Intermediate Goods and Misallocation in China's Manufacturing Sector

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Abstract

Substantial misallocation of inputs across firms is documented in China Industrial Enterprise Survey (CIES) (Hsieh and Klenow, 2009; Brandt, Van Biesebroeck, and Zhang, 2012). This paper quantifies the novel role of intermediate goods frictions, i.e. time-to-order and borrowing constraints, in accounting for measured misallocation in the CIES data. With a gross output production function, I incorporate intermediate goods frictions into the firm investment model of Cooper and Haltiwanger (2006). Firms order and prepay for a fraction of intermediate goods one period in advance (time-to-order), and face one borrowing constraint on capital and intermediate goods. Firms also face capital adjustment costs. Following Hsieh and Klenow (2009), I measure misallocation by the potential gross output gain if intermediate goods, capital and labor were hypothetically reallocated to equalize marginal products across firms. Over 1998-2007, misallocation in the CIES data averages 140 percent of actual gross output. The model accounts for around 70 percent of this misallocation, when calibrated to key moments in firm-level debt, productivity and market share distribution in the CIES data. Half of the misallocation in the model is attributed to intermediate goods frictions: 34 percent from borrowing constraints, and 16 percent from time-to-order. While borrowing constraints on capital induce small misallocation, capital adjustment costs account for the other half. Larger misallocation with intermediate goods frictions than without arises from its 70 percent gross output revenue share and recurrent need of financing. This tightens the borrowing constraint and interrupts the self-financing mechanism for capital accumulation. The importance of intermediate goods frictions in misallocation could be applied to other countries with an underdeveloped financial system.

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1 Introduction

Substantial measured misallocation of inputs across firms has been documented in China Industrial Enterprise Survey (CIES). According to Hsieh and Klenow (2009), output could be doubled if marginal products of capital and labor were equalized across firms. Several explanations of misallocation have been proposed, focusing on firm-level distortions on labor,[1] and capital, i.e. financial frictions and adjustment costs. However, the substantial magnitude of misallocation in the firm-level data found in Hsieh and Klenow (2009) remains largely unexplained.[2]

The potential impact of intermediate goods frictions on misallocation has not been investigated. Similar to capital, intermediate goods at the firm-level are subject to borrowing constraints in financing and real frictions in adjustment. According to the trade credit and working capital management literature (e.g. Jose, Lancaster, and Stevens, 1996; Petersen and Rajan, 1997), intermediate goods need time to order, and are purchased about half a year before receipt of sales from buyers. This creates a borrowing need for intermediate goods expenditure,[3] which is arguably subject to financial frictions under China's underdeveloped financial system. Given that intermediate goods account for 70% of gross output revenue, intermediate goods frictions could potentially generate a large dispersion in marginal products of intermediate goods, and thus cause measured misallocation in China.

This paper first establishes evidence that suggests distorted intermediate goods allocation in the CIES data. First, following the approach in Hsieh and Klenow (2009) for value-added, I compute the potential gross output gain by equalizing marginal products of one input across firms, *holding the other two at the firm-level fixed*. Gross output increases by a sizable 30 percent for the case of intermediate goods. This is 15 times as large as that of capital or labor, despite a lower coefficient of variation for marginal products of intermediate goods in the data. This exercise suggests that intermediate goods frictions could potentially cause a large misallocation. Second, firms in China purchase intermediate goods 160 days before collection of sales(time-to-order). Third, marginal products of intermediate goods are more dispersed among firms with low net worth. This

[1] See, for example, Hopenhayn and Rogerson (1993), for labor firing cost and misallocation.

[2] One strand of the literature models the distribution of firm-level productivity as a result of costly experiments or human capital investment (e.g. Da-Rocha, Tavares, and Restuccia, 2016, Gabler and Poschke, 2013 and Castro and Sevcik, 2016). The impact of distortions on misallocation can be amplified through distorting allocations of inputs as well as the productivity improvement process. However, the output loss implied in these studies deviates from the exercise in Hsieh and Klenow (2009) that assumes a fixed productivity distribution for computing misallocation.

[3] There are similar ideas of working capital in the literature. See, for instance, Pratap and Urrutia (2012) and Mendoza and Yue (2012) for working capital on intermediate goods, and Quadrini (2011) for a survey of papers about working capital on wage payment.

is consistent with the idea that financial frictions constrain productive firms from buying more intermediate goods.

How much can time-to-order and borrowing constraints on intermediate goods quantitatively account for misallocation in China? To answer this question, I incorporate these two frictions on intermediate goods, as well as borrowing constraints on capital, into a standard firm investment model of Cooper and Haltiwanger (2006). Similar to their model, firms in this paper maximize the discounted net present value of future dividends, facing an idiosyncratic AR(1) productivity process and capital adjustment costs.

Unlike the standard heterogeneous firm investment model, this paper models intermediate goods frictions as well as borrowing constraints on capital. Specifically, firms order and prepay for a fraction of intermediate goods one period ahead (time-to-order). Firms also face a fixed cost and a convex adjustment costs when choosing their capital for next period. Payments of intermediate goods and capital investment are financed by retained earnings, and borrowings if necessary. Firm-level borrowing is subject to a constraint that endogenously depends on firms' default risk and net worth. When stochastic productivities are realized at the beginning of a period, firms choose to continue or exit under limited liability. If continue, they choose optimal labor, and intermediate good usage that cannot exceed the pre-ordered level. In other words, the particular intermediate goods adjustment cost is infinitely large when firms scale it up and zero when they scale it down.

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 and productivity, as well as the market share distribution over firm age groups in the CIES data over 1998-2007. In particular, the calibration takes into account the fact that the CIES has a threshold sales of 5 million yuan, and only includes top 20% manufacturing firms in the sales distribution.[4] The purpose is to reasonably capture the fact that a large fraction of firms take years to accumulate capital before they grow above the threshold sales.

Following Hsieh and Klenow (2009), the measure of misallocation is defined as gross output gain if marginal products of intermediate goods, capital and labor were *all* equalized across firms. I find that the model generates substantial misallocation and accounts for 69% of measured misallocation in the CIES data. Specifically, gross output gain is 96% of the actual output in the simulated data, and averages 140% in the CIES data over 1998-2007. In other words, gross output could be nearly doubled in the model, and more than doubled in the CIES, if marginal products of intermediate

[4]To be more specific, the CIES data has a 5 million yuan sales threshold for private-owned firms to be included. Such a threshold gives approximately the top 20% firms in sales according to the aggregate statistics in 2004. Further details would be discussed in Section 4.1.

goods, capital and labor were equalized across firms.

There are four frictions that cause misallocation in the benchmark model: borrowing constraints and time-to-order on intermediate goods, and borrowing constraints and adjustment costs on capital. To decompose the contribution of each friction to misallocation, I eliminate frictions one by one from the benchmark model. My first counterfactual experiment removes borrowing constraints on intermediate goods. The resulting potential output gain in this counterfactual specification is 64%. This suggests that borrowing constraints on intermediate goods induce 33% (32/96) of misallocation in the benchmark model, and accounts for 23% (32/140) of misallocation in the CIES data. Second, I further remove time-to-order on intermediate goods by allowing firms to choose the static optimal amount of intermediate goods after their productivity shocks. This experiment lowers the misallocation to a 49% potential gross output gain. Therefore, time-to-order on intermediate goods accounts for 16% (15/96) of misallocation in the model and 11% (15/140) of that in the CIES data. The two frictions on intermediate goods together generate 49% of misallocation in the benchmark model, and 34% of that in the CIES data.

I find that further eliminating borrowing constraints has a small impact on misallocation. The potential gross output gain in this counterfactual specification is 48%, only 1% lower than that in the second. This implies that while capital adjustment costs account for 50% (48/96) and 35% (48/140) of misallocation in the model and in the CIES data, borrowing constraints on capital induce a small amount of misallocation. This result is consistent with Midrigan and Xu (2014) and Moll (2014), and is a consequence of persistent productivities and firms' ability to save such that top productive firms own a large share of capital regardless of the constraint.

The intuition why intermediate goods frictions have a large impact on misallocation is due to its high revenue share in production, and the recurrent need to finance because of one-period depreciation. For illustration, set the reference model as the one with adjustment costs and borrowing constraints on capital only in which firms choose the static optimal amount of intermediate goods. At time t, pre-order and down-payment for intermediate goods increase the borrowing need for firms, on top of capital investment. Capital investment is therefore crowded out, which lowers profit and net worth at time $t+1$. Additionally, at time $t+1$, firms cannot buy more intermediate goods intra period after high productivity shocks because of time-to-order. The consequent profit is lower. The lower current net worth at $t+1$ caused by the above two effects further lowers capital investment and more importantly, intermediate goods for time $t+2$, and so forth. This low net worth effect is long lasting since financing intermediate goods is recurrent by one-period depreciation and puts much more stress on borrowing constraints. Consequently, capital accumulation is slowed and the stationary distribution features firms with lower capital stocks.[5]

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 around 50% in most countries, while the working capital management literature about other countries (e.g. Jose et al., 1996) document a similar time length between intermediate goods purchases and collection of sales. 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 even in modern developed countries in a certain historical stage.[6]

This paper is related to a growing literature on misallocation.[7] Several papers have studied productivity and misallocation in China. Hsieh and Klenow (2009) first document large firm-level distortions and substantial misallocation in manufacturing firm-level data. Brandt et al. (2012) further document limited input reallocation across firms in China despite a high TFP growth over 1998-2007. Several explanations have been proposed in the literature: capital misallocation caused by preferred lending to state-owned firms (Brandt, Tombe, and Zhu, 2013), trade and migration costs (Tombe and Zhu, 2015), entry costs (Storesletten, Kambourov, and Brandt, 2016), and financial frictions (Bai, Lu, and Tian, 2016). Unlike these studies, this paper focuses on the novel intermediate goods frictions and provides a quantitative model to assess their roles in accounting for misallocation.

