map the current framework to the conventional framework of misallocation as in Hsieh and Klenow (2009). My exposition focuses on three aspects. First, I show how firms' state variables change over time when a group of hypothetical firms living in a model with capital frictions alone are suddenly imposed of extra intermediates frictions.

Second, I discuss the implications of endogenous borrowing constraints. I show that the model induced borrowing limits in Benchmark model and Experiment 2 negatively correlate with firm-level productivities, and endogenously create an extra margin of size-dependent distortions. The negative correlation is stronger for young and more productive firms.

Lastly, I connect the misallocation measures presented above to the ones from value added approach. I show that the latter substantially overstates misallocation. Thus, having intermediate goods in production function and acknowledging its potential distortions are crucial to properly quantify misallocation.

Role of Intermediate Goods Frictions I discuss role of intermediate goods frictions for incumbents and entrants separately. The experiment is as follows. I first sample incumbents from the

Figure 2: Firms' Response of One-period Intermediate Goods Frictions



stationary distribution in Experiment 2 at $t = 1$, and entrants from the joint distribution of initial productivity and wealth at $t = 0$.

In the next step, two versions of the experiment are implemented. In the first version, incumbents and entrants are unexpectedly imposed of intermediate goods frictions for one period at $t = 1$. Starting from $t = 2$, intermediate goods frictions are then removed unexpectedly. The purpose of this experiment is to highlight how one-period intermediate goods frictions have long-lasting effects on firms. In the second version, both incumbents and entrants are unexpectedly imposed of intermediate goods frictions starting from $t = 1$ permanently. This version shows how the per-period intermediate goods frictions could reinforce intertemporally, and slower down firms' growth.

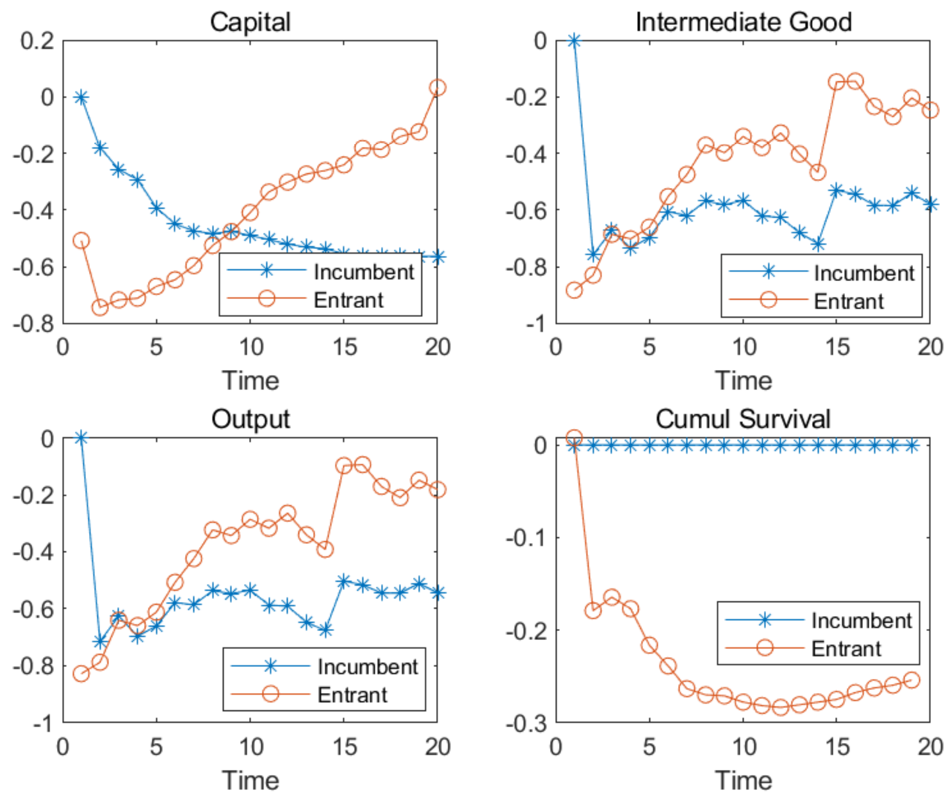
Figure 2 plots firms average capital, intermediate goods usage, output and cumulative survival after one-period intermediate goods frictions shock for 20 periods. I compare these levels to the same set of firms that live in Experiment 2. For incumbents, extra financing for intermediate goods induce a lower capital investment. Thus, at $t = 2$, capital, intermediate goods and output are around 18%, 75% and 71% lower, respectively, than firms in Experiment 2. Firms do not exit more because of the shock of intermediate goods frictions. When intermediate goods frictions are removed from $t = 2$, firms choose the static optimal level of intermediate goods to maximize per-period profit starting from $t = 3$. Firms hence recover gradually in capital due to adjustment costs and financial constraints. Overall, the negative effects of one-period intermediate good frictions on capital, intermediate goods and output are persistent, and steadily 10% lower than in Experiment 2 starting from $t = 3$.

Entrants are slightly different. Note that I impose intermediate goods frictions after they draw initial productivities and wealth and during their decision-making for first period production. At $t = 1$ when they start to produce, capital is about 50% lower, while intermediate goods and output are more than 80% lower compared to the same set of entrants in Experiment 2. Firms borrow more and average borrowings increase from 128 to 376 by almost 3 times. As a result, exit increases at $t = 2$ and the difference of cumulative survival is a negative 28% compared to Experiment 2, which gradually shrinks after removal of intermediate goods frictions. Such a strong cleansing makes the remaining firms selectively productive. Hence, levels of capital, intermediate goods and output exceed those in Experiment 2.

In the second version of the experiment, firms are imposed of intermediate goods frictions starting from $t = 0$ permanently. Figure 3 plots average capital, intermediate goods usage, output and cumulative survival for 20 periods in this version. Compared to the earlier case, incumbent firms are even smaller, and converge to an average size that is about 60% smaller of firms in Experiment 2 in terms of capital, intermediate goods usage and output. Capital stock of entrants grow at a much slower rate, and gradually converge to entrants in Experiment 2 at $t = 20$. Because of intermediate goods frictions, intermediate goods and output for entrants are steadily below Experiment 2. Similar to Figure 2, exit rates are higher for entrants but not for incumbents. These results suggest that per period intermediate goods frictions reinforce its negative effect in Figure 2 intertemporally, and hence induce greater misallocation in the Benchmark model.