This paper is also related to work on capital misallocation across firms. Bartlesman, Haltiwanger, and Scarpetta (2013) argue a dynamic capital investment model with other firm-level distortions important in accounting for cross-country differences in size-productivity covariances. Asker, Collard-Wexler, and De Loecker (2014) find that stochastic productivities combined with capital adjustment costs are important in accounting for dispersions in marginal products of capital. A number of papers study financial frictions and capital misallocation. The argument is that firms of low net worth are financially constrained, and cannot consequently choose inputs in response to productivities. However, a counter-argument lies in the dynamic process that firms self-finance and grow out of constraints, which results in a small misallocation in the steady state. This self-financing does not undo misallocation if (1) productivity is less persistent (see Caselli and Gennaioli, 2013;

[5]The crowding-out effect of working capital on capital investment is consistent with Fazzari and Petersen (1993). They find that working capital at the firm-level has a negative impact on fixed capital investment for financially constrained U.S. firms with zero dividend payments during 1970-1979.

[6]See, for instance, Ziebarth (2013) that finds a comparable amount of misallocation in the 19th century U.S. manufacturing sector as in modern China and India.

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

Moll, 2014); (2) firms cannot save (see Amaral and Quintin, 2010); (3) transition dynamics start from a pre-misallocated economy (see Buera and Shin, 2013); (4) entrepreneurs slowly accumulate wealth before paying entry costs (see Midrigan and Xu, 2014); and (5) the borrowing constraint is endogenous (see Bai et al., 2016). This paper combines the real frictions and financial frictions of capital, and extend them to the discussion of intermediate goods. The key of misallocation in the stationary distribution in this paper comes from the recurrent financing need of intermediate goods that slows down firms' capital accumulation.

Lastly, this paper is related to the work linking intermediate goods with TFP. Jones (2011) argues that vertical linkages of industries through intermediate goods can amplify distortions in resource allocation and explain cross-country TFP differences. Mendoza and Yue (2012) and Pratap and Urrutia (2012) find working capital constraints on intermediate goods in emerging markets important in explaining TFP drops post financial crisis. This paper differentiates from these studies in arguing the role of intermediate goods frictions in slowing capital accumulation and causing misallocation.

The rest of this paper is structured as follows. Section 2 illustrates distortions of intermediate goods allocation in the CIES 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 in Data

This section presents four facts related to intermediate goods in the CIES data. The first two facts motivate this paper to explore the role of intermediate goods in measured misallocation. First, intermediate goods cost is about 70% of gross output revenue in China. Second, because of its large revenue share, reallocating intermediate goods alone generates more gross output gain than reallocating capital or labor alone.

The latter two facts motivate the model to consider two candidates for intermediate goods frictions, i.e. time-to-order and borrowing constraints. For the third fact, intermediate goods purchases happen on average 90 days before production, and 160 days before collection of sales. This time-to-order creates a need of working capital, and firms could be constrained in intermediate goods choice if there are financial frictions. The fourth fact confirms this and finds that marginal products of intermediate goods and capital have a larger dispersion among firms with low net worth.

Data Description This paper uses the China Industrial Enterprise Survey (CIES) from 1998 to 2007, which has been extensively used in the literature (see, e.g. Hsieh and Klenow, 2009; Brandt, Van Biesebrock, and Zhang, 2014; Bai et al., 2016). The CIES covers all state-owned manufacturing firms, and private-owned manufacturing firms with sales above 5 million yuan every year before 2007 (approximately 800 hundred thousand U.S. dollars).[8] During this period, the number of manufacturing firms grew substantially, from 147,690 in 1998 to 304,599 in 2007.

The dataset combines firm-level information on balance sheets, income and cash flow statements, including variables of gross output (sales), book value of capital, employment, wage bill, intermediate goods cost, birth years, inventory, account receivables, ownership and industries (see Table A1 in Appendix for variable definitions).[9] Industries in this dataset are classified according to the 4-digit China Industrial Classification code (CIC). In all, there are 544 4-digit CIC industries, and 30 2-digit CIC industries in the manufacturing sector.[10] To obtain firm-level capital stock, I construct an unbalanced panel from 1998 to 2007 using information of registration I.D., name of the firm, name of legal representatives, phone number, industry and main products to merge firms across years, following the method of Brandt et al. (2012). The capital stock of a firm is then constructed using a perpetual inventory method.

The CIES data only surveys private-owned firms with at least 5 million yuan in sales.[11] Compared to the aggregate information in Economic Census 2004 and 2008,[12] firms in the CIES data are roughly the top 20% manufacturing firms in sales according to Table 1.[13] They hire around 70% manufacturing workers, pay 80% of wage bill and produce more than 90% of gross output. This difference between the CIES data and the China's manufacturing sector is important and will be revisited in the model calibration stage.

Intermediate Goods Share Intermediate goods have a high revenue share in production

[8]The observation of production units in the CIES data are firms, not establishments. In 2004, 95% of firms have only one establishment. According to National Bureau of Statistics, starting from 2007, the 5 million threshold sales is required for both state-owned and non-state owned firms to be included in the CIES data. In 2011, the threshold sales increases to 20 million yuan.

[9]See Table A3 in Appendix for summary statistics of the dataset.

[10]Example 4-digit industries are manufacture of candy and confectionery, manufacture of leather shoes, manufacture of biochemistry pesticide and manufacture of metal forming machine to name a few. See Table A2 in Appendix for a full list of 2-digit CIC industries.

[11]All state-owned firms are included in the data.

[12]Aggregate Economic Census information for 2004, 2008 and 2013 are available at National Bureau of Statistics website `http://www.stats.gov.cn/tjsj/pcsj/`. The 2004 census information is also available at China Data Online.

[13]I abuse the language a little here since state-owned firms with sales below 5 million yuan are also included in the CIES. This impact is, however, minor as state-owned shares are small in 2004. See Table A3 in Appendix.

Table 1: Aggregate Statistics of Above & Below 5 Million Sale Manufacturing Firms

	Number	Gross Output (billion)	Total Wage (billion)	Employment (10,000)
2004				
Below	1,001,587	1,867.76	196.54	2413.28
Above	256,999	17,528.35	791.97	5667.34
% of above size firms	**20.42%**	**90.37%**	**80.12%**	**70.13%**
2008				
Below	1,356,124	3,318.36	382.68	2889.91
Above	396,950	44,135.83	2,678.62	7,731.57
% of above size firms	**22.64%**	**93.01%**	**87.50%**	**72.79%**

Current price. Source: The First and Second Economic Census (2004,2008), National Bureau of Statistics

in China. At the aggregate CIES data level, intermediate goods share is defined as the ratio of aggregate intermediate goods and aggregate gross output.

Table 2 shows that the aggregate intermediate goods of all firms is 74% of aggregate gross output in the CIES, with a similar share for state-owned firms and non-state owned ones. The share of intermediate goods is similar across most industries, with a few industries that have an intermediate goods share close to 0.5 or 0.9 (see Figure A1 in Appendix). While a slightly lower level 68% is reported in Jones (2011) using input-output information for the entire economy,[14] China resembles South Korea and Japan in early 1970s and exceeds the average intermediate goods share 50% among OECD countries (Jones, 2011).

Productivity Measure A key variable for measuring misallocation is firm-level productivity. Productivity for firm i in industry s, TFP_{is}, is defined as follows:

$$TFP_{is} = logy_{is} - \alpha_l^s logl_{is} - \alpha_m^s logm_{is} - \alpha_k^s logk_{is} \tag{1}$$

while y_{is} and m_{is} are real gross output and intermediate inputs, deflated using 2-digit CIC industry deflators from the on-line appendix of Brandt et al. (2012).[15] I use the wage bill to proxy labor inputs l_{is} as in Hsieh and Klenow (2009), deflated by the CPI from National Bureau of Statistics. The capital measure k_{is} at firm-level is constructed using a perpetual inventory method that further

[14]Input-output table for China can be downloaded from World Input-Output Database http://www.wiod.org/new_site/database/niots.htm

[15]See http://feb.kuleuven.be/public/N07057/CHINA/appendix/

Table 2: Shares of Intermediate Goods in Gross Output, CIES

	All	State-Owned	Non-State Owned
1998	78.01%	77.29%	78.84%
1999	77.18%	76.43%	77.88%
2000	75.34%	74.27%	76.04%
2001	75.96%	74.71%	76.53%
2002	76.43%	75.15%	76.91%
2003	74.67%	74.25%	74.78%
2004	73.38%	73.55%	73.35%
2005	70.88%	72.54%	70.63%
2006	69.79%	72.23%	69.49%
2007	69.80%	73.33%	69.39%
1998-2007 Average	74.14%	74.38%	74.38%

utilizes the capital goods deflator from Brandt et al. (2012). With a Cobb-Douglas production function in mind, I compute shares of labor α_l^s, intermediate goods α_m^s and capital α_k^s as the medians of firm-level revenue shares within 2-digit CIC industries.