Endogenous Borrowing Constraint This paper differentiates from the rest of literature in modeling borrowing constraints endogenously. In papers of Midrigan and Xu (2014), Moll (2014) and others, borrowing constraint is modeled as a limit no more than a constant fraction of capital, regardless of firms' state variables such as productivity and capital stock. The fraction generally reflects the friction of debt enforcement problem, and is small when enforcement is weak. Here I show that an endogenous borrowing constraint dependent on state variables in this paper deliv-

Figure 3: Firms' Response of Permanent Intermediate Goods Frictions



ers borrowing limits that are more negatively correlated with productivities, especially for young firms.

I illustrate my statement in two versions of my model, Benchmark and Experiment 2. Note that debt is used to finance both capital and intermediate goods in the former case, and capital alone in the latter case. Hence, similar to the idea of exogenous borrowing constraint, a model induced firm-level debt limit in the Benchmark model Δ_0 and in Experiment 2 Δ_2 could be defined as

$$\Delta_0 = \frac{\text{Debt}}{\text{Capital} + \text{Intermediate Goods}} \tag{36}$$

and

$$\Delta_2 = \frac{\text{Debt}}{\text{Capital}} \tag{37}$$

for firms that are constrained with interest rates greater than the prime rate.[25]

Table 12: Endogenous Borrowing Limits Δ in Benchmark Model and Experiment 2

	Benchmark	Experiment 2
Mean	0.33	0.82
Corr(Δ, log TFPQ)	-0.2550	-0.0643

Notes: Mean of Δ and correlation between borrowing limits and log $TFPQ$ are among firms that borrow and pay interest rates more than the prime rate in both models.

Table 12 suggests that borrowing limit is 33% of the sum of capital and intermediate goods in Benchmark model, and 82% of capital in Experiment 2. If one replaces the endogenous borrowing constraint by an exogenous 33% or 82%, borrowing limits are independent with firms' productivities and hence correlations between Δ and log $TFPQ$ would be zero. This is not the case in Table 12 when constraints are endogenous. Correlation coefficients of -0.2550 and -0.0643 suggest that productive and constrained firms have a lower borrowing limit as a fraction of production inputs they intend to finance for.

The left panel of Figure 4 further illustrates that this negative correlation is more pronounced for young firms in the Benchmark model. In Experiment 2, there is also some tendency that young firms have a more negative correlation with exceptions on age smaller than 2. This pattern however does not suggest that young firms have a relatively low borrowing limit in the Benchmark

[25] Constrained firms could pay a prime interest rate or more when borrowing constraints binds. It is thus sufficient to derive Δs among firms that pay more interest rates than the prime rate.

Figure 4: Correlation between Borrowing Limits and Productivity, and Average Limits, over Ages

Notes: Age 15 collapses all firms more than 15 years old.

model. In fact, because of a low initial capital stock and hence a high demand for financing, borrowing limits for young firms are highest and gradually decline over time as they increase in size. Therefore, the negative correlation comes from the fact that some productive firms have a low draw of initial wealth, and hence a low borrowing limit. Vice versa. Without needs for financing intermediate goods, the monotonic decline of borrowing limits is not there in Experiment 2.

Comparison with Value Added Approach Note that value added misallocation here is defined as percentage of total value added gains when all inputs are reallocated. In their seminal paper, Hsieh and Klenow (2009) uses a value added production function with capital and labor inputs, and quantify potential value added gains if there are no dispersions in marginal revenue products of the two. A natural question is that how does value added misallocation under the gross output approach, compared to that in Hsieh and Klenow (2009)?

To answer the question, I first replicate their results step-by-step using $\sigma = 3$, cost shares of capital and labor as 0.5, and the same trimming procedure. Value added misallocation over 1998-2007 under this approach is 93.79%, i.e. GDP would increase 93.79% if marginal revenue products of capital and labor were equalized. This number is about the same as theirs. Since I use $\sigma = 6.67$ in this paper, I then vary σ from 3 to 7 with cost shares of capital and labor unchanged. Figure 5 shows that amount of misallocation in data increases dramatically and is very sensitive to σ. When $\sigma = 7$, value added misallocation triples to a extremely high level of 317.71%. The monotonic increase is due to an increasing loss caused by input misallocation when products by different firms become more substitutable with each other. However, if I further plot value added misallocation under gross output approach, the levels of value added misallocation declines substantially. Value added misallocation is only 43% when $\sigma = 3$ and increases to 98% when $\sigma = 7$ in the data. Figure 5 also plots value added misallocation in the Benchmark model using the two approaches with different σs. One can see that value added misallocation of the two approaches in model closely tracks those in AIES. These results suggest that the conventional value added approach could potentially overstate the amount of misallocation in firm-level datasets.

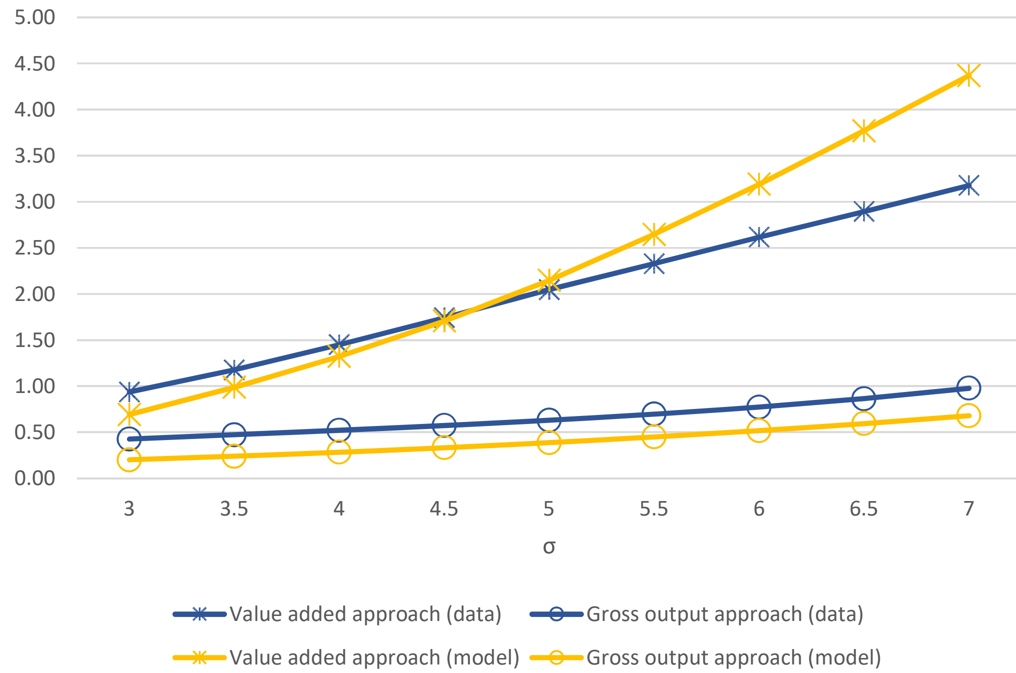
The reason why value added approach overstates misallocation lies in intermediate goods frictions. When intermediate goods are efficiently allocated, $TFPR_i$ dispersion under the value added approach equals to that in the gross output approach. But when there are intermediate goods frictions, the dispersions of $TFPR_i$ exceeds those under the gross output approach. The exact same distortion biased $TFPR_i$ and $TFPQ_i$ in the same direction, and hence induces the fact that more "productive firms" have higher $TFPR_i$.[26] For example, using $\sigma = 6.67$, value added TFP measure correlates with value added $TFPR$ with a coefficient of 0.9789 in AIES 1998, much higher than those under the gross output approach 0.7745. In the same year, the coefficient of variance in value added $TFPR$ is 3.43, about 6 times that of gross added $TFPR$.

Combined with early results, intermediate goods play two seemingly opposite yet consistent roles in understanding misallocation. First, intermediate goods frictions distorts firm-level $TFPQ$ and increases dispersions of $TFPR$ under the value added approach. By acknowledging intermediate goods frictions and using gross output approach, the magnitude of misallocation in data decreases, not increases. Second, a model with intermediate goods frictions, particularly borrowing constraints on intermediate goods, helps us to account more of misallocation in the data, once we use the gross output approach to quantify misallocation.

To summarize, this section dissects economic mechanisms on intermediate goods frictions that are accountable for a larger misallocation in Section 4.3. This section also discusses how misallocation using gross output approach could be mapped back to misallocation measures in conventional

[26] More rigorously, the equivalence of gross output approach and value added approach is only true when product markets are perfectly competitive, i.e. $\sigma = \infty$, and when there are no intermediate goods frictions. See Appendix for mathematical details on how value added gains under value added approach could be mapped to the gains using gross output approach.

Figure 5: Value Added Misallocation by Two Approaches, Model (Benchmark) and Data



value added approach.

5 Conclusion

Most of the existing literature on misallocation study distortions in firm-level capital and labor input. This paper introduces intermediate goods frictions, and builds a quantitative model to evaluate their relative importance in accounting for misallocation in China's NBS firm-level data.

I first empirically quantify the magnitude of intermediate goods misallocation, using a Cobb-Douglas gross output production function. For an average 2-digit industry in China, if marginal revenue products of intermediate goods were equalized, gross output and value added would increase by a similar magnitude compared to equalizing marginal revenue products of capital. To account for the misallocation, I find evidence in support of pre-pay friction, and borrowing constraint on intermediate goods.

I then build a model that incorporates borrowing constraints and pre-pay on intermediate goods, as well as borrowing constraints on capital, into a standard firm investment model Cooper and Haltiwanger (2006) . When calibrated to key moments in China, reallocation exercises in model simulated firm-level data suggest that the model well captures intermediate goods misallocation, and the overall gross output and value added gains if marginal revenue products of capital, labor and intermediate goods were all equalized.

Further counterfactuals indicate that borrowing constraints on intermediate goods and capital contribute about half-half of the difference in misallocation between the Benchmark model and the model left with only one-period time-to-build on capital. The reason why borrowing constraint on intermediate goods matter lies in its high cost share and recurrent financing needs every period. Therefore, adding intermediate goods frictions into the misallocation discussion could help to account for more of the quantified misallocation in data, and consequently to understand the TFP differences across countries.

There are a few directions for future work. First, the idea that firms may be borrowing constrained in intermediate goods could be applied to study misallocation in other developing countries and also countercyclical misallocation in developed economies (Kehrig, 2015). Second, this paper takes the partial equilibrium framework to understand the first-order effect of intermediate goods frictions. One could close the economy using the input-output structure across industries. In principle, because of the intermediate goods frictions, output prices of financially vulnerable industries increase and hence reduces intermediate goods usage in downstream industries. How would this inter-sector linkage amplify output losses, following the idea of Jones (2011)? What are the relative magnitudes of direct output loss as in this paper, and indirect output loss caused by the linkage? These important questions are aligned with the general research agenda to understand interconnectedness of an economy, and how distortions and negative shocks affect its GDP and welfare (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012; Bartelme and Gorodnichenko, 2015).

References

Acemoglu, Daron, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2012), "The network origins of aggregate fluctuations." *Econometrica*, 80, 1977–2016.

Amaral, Pedro S. and Erwan Quintin (2010), "Limited Enforcement, Financial Intermediation and Economic Development: A Quantitative Assessment." *International Economic Review*, 51(3), 785–811.

Asker, John, Allan Collard-Wexler, and Jan De Loecker (2014), "Dynamic Inputs and Resource (Mis)Allocation." *Journal of Political Economy*, 122(5), 1013–1063.

Bai, Yan, Dan Lu, and Xu Tian (2018), "Do financial frictions explain chinese firms saving and misallocation?" Technical report, National Bureau of Economic Research.

Bartelme, Dominick and Yuriy Gorodnichenko (2015), "Linkages and economic development." Working Paper 21251, National Bureau of Economic Research.

Bartlesman, Eric, John Haltiwanger, and Stefano Scarpetta (2013), "Cross-Country Differences in Productivity: The Role of Allocation and Selection." *American Economic Review*, 103(1), 305–334.

Bento, Pedro and Diego Restuccia (2015), "Misallocation, Establishment Size, and Productivity." *2015 Meeting Papers. No. 1391, Society for Economic Dynamics*.

Boehm, Johannes and Ezra Oberfield (2018), "Misallocation in the Market for Inputs: Enforcement and the Organization of Production." *NBER Working Paper*.