The reason to use industry level factor shares instead of constant factor shares across industries is to capture industry heterogeneity. While costs on intermediate goods and labor are observable, costs on capital at firm-level is calculated as the product of capital stock k_{is} multiplied by an imputed rental rate of 13%.[16] Firm-level factor share α_x^{is} is consequently

$$\alpha_x^{is} = \frac{\text{Cost on Input } x}{\text{Gross Output}}, \quad x \in \{k, l, m\} \tag{2}$$

Industry-specific shares α_x^s are set as medians of α_x^{is} across firms, for $x \in \{k, l, m\}$, within the industry s.

Misallocation in Intermediate Goods This subsection outlines some preliminary evidence of misallocation in intermediate goods in the CIES data. Following Hsieh and Klenow (2009), misallocation in intermediate goods is large, if its marginal products are dispersed such that reallocating

[16] I impute the cost on capital by inferring a median rental rate from World Bank Data Survey (2012). In the survey, firms are asked the fraction of land and buildings they rent and the rental cost. Thus, the rental rate for land and buildings are estimated at 7% annually. Although they are also asked the rental cost for vehicles, machinery and equipment, there is no information about its rented value. The rental rate for capital is thus estimated by 13%, with a depreciation of 9% on general capital, and 3% on structures in mind.

the intermediate goods across firms significantly increases aggregate gross output.

Since industries differ in the types of intermediate goods they use, I quantify misallocation in intermediate goods within 4-digit CIC industries. The dispersion measure I use is the Coefficient of Variation (CV) in marginal products of intermediate goods across firms. In particular, marginal products for any input x is given at firm i as:

$$MP_{i,x} = \alpha_x^s \frac{y_i}{x_i},\ x \in \{k, l, m\} \tag{3}$$

while the share of inputs α_k^s, α_l^s and α_m^s are the same as in Equation (1). The potential aggregate gross output gain is defined as the percentage increase of gross output if intermediate goods were reallocated across firms within 4-digit CIC industries, *holding the other two inputs at the firm-level fixed*. These two measures are also computed for capital and labor as a comparison.

Table 3 presents CVs and output gains for intermediate goods, capital and labor. For each input, the top and bottom 1% of its marginal product distribution are trimmed within a 4-digit CIC industry in a given year.[17] Across industries, mean and median CVs for intermediate goods are much smaller than those for capital and labor. However, reallocating intermediate goods alone results in a much higher gross output gain. On average, a 4-digit CIC industry increases its output by 30% if marginal products of intermediate goods are equalized across firms within the industry. This is 15 times that the gain from reallocating capital or labor alone. Although the median 4-digit CIC industry gains less than an average industry from reallocation of each input alone, reallocating intermediate goods still generates most gross output gain.

Table 3: Dispersions in Marginal Products and Output Gain by Reallocating One Input within CIC 4-digit Level Industries, 1998-2007

	Intermediate Goods		Capital		Labor	
	CV	Gross Output Gain	CV	Gross Output Gain	CV	Gross Output Gain
Median	0.21	0.05	1.51	0.02	1.07	0.02
Mean	0.27	0.30	1.62	0.02	1.08	0.02

Means and medians of CV and Gross Output Gain are calculated across 4-digit CIC industries in any year over 1998-2007. Numbers reported above are averages of means and medians across years.

This contrast between the output gain measure and the CV measure highlights the importance of input shares in generating misallocation defined as in Hsieh and Klenow (2009). Although dispersions of marginal products are indicative for misallocation, inputs with low dispersions and

[17] There are 4-digit industries that have fewer than 100 firms. I drop these industries.

high revenue shares may account for more misallocation than inputs with high dispersions and low revenue shares.

Real Frictions on Intermediate Goods One potential explanation for the dispersion in marginal products of intermediate goods across firms is real frictions. If firms adjust intermediate goods in response to productivity shocks, misallocation in intermediate goods should not exist. In practice, production takes time from purchasing intermediate goods to production, and from sales of output to collection of sales.

To examine the production process, I borrow the concept of operating cycle from the trade credit and working capital management literature (e.g. Jose et al., 1996; Petersen and Rajan, 1997). The operating cycle, OC, for firm i is defined as:

$$OC_i = \frac{\text{Inventory}_i + \text{Account Receivables}_i}{\text{Sales}_i} * 365 \tag{4}$$

where Inventory_i, $\text{Account Receivables}_i$ and Sales_i are the corresponding accounting entries in the CIES data. OC measures days between intermediate goods purchases[18] and collection of sales, standardized in 365 days.

The operating cycle can be further decomposed into two parts, from materials to finished products and from sales of finished products to collection of sales. The first part corresponds to a measure, Days in Inventory, DI_i, defined as:

$$DI_i = \frac{\text{Inventory}_i}{\text{Sales}_i} * 365 \tag{5}$$

and the second part corresponds to another measure, Days in Receivables, DR_i, defined as:

$$DR_i = \frac{\text{Account Receivables}_i}{\text{Sales}_i} * 365 \tag{6}$$

Table 4: Operating Cycle, Days in Inventory and Days in Receivables, CIES 1998-2007

	OC	DI	DR
Mean	161.20	86.39	74.81
Median	107.89	46.94	42.92

The mean and median OC, DI and DR are calculated across firms in each year, and then average out over 1998-2007.

In the CIES data, I calculate the mean and the median OC, DI and DR across firms in each year, and average the means and medians over 1998-2007. Table 4 shows that there are an average

[18]Inventory includes materials, semi-finished products and finished products, with each takes up about a third of inventory in the World Bank Enterprise Survey (2012).

of 160 days, and a median of 108 days between intermediate goods purchases and collection of sales revenue. Days on inventory are 87, and days on receivables 75, with each accounting for roughly half of the operating cycle. These evidences suggest a time-to-order real friction, as well as a working capital need on intermediate goods.

Financial Frictions on Intermediate Goods To finance purchases of intermediate goods and capital, firms may need to borrow. If borrowing constraints on intermediate goods are important, one should expect them to be binding for low net worth firms. In turn, this suggests that marginal products of intermediate goods and capital among low net worth firms shall be more dispersed than those among high net worth firms.

Table 5: CV of Marginal Products among Top and Bottom Quartile Firms in Capital Stock

	Intermediate Goods		Capital	
	Top	Bottom	Top	Bottom
Mean	0.25	0.37	0.98	1.99
95% C.I.	[0.24, 0.26]	[0.33, 0.41]	[0.95,1.00]	[0.91, 2.07]
Nobs	290		290	

Each observation is industry-year level, with a industry defined at CIC 2-digit level. The top quartile group is defined as top 25% firms in capital stock at this industry-year level, and the bottom group as the bottom 25%.

Using capital stock as a proxy for net worth, I compare CVs of marginal products of intermediate goods and capital among firms with the top quartile capital stock to those among firms with the bottom quartile of capital stock. Since more than 60% of 4-digit CIC industries have less than 200 firms, CVs are first calculated at the 2-digit CIC industry level for each year. Mean CVs and confidence intervals reported in Table 5 are then calculated when pooling CVs at 2-digit CIC industry level over years. Firms in the bottom quartile of capital stock distribution have a 50% higher dispersion in the marginal product of intermediate goods, and 103% higher in that of capital. The differences are statistically significant as the 95% confidence intervals for the top subsample do not contain the average CVs in the bottom subsample, and vice versa.

Table 5 is consistent with a story that financial frictions not only hamper capital investment, but also distort intermediate goods choice at the firm-level. While the former has been extensively studied in the literature, the latter motivates this paper to model financial frictions on intermediate goods in discussing misallocation.

Summary This section presents misallocation in intermediate goods in the CIES data. Removing distortions in intermediate goods alone generates more output gain than the case of removing distortions in capital or labor alone.

This section also suggests two specific distortions in intermediate goods. First, firms order intermediate goods 87 days before production and 160 days before realization of sales. Second, a smaller dispersion of its marginal products among large firms has its consistency with borrowing constraints on intermediate goods. Motivated by the data evidence, the model in the next section incorporates the time-to-order and borrowing constraints on intermediate goods.

3 Model

To quantify how borrowing constraints and time-to-order on intermediate goods generate misallocation, this paper incorporates these frictions into a standard firm investment model of Cooper and Haltiwanger (2006). Two types of agents live in the model: 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 the net present value of dividends is smaller than exiting and liquidating its assets. Under limited liability, default happens when the liquidation value cannot cover debt repayment. Financial intermediaries consequently 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. Firms maximize their present values of future dividends and live forever until they exit. After entry, firms cannot issue new equity and only access to one-period borrowings and savings at financial intermediaries. When exit, firms pay debt up to its liquidated assets under the limited liability.

Production Function Firms produce in a gross output production:

$$y_t = exp(z_t) k_t^{\alpha_k} l_t^{\alpha_l} m_t^{\alpha_m} \tag{7}$$

where y_t is gross output, z_t is productivity, and k_t, l_t, and m_t are capital, labor and intermediate goods with their respective revenue shares α_k, α_l, and α_m. The production technology is assumed to satisfy decreasing return to scale, $\alpha_k + \alpha_l + \alpha_m < 1$.

Firm-level productivity z_t is stochastic and evolves according to an AR(1) process:

$$z_{t+1} = (1-\rho)\mu_z + \rho z_t + \epsilon_{t+1} \tag{8}$$

where μ_z is its unconditional mean and common across firms, ρ describes the persistence of productivity, and ϵ_{t+1} is the shock term that follows $N(0, \sigma_\epsilon^2)$. The consequent unconditional distribution for productivity z_t is $N(\mu_z, \sigma_z^2)$, where $\sigma_z = \frac{\sigma_\epsilon}{\sqrt{1-\rho^2}}$.