Brandt, Loren, Gueorgui Kambourov, Kjetil Storesletten, et al. (2018), "Barriers to entry and regional economic growth in china." Technical report.

Brandt, Loren, Trevor Tombe, and Xiaodong Zhu (2013), "Factor Market Distortions across Time, Space and Sectors in China." *Review of Economic Dynamics*, 16, 39 – 58.

Brandt, Loren, Johannes Van Biesebrock, and Zhang (2014), "Challenges of Working with the Chinese NBS Firm-level data." *China Economic Review*, 30, 339–352.

Brandt, Loren, Johannes Van Biesebroeck, and Yifan Zhang (2012), "Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing." *Journal of Development Economics*, 97, 339–351.

Braun, Matias (2003), "Financial Contractibility and Asset Hardness." *University of California-Los Angeles mimeo*.

Buera, Francisco and Yongseko Shin (2013), "Financial Frictions and the Persistence of History: A Quantitative Exploration." *Journal of Political Economy*, 121(2), 221–272.

Buera, Francisco J., Joseph P. Kaboski, and Yongseok Shin (2015), "Entrepreneurship and Financial Frictions: A Macrodevelopment Perspective." *Annual Review of Economics*, 7, 409–436.

Caselli, Francesco and Nicola Gennaioli (2013), "Dynastic Management." *Economic Inquiry*, 51, 971–996.

Cooley, Thomas F. and Vincenzo Quadrini (2001), "Financial Markets and Firm Dynamics." *American Economic Review*, 91(5), 1286 – 1310.

Cooper, Russell W. and John C. Haltiwanger (2006), "On the Nature of Captial Adjustment Costs." *Review of Economic Studies*, 73, 611–633.

David, Joel M., Hugo A. Hopenhayn, and Venky Venkateswaran (2016), "Information, Misallocation, and Aggregate Productivity." *Quarterly Journal of Economics*, 131, 943–1005.

David, Joel M. and Venky Venkateswaran (2019), "Capital Misallocation: Frictions or Distortions?" *NBER Working Paper*.

De Loecker, Jan and Frederic Warzynski (2012), "Markups and Firm-Level Export Status." *American Economic Review*, 102(6), 2437–2471.

Fan, Joseph P.H. and Randall Morck (2013), *Capitalising China*. The University of Chicago Press.

Fazzari, Steven M. and Bruce C. Petersen (1993), "Working Capital and Fixed Investment: New Evidence on Financing Constraints." *The RAND Journal of Economics*, 24, 328–342.

Gao, Xiaodan (2017), "Corporate cash hoarding: The role of just-in-time adoption." *Management Science*, 64, 4858–4876.

Ghate, Chetan and Kenneth Kletzer (2012), *Financial Frictions and Monetary Policy Transmission in India*. Oxford University Press.

Gopinath, Gita, Şebnem Kalemli-Özcan, Loukas Karabarbounis, and Carolina Villegas-Sanchez (2107), "Capital Allocation and Productivity in South Europe." *The Quarterly Journal of Economics*, 132(4), 1915–1967.

Guner, Nezih, Gustavo Ventura, and Yi Xu (2008), "Macroeconomic Implications of Size-Dependent Policies." *Review of Economic Dynamics*, 11, 721–744.

Haltiwanger, John, Robert Kulick, and Chad Syverson (2018), "Misallocation measures: The distortion that ate the residual." Technical report, National Bureau of Economic Research.

Hopenhayn, Hugo A. (1992), "Entry, Exit, and firm Dynamics in Long Run Equilibrium." *Econometrica*, 60(5), 1127–1150.

Hopenhayn, Hugo A. (2014), "Firms, Misallocation, and Aggregate Productivity: A Review." *Annual Review of Economics*, 6, 735–770.

Hsieh, Chang-Tai and Peter J. Klenow (2009), "Misallocation and Manufacturing TFP in China and India." *The Quarterly Journal of Economics*, 124 (4), 1403–1448.

Jones, Charles I. (2011), "Intermediate Goods and Weak Links in the Theory of Economic Development." *American Economic Journal: Macroeconomics*, 3(2), 1–28.

Jose, Manuel L., Carol Lancaster, and Jerry L. Stevens (1996), "Corporate Returns and Cash Conversion Cycles." *Journal of Economics and Finance*, 20(1), 33–46.

Kehrig, Matthias (2015), "The cyclical nature of the productivity distribution." *Working Paper*.

Li, Han and Zhigang Li (2013), "Road Investments and Inventory Reduction: Firm Level Evidence from China." *Journal of Urban Economics*, 76, 43–52.

Manova, Kalina (2013), "Credit Constraints, Hetereogenous Firms, and International Trade." *Review of Economic Studies*, 80, 711–744.

Mendoza, Enrique G. and Vivian Z. Yue (2012), "A General Equilibrium Model of Sovereign Default and Business Cycles." *The Quarterly Journal of Economics*, 127, 889–946.

Midrigan, Virgiliu and Daniel Yi Xu (2014), "Finance and Misallocation: Evidence from Plant-Level Data." *American Economic Review*, 104(2), 422–458.

Moll, Benjamin (2014), "Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation." *American Economic Review*, 104(10), 3186–3221.

Peters, Michael (2013), "Heterogeneous mark-ups, growth and endogenous misallocation."

Petersen, Mitchell A. and Raghuram G. Rajan (1997), "Trade Credit: Theories and Evidence." *Review of Financial Studies*, 10, 661–691.

Pratap, Sangeeta and Carlos Urrutia (2012), "Financial Frictions and Total Factor Productivity: Accounting for the Real Effects of Financial Crises ." *Review of Economic Dynamics*, 15, 336 – 358.

Rauch, James E. (1999), "Networks versus markets in international trade." *Journal of International Economics*, 48(1), 7–35.

Restuccia, Diego and Richard Rogerson (2008), "Policy Distortions and Aggregate Productivity with Heterogeneous Establishments." *Review of Economic Dynamics*, 11(4), 707–720.

Restuccia, Diego and Richard Rogerson (2013), "Misallocation and Productivity." *Review of Economic Dynamics*, 16, 1–10.

Tauchen, George (1986), "Finite State Markov-Chain Approximations to Univariate and Vector Autoregressions." *Economics Letters*, 20, 177 – 181.

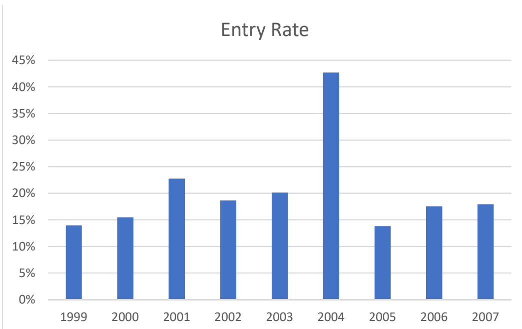
Tombe, Trevor and Xiaodong Zhu (2019), "Trade, migration, and productivity: A quantitative analysis of china." *American Economic Review*, 109, 1843–72.

Uras, Burak R. and Ping Wang (2018), "Production Flexibility, Misallocation and Total Factor Productivity." *NBER Working Paper NO. 23970*.

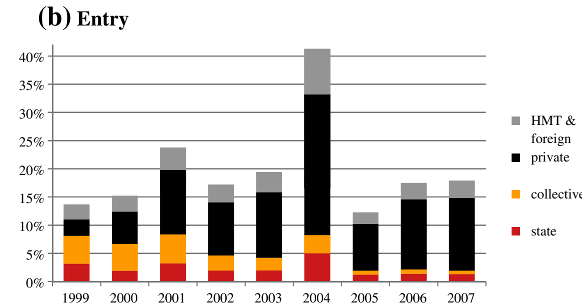
Ziebarth, Nicolas L. (2013), "Are China and India Backward? Evidence from the 19th Century U.S. Census of Manufactures." *Review of Economic Dynamics*, 16, 86 – 99.

Figure A1: Entry and Exit Rates in AIES Data, Compared to Brandt et al. (2014)

(a) Entry: This Paper

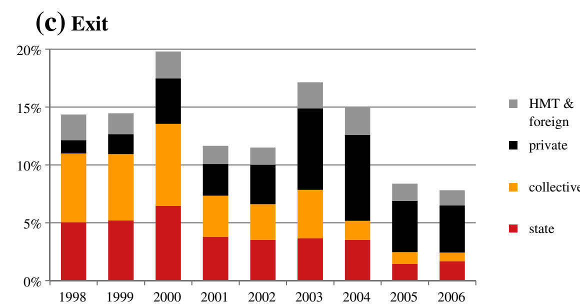


(b) Entry: Brandt et al. (2012)



(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.

Appendix

Matching Firms across Years AIES datasets are cross-sectional, and need matching over time for understanding firm dynamics. I match firms across years based on codes in Brandt et al. (2012) with some modifications. Firms are matched step-by-step according to 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 combined founding 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 entry and exit in AIES data are not equivalent to those in the model. In addition, I use the same perpetual inventory method from their paper to construct firm-level real capital stock over time.

One-Input Reallocation This appendix introduces how Section 2.2 calculates gross output and value added gains by reallocating one input at a time. To simplify the notation, I use A_{is} to represent $exp(z_{is})$ in the paper. Note industry-level industry average level $T\bar{FPR}_s$

$$T\bar{FPR}_s = \frac{P_s Y_s}{K_s^{\tilde{\alpha}_k^s} L_s^{\tilde{\alpha}_l^s} M_s^{\tilde{\alpha}_m^s}} = \frac{\sum_{i=1}^{N_s} P_{is} Y_{is}}{K_s^{\tilde{\alpha}_k^s} L_s^{\tilde{\alpha}_l^s} M_s^{\tilde{\alpha}_m^s}} \tag{38}$$

and hence industry-level productivity

$$\begin{aligned} TFP_s = & \frac{Y_s}{K_s^{\tilde{\alpha}_k^s} L_s^{\tilde{\alpha}_l^s} M_s^{\tilde{\alpha}_m^s}} = T\bar{FPR}_s / P_s \\ = & T\bar{FPR}_s \left(\sum_{i=1}^{N_s} \left(\frac{A_{is}}{TFPR_{is}}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \\ = & \left(\sum_{i=1}^{N_s} \left(A_{is} \frac{T\bar{FPR}_s}{TFPR_{is}}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \\ = & \left(\sum_{i=1}^{N_s} \left(A_{is} \frac{M\bar{RPK}_s^{\tilde{\alpha}_k^s} M\bar{RPM}_s^{\tilde{\alpha}_m^s} M\bar{RPL}_s^{\tilde{\alpha}_l^s}}{MRPK_{is}^{\tilde{\alpha}_k^s} MRPM_{is}^{\tilde{\alpha}_m^s} MRPL_{is}^{\tilde{\alpha}_l^s}}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \end{aligned} \tag{39}$$

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 (39), industry TFP_s in the data could be computed with a multiplier $(P_s^{\sigma} Y_s)^{-\frac{1}{\sigma-1}}$.

If only intermediate goods is reallocated to equalize its marginal revenue products within industries, $M\bar{RPM}_s = MRPM_{is}$ holds after reallocation. The reallocation change firm-level gross output revenue

$$R'_{is} = (P_{is} Y_{is})' = A_{is} K_{is}^{\tilde{\alpha}_k^s} L_{is}^{\tilde{\alpha}_l^s} M_{is}^{\prime \tilde{\alpha}_m^s} (Y'_s P_s^{\prime\sigma})^{\frac{1}{\sigma}} \tag{40}$$

where R'_{is} or $(P_{is} Y_{is})'$, M'_{is}, Y'_s, and P'_s denote revenue, intermediate goods, industry output quantity, industry-level price after 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 $(Y'_s P_s^{\prime\sigma})^{\frac{1}{\sigma}}$ in equation (39) after reallocation. The new industry TFP_s is

$$TFP'_s = \left(\sum_{i=1}^{N_s} \left(A_{is} \frac{M\bar{RPK}_s^{\prime \tilde{\alpha}_k^s} M\bar{RPL}_s^{\prime \tilde{\alpha}_l^s}}{MRPK_{is}^{\prime \tilde{\alpha}_k^s} MRPL_{is}^{\prime \tilde{\alpha}_l^s}}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \tag{41}$$

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

$$TFP'_s / TFP_s - 1 \tag{42}$$

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

$$\sum_{s=1}^{S} \theta_s TFP_s' / TFP_s - 1 \tag{43}$$

Gross output gains from reallocating capital or labor are computed similarly.