Given productivity z_t, capital k_t and intermediate goods m_t, firms choose labor input l_t to maximize its gross output net of labor payment, π_t:

$$\pi_t = \max_{l_t} p_y y_t(z_t, k_t, m_t, l_t) - w l_t \tag{9}$$

where p_y is output price and w is wage. The separability of labor inputs from other choices as above is because labor inputs can be adjusted intra period without any frictions.

Since this paper considers firms in a partial equilibrium framework, output demand and input supplies are not modeled here. Consequently, I assume constant exogenous prices of output p_y and wage w, and set them to 1. Similar for intermediate goods price p_m in the later subsection.

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

$$\Pi_{t+1} = \max_{\bar{m}_{t+1} \leq m_{t+1}} \pi_{t+1}(z_{t+1}, k_{t+1}, \bar{m}_{t+1}) - (1-\omega)m_{t+1} + (m_{t+1} - \bar{m}_{t+1}) \tag{10}$$

Capital Adjustment Costs Firms can adjust capital stock using two technologies that involve different adjustment costs: a maintenance type mt that can be used for small changes in capital stock, and a construction type ct that allows large investment/divestment.

In particular, while next period capital k_{t+1} can be any value in the construction type ct, in the maintenance type mt, next period capital k_{t+1} is restricted to a small range around the depreciated current capital stock $(1-\delta)k_t$, i.e. $k_{t+1} \in [(1-\delta-\zeta)k_t, (1-\delta+\zeta)k_t]$. There is no fixed cost ξk_t with the maintenance type mt, while a convex cost with parameter θ exists in both two types. Thus, the cost structure $C(k_t, k_{t+1}|x)$ under type $x \in \{ct, mt\}$ is

$$C(k_t, k_{t+1}|x) = \begin{cases} \xi k_t + \frac{\theta((1-\delta)k_t - k_{t+1})^2}{2(1-\delta)k_t} & \text{if } k_{t+1} \notin [(1-\delta-\zeta)k_t, (1-\delta+\zeta)k_t], x = ct \\ \frac{\theta((1-\delta)k_t - k_{t+1})^2}{2(1-\delta)k_t} & \text{if } k_{t+1} \in [(1-\delta-\zeta)k_t, (1-\delta+\zeta)k_t], x = mt \end{cases} \tag{11}$$

Note that there is no cost when firms choose to let capital depreciates and do nothing, i.e. $k_{t+1} = (1-\delta)k_t$.

This capital adjustment cost structure in (11) is similar to that in Cooper and Haltiwanger (2006) with an addition of the fixed cost free investment range $[(1-\delta-\zeta)k_t, (1-\delta+\zeta)k_t]$.

Borrowing Constraints Firms can save or borrow at financial intermediaries. To save, they purchase bonds issued by financial intermediaries with a competitive price q^1_{t+1} at time t and get paid back \$1 at time $t+1$. The saving interest rate is thus $r_1 = \frac{1}{q^1_{t+1}} - 1$.

When firms borrow, they issue one-period corporate bonds. As detailed later in the section on financial intermediaries, the price of corporate bonds, $q^2_{t+1}(z_t, b_{t+1}, k_{t+1}, m_{t+1})$, depends on firms' fundamentals: current productivity z_t, future debt b_{t+1}, future capital stock k_{t+1} and future intermediate goods m_{t+1}. The price of bonds q^2_{t+1} decreases with the expected default probability, implying a higher interest rate for borrowing. In the extreme case with no default probability, debt price $q^2_{t+1} = \frac{1}{1+r_2}$ where r_2 is called the prime borrowing interest rate.

The prime borrowing interest rate r_2 is greater than the saving interest rate r_1 by assuming intermediation costs for financial intermediaries. With the spread $r_2 - r_1$, firms never find it optimal to have savings and borrowings at the same time. Therefore, I collapse borrowings and savings into one variable b_{t+1}. When $b_{t+1} > 0$, firms borrow at the price $q_{t+1} = q^1_{t+1}$. When $b_{t+1} < 0$, firms save at the price $q_{t+1} = q^2_{t+1}$.

Since firms cannot issue new equity, dividend by the end of each period d_t shall be nonnegative after payments for next period intermediate goods ωm_{t+1},capital investment $k_{t+1} - (1-\delta)k_t + C(k_t, k_{t+1}|x)$, repayment of debt or saving b_t, new borrowings or savings $q_{t+1}(z_t, b_{t+1}, k_{t+1}, m_{t+1})b_{t+1}$ and operation cost c_o:

$$d_t = \Pi_t(z_t, k_t, m_t) + (1-\delta)k_t - \omega m_{t+1} - k_{t+1} - C(k_t, k_{t+1}|x) - b_t + q_{t+1}(z_t, b_{t+1}, k_{t+1}, m_{t+1})b_{t+1} - c_o \geq 0 \tag{12}$$

The above constraint is endogenous, since the price of corporate bonds depends on how much firms borrow.

Value of Continuation 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

$$V^c(z, b, k, m) = \max_{b',k',m',x\in\{ct,mt\}} \Pi(z, k, m) + (1-\delta)k - \omega m' - k' - C(k, k'|x) - b + q'(z, b', k', m')b'$$

$$- c_o + \beta E_{z'|z} V(z', b', k', m') \tag{13}$$

$$s.t. \quad \Pi(z, k, m) + (1-\delta)k - \omega m' - k' - C(k, k'|x) - b + q'(z, b', k', m')b' - c_o \geq 0$$

$$b' \leq \bar{b} \qquad \text{(No-Ponzi Game)}$$

where β is the discounting factor, and $\bar{b}$ is a debt limit to prevent firms from playing Ponzi Games. Note that β cannot be greater than $\frac{1}{1+r_2}$, because otherwise firms borrow indefinitely and store the cash. 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 $\beta = \frac{1}{1+r_2}$.

Solutions to problem (13) are policy functions

$$\text{Demand of debt/saving: } b'^d = b'^d(z, b, k, m; q') \tag{14}$$

$$\text{Next period capital: } k' = k'(z, b, k, m; q') \tag{15}$$

$$\text{Next intermediate goods: } m' = m'(z, b, k, m; q') \tag{16}$$

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 partition of future state (b', k', m') and is defined as:

$$\mathbb{T}(z, b, k, m; b', k', m') = \begin{cases} 1 & \text{if (14), (15), and (16) hold for firm } (z, b, k, m) \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

Exit and Default The value of exit is straightforward. 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 is costly and consumes some resources. Under limited liability, value of exiting $V^x(z, b, k, m)$ for the firm

$$V^x(z, b, k, m) = \max\{\gamma_2 \Pi(z, k, m) - b[\mathbb{1}(b \leq 0)\gamma_2 + \mathbb{1}(b > 0)] + \gamma_1(1-\delta)k, 0\} \tag{18}$$

An endogenous exit decision $\chi(z, b, k, m)$ is made by comparing the continuation value V^c and the exiting value V^x:

$$\chi(z, b, k, m) = \mathbb{1}\{V^x(z, b, k, m) > V^c(z, b, k, m)\} \tag{19}$$

Therefore, the value function $V(z, b, k, m)$ before the exit decision is made is:

$$V(z, b, k, m) = \max\{V^x(z, b, k, m), V^c(z, b, k, m)\} \tag{20}$$

Default on debt repayment only happens when firms exit, while debts are rolled over when firms choose to continue.[19] However, firms may exit without default. First, if firms save $b \leq 0$, there is no meaningful default discussion. Second, if the liquidation value of capital and cash $\gamma_2\Pi(z, k, m) + \gamma_1(1 - \delta)k$ is greater than debt repayment b, firms repay all.

Thus, the only case when an exiting firm defaults is that it borrows and the liquidation value of asset is smaller than the debt. Loss for lenders in this case is:

$$b - \gamma_2\Pi(z, k, m) - \gamma_1(1 - \delta)k \tag{21}$$

3.2 Entrants and Firm Size Distribution

In each time period t, there are a mass of $\mu_{ent}M_t$ entrants. Each entrant draws an initial productivity z_0 and an initial wealth $b_0 < 0$ independently. Entrants do not differ from incumbents in the unconditional productivity distribution, i.e. $z_0 \sim N(\mu_z, \sigma_z^2)$. The initial wealth $b_0 < 0$ is from a Pareto distribution with a density function $g(-b_0)$:

$$g(-b_0) = \begin{cases} \frac{\alpha a_{\min}^{\alpha}}{(-b_0)^{\alpha+1}} & if - b_0 \geq a_{\min}, \\ 0 & if - b_0 < a_{\min}. \end{cases} \tag{22}$$

where a_{min} is the minimum wealth. Note that firms have zero initial capital stock and intermediate goods, i.e. $k_0 = 0, m_0 = 0$.

By the above assumptions, 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 and wealth b_0. Since $k_0 = 0$, entrants do not pay capital adjustment costs. Their choices of debt/saving $b'_{ent}(z_0, -b_0, 0, 0)$, capital $k'_{ent}(z_0, -b_0, 0, 0)$, and intermediate

[19] See, for instance, Bai et al. (2016) for default when firms continue.

goods $m'_{ent}(z_0, -b_0, 0, 0)$ are given by maximizing the value function of entrants $V_{ent}(z_0, b_0, 0, 0)$: [20]

$$
\begin{aligned}
V_{ent}(z_0, b_0, 0, 0) = & \max_{b', k', m'} -\omega m' - k' - b_0 + q'(z, b', k', m')b' \\
& - c_o + \beta E_{z'|z_0} V(z', b', k', m') && (23) \\
& s.t. -\omega m' - k' - b_0 + q'(z, b', k', m')b' - c_o \geq 0 && (24) \\
& b' \leq \bar{b} \qquad \text{(No-Ponzi Game)}
\end{aligned}
$$

where the next period z' evolves in the same AR(1) process as for incumbents in Equation (8), and V is the value function of incumbents in Equation (20). This implies that from $t+1$ on, the mass of $\mu_{ent} M_t$ entrants start production and behave the same as incumbents.