To compute value added gain, note industry-level value added VA_s

$$VA_s = Y_s - M_s \tag{44}$$

The economy wide value added gain after reallocating intermediate goods is

$$\frac{\prod_{s=1}^{S} (Y_s')^{\theta_s} - \prod_{s=1}^{S} (Y_s)^{\theta_s}}{\prod_{s=1}^{S} (Y_s)^{\theta_s} - \sum_{s=1}^{S} M_s} \tag{45}$$

The numerator is gross output gain, and the denominator is value added before reallocation. Note

$$\begin{aligned}
\frac{\prod_{s=1}^{S} Y_s^{\theta_s}}{\sum_{s=1}^{S} M_s} &= \frac{P \prod_{s=1}^{S} Y_s^{\theta_s}}{P \sum_{s=1}^{S} M_s} \\
&= \frac{\sum_{s=1}^{S} P_s Y_s}{P \sum_{s=1}^{S} M_s} \\
&= \frac{1}{\alpha_m}
\end{aligned} \tag{46}$$

The second equation holds because of zero-profit for the Cobb-Douglas aggregator, and α_m is the economy-wide intermediate goods revenue share. Therefore, the value-added gain is

$$\sum_{i=1}^{S} \frac{\theta_s}{1 - \alpha_m} (TFP_s' / TFP_s - 1) \tag{47}$$

Operating Cycles This appendix investigates how the length of operating cycle (OC), days on receivables (DR) and days on inventory (DI) vary across different ownerships, firm sizes, ages and exporter statuses.

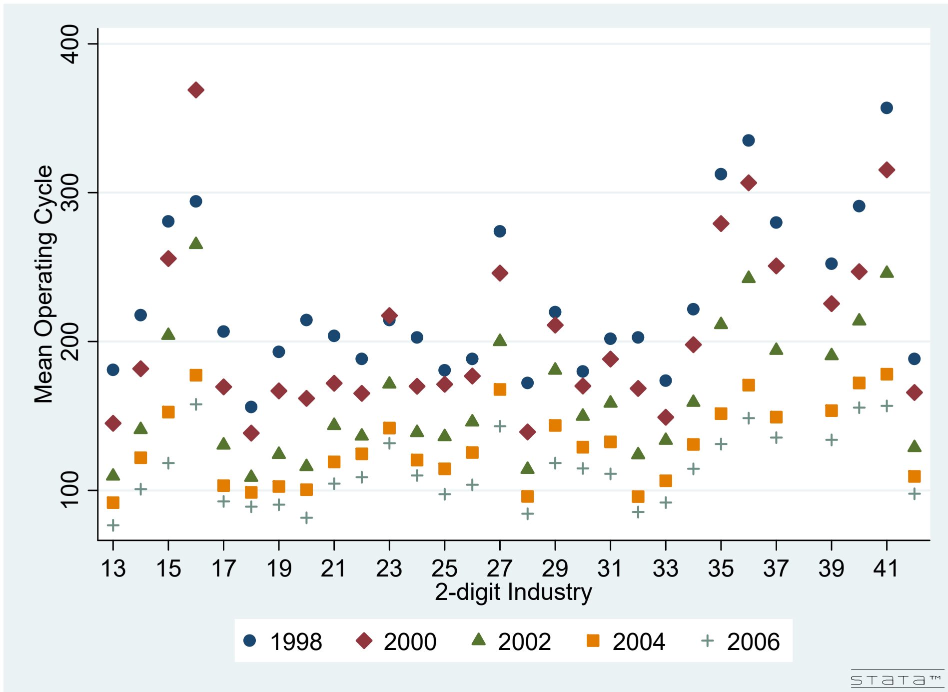
In Table A1, I first trim off the top and bottom 1% of the distribution of OC across firms every year, and calculate the average and median OC, DR, DI given a certain group. These averages and medians are then averaged over 1998-2007.

There are several observations in Table A1. First, state owned firms have a longer operating cycle, more days on inventory and receivables. Second, there is not much difference between exporters and non exporters. Third, older and larger firms have longer operating cycles.

Table A1: Average and Median OC, DI, DR across Different Groups of Firms, 1998-2007

	Mean			Median		
	OC	DI	DR	OC	DI	DR
Total	161.21	86.40	90.00	107.88	46.94	42.83
Ownership						
StateOwned	203.65	112.53	164.02	129.83	57.31	49.13
PrivateDomestic	134.29	68.91	65.41	97.18	41.21	39.41
Foreign	154.83	80.87	74.07	119.65	53.68	50.821
Exporter Status						
Exporter	165.55	88.32	98.58	108.23	45.37	42.54
NonExporter	149.49	81.01	69.00	107.31	50.78	43.34
Age						
5 years or less	128.14	66.99	62.34	89.25	38.29	35.08
5 to 10 years	151.41	77.76	75.59	105.74	43.75	44.24
10 years or more	201.83	111.52	137.29	135.05	61.52	52.73
Employment						
20 employees or fewer	185.07	95.34	117.48	99.93	36.77	42.17
20 to 100 employees	147.86	74.99	80.43	97.63	37.69	40.98
100 to 500 employees	161.77	89.27	79.76	110.55	50.62	42.37
500 to 1000 employees	183.82	104.70	80.25	126.29	63.74	47.58
1000 employees or more	190.09	108.81	256.23	134.59	71.15	49.98

Figure A2: Average Operating Cycle across 2-digit Industries over 1998-2007



There exists some variation of operating cycles across 2-digit industries. Industries with agricultural goods as the upstream industry, such as tabacco (2-digit code 16, similar henceforth), have more days. The second type of long operating cycle industries are those with potentially long value added chains, such as transportation equipment (38). There also exists a decreasing time trend in. In particular, the average OC drops from 225 days in 1998 to 105 days in 2007. This partially reflects the composition changes by a declining share of state owned firms. But the similar time trend of decreasing OC also exists within private owned firms for each industry.

Further breakdown suggests that most of the drops in OC comes from a declining inventory-sales ratio, not from a shortening period of receiving sales. While the quantitative model in this paper does not distinguish between DI and DR, one could explicitly distinguish inventory management from account receivables management, and check if an improved inventory management technology is adopted in China over this time period.

Financial Vulnerable Measures Table A2 lists asset tangibility and external finance dependence measures for 28 2-digit industries.

AIES and Census 2004 AIES data 1998-2007 have threshold sales of 5 million yuan. Table A3 de-

Figure A3: Average Days on Inventory across 2-digit Industries over 1998-2007

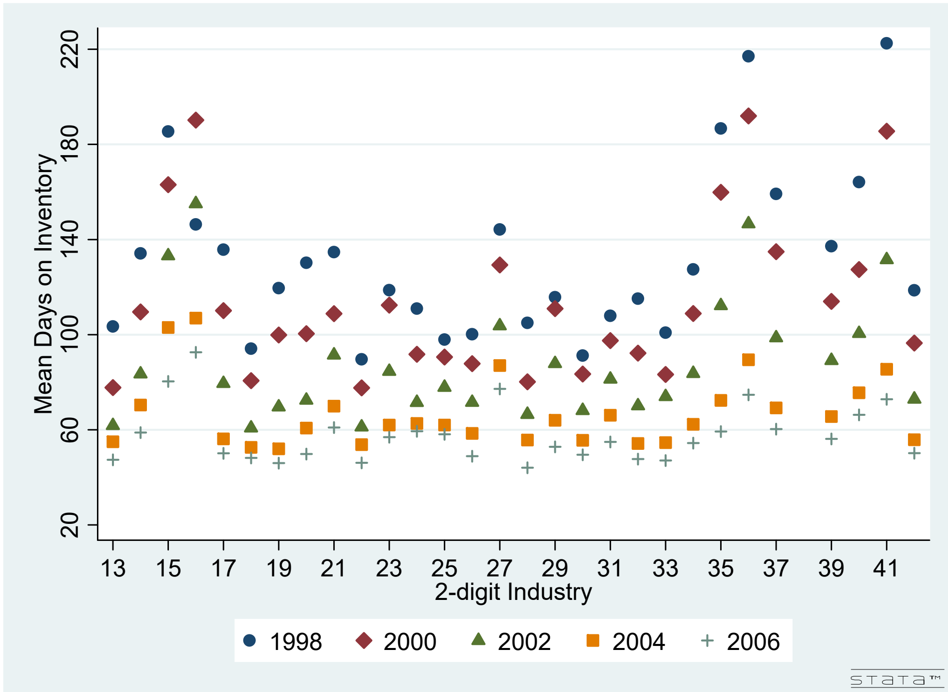


Figure A4: Average Days on Receivables across 2-digit Industries over 1998-2007

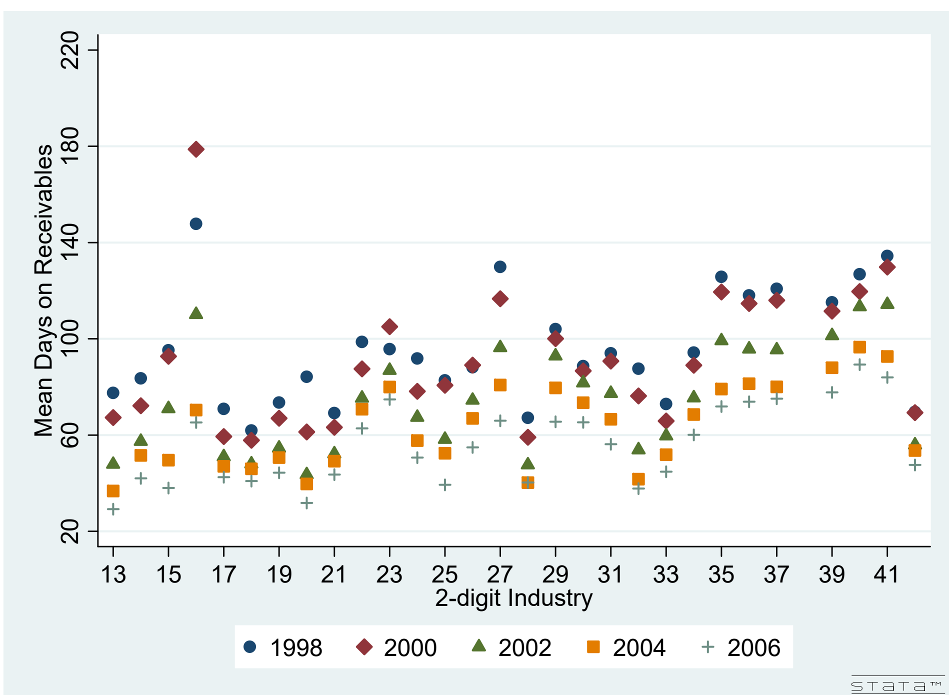


Table A2: Asset Tangibility and External Finance Dependence Measures in 2-digit CIC Industries

2-digit CIC Code	Industry Name	Asset Tangiblities	External Finance Dependence
13	Primary Food Processing	0.3777	0.1368
14	Manufacture of food	0.3777	0.1368
15	Manufacture of beverage	0.2794	0.0772
16	Manufacture of tobacco	0.2208	-0.4512
17	Manufacture of textile	0.3730	0.4005
18	Garments and products	0.1317	0.0286
19	Leather, furs and down products	0.0906	-0.1400
20	Timber processing	0.3796	0.2840
21	Manufacture of furniture	0.2630	0.2357
22	Paper making and products	0.5579	0.1756
23	Printing and publishing	0.3007	0.2038
25	Petroleum refineries	0.6708	0.0420
26	Raw chemical materials	0.4116	0.2050
27	Medical and pharmaceutical products	0.1973	0.2187
28	Chemical fiber	0.1973	0.2187
29	Rubber products	0.3790	0.2265
30	Plastic products	0.3448	1.1401
31	Nonmetal mineral products	0.4200	0.0620
32	Ferrous metals	0.4581	0.0871
33	Nonferrous metals	0.3832	0.0055
34	Metal products	0.2812	0.2371
35	Ordinary machinery	0.1825	0.4453
37	Transport equipment	0.2548	0.3069
39	Electric equipment and machinery	0.2133	0.7675
40	Electronic and telecom equipment	0.2133	0.7675
41	Professional and scientific equipment	0.1511	0.9610
42	Other manufacturing	0.1882	0.4702

Notes: Numbers are from Table I in Braun (2003).