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. Note that an initial misallocation on entrants arises due to the constraint of (24). A high productivity entrant with a low draw of wealth finds quite hard to finance the first period capital stock and intermediate goods without retained earnings from the past.

3.3 Financial Intermediaries

There exists a continuum of risk-neutral competitive intermediaries that take deposits and lend.[21] For every dollar of intermediation, the cost includes a deposit interest rate r_1 and an intermediate cost c_I.

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:

$$
\begin{aligned}
& \max_{b'} (1 - E_{z'|z}\chi'(z', b', k', m'))b' + E_{z'|z}\{\chi'(z', b', k', m')(b' - \gamma_2 \Pi(z', k', m') && (25) \\
& \quad - \gamma_1(1-\delta)k')\} - (1 + r_1 + c_I)q'b'
\end{aligned}
$$

[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, an endogenous entry means that there is an equilibrium mass of entrants, such that the value of entry equates entry costs for the marginal entrants. If there are more entrants than the equilibrium, value of entry is too low because output price is lower, and input prices are higher than those in equilibrium, and vice versa. Since this paper adopts a partial equilibrium framework, there are no price channels to shape the endogenous entry. The approach here is rather to take some equilibrium mass of entrants, as well as their distribution of productivity and wealth as given.

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

The first term here presents debt repayment b'^s with the probability that firms continue and debt is rolled over $1 - E_{z'|z}\chi'(z', b'^s, k', m')$. The second term gives an expected loss when the firm defaults when productivity is below some threshold.

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 (13), and the exit rule $\chi(z, b, k, m)$ solves the exiting problem (19).

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 (25).

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

$$\mathbb{T}(z, b, k, m; b', k', m')b'^d(z, b, k, m; q') = b'^s(z, k', m'; q') \text{ for incumbents} \tag{26}$$

and

$$\mathbb{T}_{ent}(z, b_0, 0, 0; b', k', m')b'^d_{ent}(z, b, 0, 0; q') = b'^s(z, k', m'; q') \text{ for entrants} \tag{27}$$

with a special case $q'(z, b', k', m') = \frac{1}{1+r_1+c_I}$ when there is zero expected default probability. The consequent interest rate $r_2 = r_1 + c_I$ is the prime borrowing interest rate previously named.

4. the distribution and mass of firms f' and M' evolve recursively as in (28) and (29), 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:

$$\begin{aligned} f'(z', b', k', m') = \chi'(z', b', k', m')\{ &\int_z \int_b \int_k \int_m f(z, b, k, m)\mathbb{T}(z, b, k, m; b', k', m')\pi(z'|z)dzdbdkdm \\ &+ \mu_{ent} \int_z \int_b \phi(z)g(-b)\mathbb{T}_{ent}(z, b, 0, 0; b', k', m')dzdb\} \end{aligned} \tag{28}$$

$$M' = M(1 - \int_{z'}\int_{b'}\int_{k'}\int_{m'} \chi(z', b', k', m') f(z', b', k', m') dz'db'dk'dm' + \mu_{ent}) \tag{29}$$

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

This section discusses how I map the model in Section 3 into the CIES data in order to quantify the role of intermediate goods frictions in shaping misallocation. I calibrate the model to the CIES data and compare the measured misallocation generated in the model to that in the CIES data. Several counterfactual experiments are then implemented to quantitatively assess misallocation generated by each friction.

To implement the calibration and counterfactual experiments, simulated data are sampled from the model implied stationary distribution. Despite not capturing the non-stationary part of China's growth,[22] the goal is to understand how intermediate goods frictions affect firm-level investment and production decisions in a stationary distribution approach.

My calibration strategy takes into account the threshold sales of 5 million yuan in the CIES data. Section 4.1 elaborates entry and exit patterns in the CIES data, and the necessity of modeling the threshold sales. The model is then parametrized and calibrated to replicate key moments in firm-level debt, productivity, as well as the market share distribution in the CIES data. Out of model fit suggests similar firm dynamics in the model and in the CIES data for a given cohort.

Section 4.2 compares the measured misallocation in the model and in the data, using Hsieh and Klenow (2009)'s definition. If marginal products of intermediate goods, capital and labor were equalized, gross output could be increased by 96% in the model and 140% on average in the CIES data over 1998-2007. In other words, the model accounts for 69% of measured misallocation in the CIES data. Section 4.3 decomposes the misallocation generated by the model into contributions by borrowing constraints and real frictions on intermediate goods and capital. I find that intermediate goods frictions account for about a half and 34% of the misallocation in the model and in the CIES data, respectively. Borrowing constraint on intermediate goods is quantitatively more important than time-to-order, and accounts for a third and 23% of the misallocation in the model and in the

[22] Unlike developed countries, China's market based economy starts since 1980s and is hard to be described as an economy in its steady state or on some balanced growth path. For countries that experience reforms, Jeong and Townsend (2007) and Buera and Shin (2013) provide a framework of transitional dynamics analysis to understand how reforms gradually change resource misallocation over time.

CIES data. While borrowing constraints on capital generates small misallocation, capital adjustment costs account for the other half of misallocation in the model, and 35% in the CIES data. With intermediate goods frictions, the capital accumulation is much slower than without. This leads to a larger amount of misallocation that is hard to get with only frictions on capital.

4.1 Parametrization

The CIES data includes only the top 20% firms in the manufacturing sector because of the minimum sales of 5 million yuan threshold (see Table 1). This impacts the mapping between model and data in firm dynamics and measured misallocation. A significant fraction of entrants and exiters in the CIES are incumbent firms crossing the 5 million threshold sales. If the CIES was taken as the manufacturing sector, several model parameters, e.g. standard deviation of firm-level productivities, would be misspecified. Therefore, I first outline how I take into account the threshold sales before discussion on model parametrization.

Entry and Exit in the CIES Because of the 5 million threshold sales, I name entrants in the CIES data as *data entrants* to distinguish from new firms in the manufacturing sector. Similarly, *data exiters* refer to firms that disappear from the CIES data. To evaluate the potential impact of the threshold sales on the model calibration, I compare the fraction and market share of these firms in the CIES to that in the U.S. manufacturing sector (Dunne, Roberts, and Samuelson, 1988).

Since the U.S. literature uses census data that are 5-year apart, I study entry and exit in the CIES over a 5-year horizon. With the birth year information, I classify data entrants into two groups depending on whether these firms are younger or older than 5 years old. I name firms who are more than 5 years old as *old data entrants*, and those less as *young data entrants*.

Table 6 presents fractions, market shares and relative sizes of data entrants over 1998-2003 and over 2002-2007. Data entrants over a 5-year horizon are the majority of firms in the CIES data. Between 1998 to 2003, 66% of firms in 2003 enter into the dataset after 1998, among which 43% are old data entrants more than 5 years old. The fraction of data entrants increases during 2002-2007, with a similar fraction of old data entrants. In terms of market share, data entrants in 2003 and 2007 produce 49% and 56% of gross output in the economy. This suggest that a CIES data entrant produces, on average, 37% to 49% of the average gross output level of CIES incumbents in 2003 and 2007.

Compared to their U.S. counterparts, the fraction and the average size of data entrants are much larger in the CIES. According to Dunne et al. (1988), entrants over a 5-year horizon are 52% of U.S. census firms, producing a market share of 17%. This suggests that an average data entrant

Table 6: CIES Data Entrants over a 5-Year Horizon

	1998-2003	2002-2007
Number of Firms		
Incumbants	32.11%	24.37%
Data Entrants (Age > 5)	29.06%	30.47%
Data Entrants (Age ≤5)	38.83%	45.16%
Total Market Share		
Incumbants	50.86%	44.42%
Data Entrants (Age > 5)	22.45%	24.85%
Data Entrants (Age ≤5)	26.69%	30.73%
Relative Size of Output		
Data Entrants (Age > 5)	0.49	0.45
Data Entrants (Age ≤ 5)	0.43	0.37

Incumbents are defined as firms who are in CIES data for both year t and $t+5$. Data entrants are defined as firms that are not in the CIES data at t, but appear in the data at $t+5$. Age is computed as observation year $t+5$ minus the birth year.

is at least two times large as its counterpart in the U.S. census data.[23]

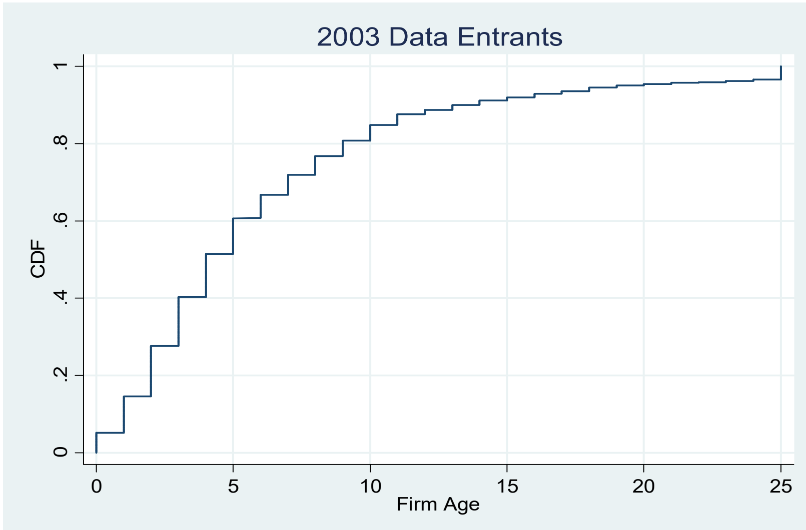
The threshold sales mean that a large fraction of new firms in the manufacturing sector are unobserved. Over time, some of these firms exit, while others accumulate capital, net worth and grow in sales. The age distribution of data entrants over 1998-2003 in Figure 1 suggests that about 30% of these firms take 5 to 15 years to grow above 5 million yuan. This implies that either the threshold sales is too high in the sales distribution, or the growth of firms is too slow. The steepness of this CDF provides an identification to gauge the role of frictions on intermediate goods and capital in slowing down firms growth. Logically, if frictions are small, productive firms grow rapidly and quickly surpasses the threshold sales. The resulting age distribution among data entrants in Figure 1 should have a large density on ages smaller than 5, and the CDF should be steep. The degree of age dependence in entering the CIES in Figure 1 reveals information on frictions of intermediate goods and capital. [24]

The interpretation of exit from the CIES data is complicated by the fact that one cannot

[23] According to Hsieh and Klenow (2014), average employment among 5- to 9- year-old firms is twice as that of firms who age from 1 to 5.

[24] The idea of age and size dependence has been studied in Davis, Haltiwanger, and Schuh (1996) and Cooley and Quadrini (2001) with the latter using financial frictions as an explanation.

Figure 1: Age Distribution of Data Entrants in 2003



Data entrants are defined as firms are not in the CIES data in 1998, but appear in the data in 2003, same to the definition in Table 6.

distinguish between firms whose sales fall below 5 million yuan and firms who truly exit. Table 7 shows that over a 5-year horizon, 59% firms in the 1998 CIES data are no longer there in 2003, with a slightly lower number 56% over 2002-2007. These 5-year rates imply an annualized exit rate around 15% to 16%, and is much higher than the annual 8% rate from a survival analysis report by State Administration for Industry and Commerce in the manufacturing sector.[25] Similar to entrants, the relative size of exiters are about 3 times large as their counterparts in U.S. census data (Dunne et al., 1988).

The above analysis suggests that accounting for the threshold sales is important to quantify how frictions shape misallocation through entry, exit and firm dynamics. Several problems arise if one takes the CIES data as the entire manufacturing sector in China. First, since firms that stay in the CIES data are relatively large, the volatility of firm-level productivities is underestimated by using the standard deviation of productivity in the cross-sectional data. This could lead to a smaller misallocation in the simulated model (Asker et al., 2014) that can hardly match that in the CIES data. Second, if old data entrants are treated as new firms, misallocation on these firms is misleadingly attributed to an initial misallocation on new firms. This bias is likely to be large, since old data entrants are about a quarter in numbers and market shares.

[25]See http://www.saic.gov.cn/zwgk/tjzl/zxtjzl/xxzx/201307/P020130731318661073618.pdf

Table 7: CIES Data Exiters over a 5-year Horizon

	1998-2003	2002-2007
Number of Firms		
Stayers	40.67%	44.34%
Data Exiters	59.33%	55.66%
Total Market Share		
Stayers	59.91%	61.23%
Data Exiters	40.09%	38.77%
Relative Size of Output		
Data Exiters	0.46	0.50

Stayers are defined as firms that are in CIES data for both year t and $t+5$. Data exiters are defined as firms that are in CIES data for year t and absent for year $t+5$.

Assigned Parameters The parameterization procedure takes two steps: assigned parameters from literature or other direct sources, and calibrated ones to match key moments in firm-level debt and productivity, as well as age and market share distributions in China Industrial Enterprise Survey Data (CIES).

Capital adjustment costs are parameterized from Cooper and Haltiwanger (2006) with a fixed cost parameter $\xi = 0.039$ and a convex adjustment cost parameter $\theta = 0.049$. The fixed cost free range for investment parameter $\zeta = 0.09$, which is equal to the capital deprecation rate $\delta = 0.09$.

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 from 1998 to 2007. Similarly, saving interest rate is set $r_1 = 0.03$ to match the average deposit rate in PBOC reports.

Capital recovery rate γ_2 upon default is set to 30%, which is the average asset recovery rate of non-performing loans from 2001 to 2006 in China (Fan and Morck, 2013, p. 85). The cash recovery rate γ_1 is lower than that of capital and equals 10%, closer to the lower bound of cash recovery rate 6.90% reported in Fan and Morck (2013).

Calibrated Parameters Given assigned parameters in the first step, the remaining parameters are calibrated to match key moments in firm-level debt, productivity, as well as age and market share distributions in the CIES.

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 (See Table A4 in Appendix). The intermediate goods share α_m is set to 0.7, between the number in Table 2 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 the CIES. 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 $\alpha_k = 0.10$.[26]

The threshold sale $y_c = 436.30$ is chosen to have 20% of firms above this level in the simulated gross output distribution. In other words, the subgroup of firms with sales above y_c in the simulated data is the model equivalent of the CIES data.

The productivity process parameters are calibrated to match the productivity moments in the simulated top 20% firms to those in the CIES data.[27] In particular, its persistence $\rho_z = 0.7$ is chosen to match the fact that 40.67% of firms in the 1998 CIES data remain by 2003. Since more than 50% of data exiters are estimated as continuing firms, it is mainly the persistence of productivity ρ, not the operating cost c_o, that shoves firms out of the CIES data. The mean $\mu_z = 0.9$ and volatility $\sigma_z = 0.7$ are calibrated so that the average and standard deviation for firm-level productivity are 1.82 and 0.45 in the simulated top 20% firms as in the CIES data.

The debt limit $log(\bar{b})$ determines access to credit. With a higher limit in the future, the chance that firms are unable to roll over debt after a low productivity shock is lower. Consequently, the incidence of exit and default is less likely, which induces more borrowing by firms with q low net worth. Therefore, the level of $log(\bar{b})$ is chosen to match the fraction of firms access to credit in the simulated data to that in the World Bank Data Survey 2012.[28] For the empirical underpinnings, I interpret firms' debt in a more general form that includes borrowings from bank and non-bank financial institutions, trade credit from suppliers and other borrowings from friends, relatives and moneylenders in the World Bank data. This gives a 34.29% of firms with debt and a calibrated debt limit $log(\bar{b}) = 6.096$.

The population exit rate differs from the exit rate in the CIES, 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 the survival analysis report of firms by State Administration for Industry and Commerce. The annual growth rate in the manufacturing population during this period is approximately 9%,

[26]This is higher than an average capital share 0.06 computed in Equation 2 when using an imputed rental rate 13%.

[27]In computation, the support of productivity is $[\mu_z - 4.5\sigma_z, \mu_z + 4.5z]$ and discretized into 15 grids. The AR(1) process is then discretized into a 15×15 transition matrix by Tauchen (1986)'s method.

[28]The liability on accounting tables of the CIES is too noisy to be a good measure of debt, since it includes several accounting items such as wages and pension payable, interest payable, customer deposits etc. Instead, the World Bank Enterprise Survey 2012 asks firms specifically whether they have borrowed for financing working capital and fixed capital investment, from banks, non-bank financial institutions, suppliers and other sources.

Table 8: Parameter Values

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	60%
Fixed cost free band	ζ	0.09	Debt limit	$log(\bar{b})$	6.096
Convex cost	θ	0.049	Operating cost	c_o	5
Interest Rates			*Productivity Process*		
Cutoff sales	y_c	436.30	Population persistence of productivity	ρ_z	0.70
Saving rate	r_1	0.03	Population S. D. of productivity	σ_z	0.70
Prime borrowing rate	r_2	0.06	Unconditional mean	μ_z	0.90
Recovery Rates			*Initial wealth Distribution of Entrants*		
Cash	γ_1	0.1	Mass of entrants	μ_{ent}	0.17
Capital	γ_2	0.3	Pareto Shape	α	0.6
			Min. Wealth	a_{min}	20

according to censuses 2004 and 2008. To match this growth rate, the relative mass of entrants μ_{ent} is chosen to be 17%.

Entrants draw productivity 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 post 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 and different percentiles of sales. Thus, the three parameters α, a_{min} and ω are jointly pinned down to match a 67.89% market share of entrants in 2003, a 59% market share of data exiters in 1998, and a market share of new firms as 1.3 times as that of old data entrants in 2003.

Table 8 lists all calibrated parameters and their levels, and Table 9 shows the differences of targeted moments in the model and in the data. The model overall replicates these key moments in the data with some room to improve on the exit rate and the market share of CIES data entrants in $t + 5$.

Table 9: Targeted Moments

Moments	Data	Model
Market share by firms of top 10% sales	84.5%	87.5%
Population exit rate*	8%	5.8%
Frac. of firms above threshold	20%	20%
Frac. of firms with debt*	34.29%	34.60%
Mean productivity (Top 20% firms)	1.82	1.80
SD of productivity (Top 20% firms)	0.45	0.43
5-year Horizon		
Frac. of CIES data exiters in t	59%	57.88%
Frac. of CIES data entrants in $t+5$	67.89%	72.20%
Market share of CIES data exiters in t	40.09%	41.29%
Market share of CIES data entrants in $t+5$	49.14%	56.38%
$\frac{\text{Market Share of Young Data Eantrants}}{\text{Market Share of Old Data Entrants}}$	1.3	1.3

Moments except for * are from the CIES data 1998-2003. The population exit rate is from a survival analysis of firms in China by State Administration for Industry and Commerce. The fraction of firms with debt is from World Bank Enterprise Survey 2012.