Table A3: Output, Capital, Employment and Firm Age in AIES and Census, 2004

	AIES		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.

scribes differences between AIES data and Census in year of 2004. One can see that AIES firms are 20% of all manufacturing firms in Census. Average sales, capital and employment in AIES are almost 6 times those in Census data. Firms in Census are also on average younger. Nevertheless, AIES produce about 90% of manufacturing output and employ 70% of workers.

Table A4: Entry in AIES Dataset over 5 Years

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

Value Added Misallocation: Two Approaches This appendix shows the equivalence of value added misallocation under gross output and value added approaches when there are no distortions on intermediate goods *and* when elasticity of substitution $\sigma = \infty$. It also shows how value added approach may overstate misallocation when there are intermediate goods distortions.

Let me denote A^v_{is} and $TFPR^v_{is}$ as firm-level $TFPQ$ and $TFPR$ under the value added approach. Corresponding industry-level $TFPQ$ and $TFPR$ are $\bar{A}^v_s$ and $T\bar{F}PR^v_s$. Note

$$log(A^v_{is}) = log(\frac{P_{is}Y_{is} - PM_{is}}{P_{is}}) - \frac{\tilde{\alpha}^s_k}{1-\tilde{\alpha}^s_m}log(K_{is}) - \frac{\tilde{\alpha}^s_l}{1-\tilde{\alpha}^s_m}log(L_{is}) \tag{48}$$

$$log(TFPR^v_{is}) = log(P_{is}Y_{is} - PM_{is}) - \frac{\tilde{\alpha}^s_k}{1-\tilde{\alpha}^s_m}log(K_{is}) - \frac{\tilde{\alpha}^s_l}{1-\tilde{\alpha}^s_m}log(L_{is}) \tag{49}$$

and $\alpha^s_k + \alpha^s_l + \alpha^s_m = 1 - \frac{1}{\sigma}$, $\tilde{\alpha}^s_k + \tilde{\alpha}^s_l + \tilde{\alpha}^s_m = 1$.

The first terms of both (48) and (49) are crucial to derive their mapping to A_{is} and $TFPR_{is}$ under the gross output approach. Note

$$\begin{aligned} log(P_{is}Y_{is} - PM_{is}) &= log(P_{is}Y_{is} - (1-\iota_{is})PM^*_{is}) \\ &= log(P_{is}Y_{is} - (1-\iota_{is})\alpha^s_m P_{is}Y_{is}) \\ &\approx log(P_{is}Y_{is}) - (1-\iota_{is})\alpha^s_m \end{aligned} \tag{50}$$

where M^*_{is} is the static optimal level of intermediate goods, of which the revenue share shall equal to $\tilde{\alpha}_m$ in Cobb-Douglas production function. ι_{is} measures the idiosyncratic distance of actual intermediate goods usage from the optimal level. Plugging this equation back to (48) and (49), the followings hold

$$log(A^v_{is}) = \frac{1}{1-\tilde{\alpha}^s_m}log(A_{is}) - \frac{\tilde{\alpha}^s_m}{(1-\tilde{\alpha}^s_m)(\sigma-1)}logM_{is} + \{\frac{\tilde{\alpha}^s_m}{(1-\tilde{\alpha}^s_m)}\frac{\sigma}{\sigma-1} + \alpha^s_m\}\iota_{is} + C_1 \tag{51}$$

$$log(TFPR^v_{is}) = \frac{1}{1-\tilde{\alpha}^s_m}log(TFPR_{is}) + \{\frac{\tilde{\alpha}^s_m}{(1-\tilde{\alpha}^s_m)} + \alpha^s_m\}\iota_{is} + C_2 \tag{52}$$

where C_1 and C_2 are constant in terms of α^s_m and σ. Economic intuition of the second term in equation (51) is that monopolistic firms charge markup over the marginal cost of intermediate goods when they produce gross output, which is absent when firms are modeled as value-added producers and charging mark-up only on marginal costs of capital and labor.

Analogously, industry-level $T\bar{F}PR^v_s$

$$log(T\bar{F}PR^v_s) \propto \frac{1}{1-\tilde{\alpha}_m}log(TFPR_s) + \{\frac{\tilde{\alpha}^s_m}{(1-\tilde{\alpha}^s_m)} + \alpha^s_m\}\bar{\iota}_s + C_2 \tag{53}$$

where $\bar{\iota}_s$ is the industry average distortion on intermediate goods.

When $\sigma \to \infty$ and $\iota_{is} = 0, \iota_s = 0$, it can be easily seen that TFP gains under value added approach is

$$log(TFP^v_s/TFP^v_{s,eff}) = log\{(\sum_{i=1}^{N_s}(\frac{A^v_{is}}{\bar{A}^v_s}\frac{T\bar{F}PR^v_s}{TFPR^v_{is}})^{\sigma-1})^{\frac{1}{\sigma-1}}\} = \frac{1}{1-\tilde{\alpha}_m}log(TFP_s/TFP_{s,eff}) \tag{54}$$

where the last term $log(TFP_s/TFP_{s,eff})$ and $\frac{1}{1-\tilde{\alpha}_m} log(TFP_s/TFP_{s,eff})$ are gross output and value added gains from gross output approach, implemented in the paper.

When $\sigma = \infty$ and $\iota_{is} \neq 0$, equation (51) and (52) suggest that both A^v_{is} and $TFPR^v_{is}$ have greater dispersions than their gross output counterparts, A_{is} and $TFPR_{is}$, as long as A_{is} and $TFPR_{is}$ are not highly negatively correlated with ι_{is}. Note in the model A_{is} and $TFPR_{is}$ are positively correlated with ι_{is}. At the same time, it shall be seen that the correlation between A^v_{is} and $TFPR^v_{is}$ is higher than that between A_{is} and $TFPR_{is}$ because of common terms in ι_{is}.

When $\sigma < \infty$ and $\iota_{is} \neq 0$, the comparison becomes less obvious. But note that the greater dispersion of $TFPR^v_{is}$ still holds. If one imposes the joint log normal distribution between A^v_{is} and $TFPR^v_{is}$ and between A_{is} and $TFPR_{is}$, the higher dispersion of $TFPR^v_{is}$, regardless of σ, immediately implies greater misallocation under the value added approach.[27]

[27] Hsieh and Klenow (2009) proves that dispersions of $TFPR_{is}$ is a sufficient statistic for magnitude of misallocation when $TFPQ$ and $TFPR$ follow a joint normal distribution.