Out of Model Fit To check whether the calibrated model reasonably captures the frictions that firms in the CIES data face, I compare the dynamics of a given cohort in the simulation to that in the CIES data for 6 years after their entry.

The specific dynamics presented here is how productivity, capital and sales of a given cohort converge to those of all firms, both in the CIES data and in the simulated top 20% subgroup. Since the CIES data only includes the top 20% of manufacturing firms, I assume that only the top 20% of the simulated data are observable every period. This suggests that firms of a given cohort that are observable may not be the same set of firms every year. For example, in the 1998 CIES data, 5024 firms report that their birth years are 1998. In 1999, 801 of the 5024 firms disappear from the CIES data, while another 3038 firms of the 1998 cohort who are below the threshold sales in 1998 enter into the 1999 CIES data.[29]

I focus on the 1998 cohort of the CIES since it provides the longest observation window. Figure 2, 3 and 4 plot the differences in average log productivity, log capital and log sale between a birth

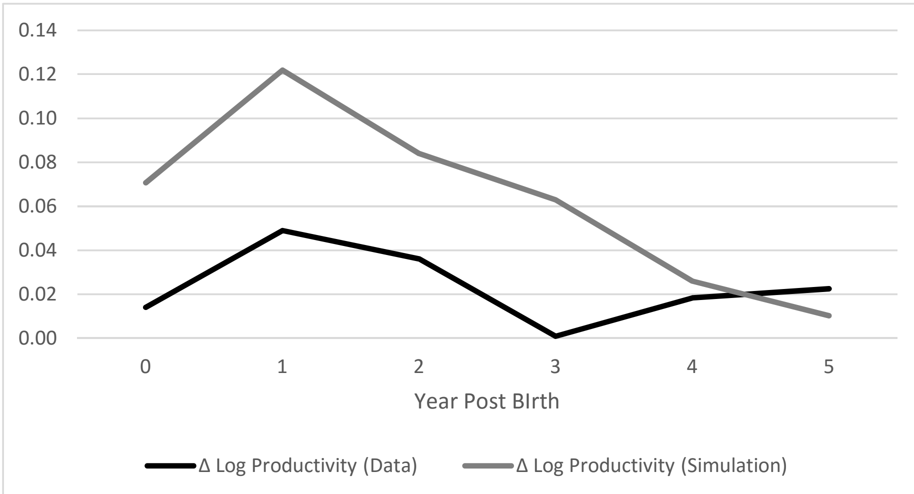
[29]See Table A7 in Appendix for more details. Table A7 also compares entry and exit of the simulated top 20% subgroup for a given cohort over time to that in the CIES data.

cohort and all firms, both in the CIES data and in the simulated top 20% firms over 6 years post birth. In Figure 2, the model replicates two features of productivity for the 1998 cohort in the CIES data. First, firms of the birth cohort that produce above threshold sales outperform other firms in productivity. Since most entrants start from a low capital stock (see Figure 3), those producing more than the threshold sales must have a higher productivity. Second, such a productivity advantage decays over time. The decaying effect is due to the Markovian process of productivity, and a lower level productivity needed to be included in the CIES data or top 20% firms by a growing average capital for the birth cohort, as evident (see Figure 3). Combining productivity and capital, log sales of birth firms first grow then get stable in Figure 4.[30] Overall, the model delivers a similar pattern of firm dynamics to that observed in CIES data.[31]

[30]I also look at 1999-2006 cohorts. The general pattern of decaying productivity, growing capital stock and sales hold in other cohorts. However, from 1998 to 2006, the relative log productivity of a birth cohort compared to all firms in the CIES data is declining over time, while the average firm-level productivity in the CIES grows. One explanation is that firm-level productivity growth, e.g. through R&D, takes place on incumbent firms rather than on new firms.

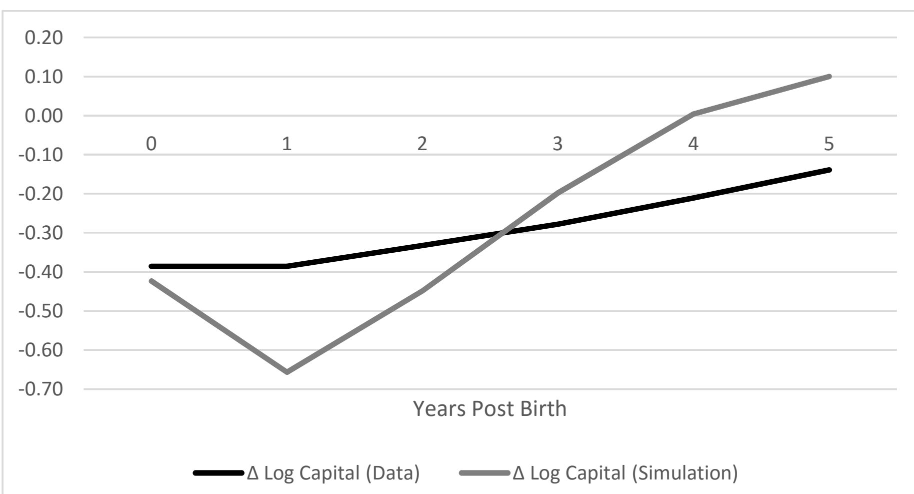
[31]The dip of log capital in Figure 4 is due to intermediate goods frictions. Note that these firms enter at time $t = -1$, and prepare in $t = -1$ before productions in $t = 0$. At time $t = -1$, the birth cohort have no retained earnings from the past and are constrained in intermediate goods m_0. At time $t = 0$, firms have retained earnings from the production and are therefore less constrained in intermediate goods choice m_1 than in $t = -1$. As a result, firms enter into $t = 1$ with more pre-ordered intermediate goods, and hence have lower capital stocks on average to produce more than the threshold sales. A similar argument applies to the spike in productivity (see Figure 3).

Figure 2: Diff. in Log Productivity of a Given Cohort Compared to All Firms above the Threshold Sales, Data vs Model



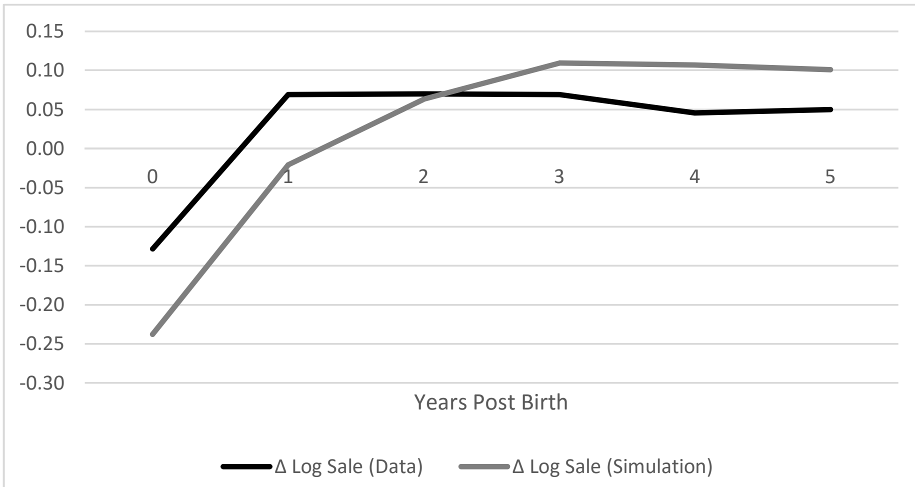
The cohort for the CIES data is 1998 cohort. Δ log productivity is defined as the difference of log productivity between 1998 cohort and all firms in the CIES data. A similar definition applies for the simulated top 20% firms in the model.

Figure 3: Diff. in Log Capital of a Given Cohort Compared to All Firms above the Threshold Sales, Data vs Model



The cohort for the CIES data is 1998 cohort. Δ log capital is defined as the difference of log capital between 1998 cohort and all firms in the CIES data. A similar definition applies for the simulated top 20% firms in the model.

Figure 4: Diff. in Log Sale of a Given Cohort Compared to All Firms above Threshold Sales, Data vs Model



The cohort for the CIES data is 1998 cohort. Δ log sale is defined as the difference of log sale between 1998 cohort and all firms in the CIES data. A similar definition applies for the simulated top 20% firms in the model.

4.2 Misallocation: Model vs Data

This section compares measured misallocation in the calibrated model with that in the CIES data. I compute measured misallocation as the percentage of gross output gain if marginal products of intermediate goods, capital and labor were equalized across firms. I find that the gross output gain averages 140% of actual gross output in the CIES data over 1998-2007, and 96% in the simulated top 20% firms. Overall, the model accounts for 69% of misallocation that is measured in the CIES data.

Measured Misallocation Following Hsieh and Klenow (2009) and Midrigan and Xu (2014), measured misallocation quantifies the potential output gain by reallocating inputs to equalize marginal products across firms, given a fixed distribution distribution of firm-level productivity. My measure of misallocation differs, however, in that the output refers to gross output rather than value-added.

Given n firms with capital stock k_i, labor employment l_i, intermediate goods m_i and actual gross output y_i for each firm i, a hypothetically efficient aggregate Y_{eff} is calculated by reallocating k_i, l_i and m_i to equate marginal products of capital MP_k, labor MP_l and intermediate goods MP_m, holding aggregate capital $\sum_i k_i$, intermediate goods $\sum_i m_i$ and labor $\sum_i l_i$ constant. This potential output Y_{eff} is achievable when all inputs are adjustable intra period without frictions, assuming that firms purchase inputs in a competitive markets without any distortions. In other words, Y_{eff} is the first-best gross output if there is a social planner that maximizes the sum of firm-level gross output, facing no real and financial frictions. Measured misallocation is calculated:

$$\text{Measured Misallocation} = \frac{Y_{eff} - Y}{Y} \tag{30}$$

while $Y = \sum_i y_i$ is the actual aggregate gross output in the data.

Misallocation in the CIES Data Using Equation (30), I compute the measured misallocation in the CIES data each year over 1998-2007. Since there are a range of industries in the CIES data, the efficient output Y_{eff} is computed to equalize marginal products within each 2-digit CIC industry.

Several pre-treatments on firm-level productivities are required for two reasons. First, the distribution of firm-level productivities in the CIES data exhibits thicker left and right tails than the log normal distribution in the model. Since the hypothetical efficient output Y_{eff} is sensitive to tail values in the productivity distribution,[32] I trim the productivity distribution in the CIES to make the data and the model share the same support of firm-level productivities. Second, there is a growth on average firm-level productivities in the CIES data, from 1.82 in 1998 to 2.12 in 2007, which is absent in the model. Therefore, the trimming scheme is adapted to take this growth into account. Specifically, in 1998, the range of productivity in CIES data is trimmed to be $[\mu_z - 4.5\sigma_z, \mu_z + 4.5\sigma_z]$ to match that in the model computation. In later years, the ranges are adjusted to be $[\mu_z + \Delta z - 4.5\sigma_z, \mu_z + \Delta z + 4.5\sigma_z]$, while Δz is the difference in productivity of a given year compared to 1998 (see Table A5 in Appendix).

Table 10: Gross Output Gain by Equalizing Marginal Products within 2-digit CIC Industry, CIES

Year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	**Average**
Gross Output Gain	1.68	1.43	1.54	1.29	1.33	1.15	1.40	1.35	1.26	1.24	**1.40**

Table 10 presents the measured misallocation in the CIES data over 1998-2007. The average 1.4 suggests that if marginal products of inputs were hypothetically equalized, gross output in the

[32]In the most extreme case, if there is a small fraction of firms with extremely high productivities yet not much inputs, the gross output gain would be tremendous. Therefore, one must take a stand whether these firms are outliers compared to firms in the model. This is more a problem when the return to scale gets closer to 1. My view here is that the productivity range in the CIES must be consistent with the calibrated model.

CIES data could be 2.4 times that of actual gross output. A general declining trend in output gain exists from 1998 to 2003, and from 2004 to 2007. There is an increase of 25 percentage points in 2004, which is potentially caused by the fact that the data entry rate in this year is more than 50%, much higher than 20% in other years during 1998-2007.[33]

Misallocation in the Model How does the model perform in accounting for the measured misallocation in the CIES data in Table 10? I compute the gross output gain in the simulated top 20% firms, which is the model equivalent of the CIES data.[34] Since the model does not distinguish industries, marginal products are equalized across all top 20% firms to calculate the efficient gross output. Table 11 presents that the gross output gain is 96% in the model, suggesting that the gross output would almost double if marginal products were equalized. Compared to the CIES data, the model accounts for close to 70% of misallocation in the data.

Table 11: Gross Output Gain, CIES Data vs Top 20% Firms in Model Simulation

CIES Data 1998-2007	Model	Model % of Data
1.40	0.96	69.34%

4.3 Decomposing Misallocation

The benchmark model has four frictions: borrowing constraints and real frictions on both intermediate goods and capital. How much does each friction account for the measured misallocation in the calibrated model? 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 carry out counterfactual experiments that remove the frictions one by one from the benchmark model. The counterfactual experiments proceed in the following order:

- Experiment 1 (Exp. 1) removes the borrowing constraint on intermediate goods. Specifically, payment for next period intermediate goods, $\omega m'$, enters into firms' objective function, but not into the endogenous borrowing constraint (see Equation 13). One interpretation of this

[33] Such a high entry rate is possibly due to the fact that the First Economic Census takes place in 2004, which includes a set of firms that have sales barely at 5 million yuan, and avoid reporting to National Bureau of Statistics prior 2004 (Holz, 2013)

[34] The measured misallocation in the simulated top 20% firms does not differ much from that in the simulated manufacturing population (see Table A6 in Appendix). This is sensible since the CIES data produces 90% of manufacturing gross output in 2004.

Table 12: Model Specifications of Counterfactual Experiments

Friction	Benchmark	Exp. 1	Exp. 2	Exp. 3
Real Frictions on Capital	✓	✓	✓	✓
Borrowing Constraints on Capital	✓	✓	✓	
Real Frictions on Intermediate Goods	✓	✓		
Borrowing Constraints on Intermediate Goods	✓			

counterfactual is that firms cannot default on any borrowings for intermediate goods purchases. Or, whenever firms default on these borrowings, intermediate goods can be seized and sold without any costs by the lenders, who are most likely intermediate goods suppliers in practice.

- Experiment 2 (Exp. 2) further removes time-to-order on intermediate goods by allowing firms to choose the static optimal amount of intermediate goods after productivity shocks. In other words, firms solve optimal labor l and intermediate goods m intra period:

$$\max_{l,m} y(z,k,l,m) - m - l \tag{31}$$

  The resulting intermediate goods m_{static} is static optimal. This specification is close to the modern sector part of Midrigan and Xu (2014) but with capital adjustment costs.

- Experiment 3 (Exp. 3) further removes borrowing constraints on capital by allowing negative dividends or new equity issuance. This is essentially Asker et al. (2014) or a gross output version of Cooper and Haltiwanger (2006) but with entry and exit.

Table 12 lists which frictions are included under benchmark and counterfactual specifications. In each experiment, the counterfactual model is simulated to obtain a new stationary distribution given calibrated parameters from the benchmark model. The threshold sales y_cs are recalculated so that there are always 20% firms above the threshold. Given these top 20% firms under each counterfactual experiment with their actual output y_i, I calculate measured misallocation as in Equation (30). This exercise answers the question how much gross output gain would be if firms in the CIES behaved as in Exp. 1, 2 and 3, if marginal products of all inputs were equalized. Results are presented in Table 13.

Table 13: Simulated Output Gain by Equalizing Marginal Products, Benchmark vs Counterfactuals

	Model Specifications							
	Benchmark		Exp. 1		Exp. 2		Exp. 3	
	Potential Gain	% of Data	Potential Gain	% of Data	Potential Gain	% of Data	Potential Gain	% of Data
	0.96	69.34%	0.64	46.69%	0.49	35.62%	0.48	34.75%
Each Friction:								
B.C. on Intm. Goods	0.32	22.65%						
R.F. on Intm. Goods			0.15	11.07%				
B.C. on Capital					0.01	0.87 %		
R.F. on Capital							0.48	34.75%

B.C. on Intm. Goods: Borrowing constraints on intermediate goods; R.F. on Intm. Goods: Real frictions on intermediate goods; B.C. on Capital: Borrowing constraints on capital; R.F. on Capital: Real Frictions on Capital.

Benchmark includes all four frictions. Exp. 1 removes borrowing constraints on intermediate Goods. Exp 2 further removes real frictions on intermediate goods. Exp 3 lastly removes borrowing constraints on capital.

Borrowing Constraints on Intermediate Goods In Exp. 1, gross output gain would be 0.64 times the actual output Y, if marginal products of capital, labor and intermediate goods were equalized among the top 20% simulated firms. Compared to the gain of 0.96 in the benchmark model, the gross output gain in Exp. 1 is 0.32 lower. Therefore, measured misallocation in Exp. 1 accounts for 46.69% of that in the CIES data, which is 22.65 percentage points lower than that in the benchmark model. This implies that borrowing constraints on intermediate goods account for 22.65% of measured misallocation in the CIES data.

Borrowing constraints on intermediate goods generate measured misallocation through three channels. First, since intermediate goods is 70% of revenue, a positive down-payment for intermediate goods increases the borrowing need and tightens the borrowing constraint. Roughly, for each \$1 of expected sales in the next period, \$0.42 of intermediate goods have to be financed on top of capital investment. This increases the amount of borrowing that are subject to the default risk from the lenders' view. Further, this increase of borrowing need is recurrent since intermediate goods depreciate in one-period.

Second, at time t, capital investment $k_{t+1} - (1-\delta)k_t$ could be crowded out because of the borrowing need for intermediate goods m_{t+1}. Since capital serves as better collateral than intermediate goods, the level of collateral decreases, causing a more tightened constraint from time t and on.

Third, while time-to-order on intermediate goods reduces profits and lowers capital investment, borrowing constraints on intermediate goods prolong this negative effect. At time t, firms cannot achieve the static optimal intermediate goods m_{static} if the pre-ordered level m_t is too low. With a lower current profit, next period capital k_{t+1} is lower than without time-to-order. If there is no borrowing constraints on intermediate goods, firms could react to order more intermediate goods m_{t+1} for $t+1$ by the persistence of productivities. This increases profit in $t+1$ and consequently alleviates the negative effect on capital from time $t+2$ and on. With borrowing constraints on intermediate goods, however, firms are constrained in the amount of intermediate goods m_{t+1} they can order. Therefore, the status of inadequate intermediate goods persists, keeps the constraint tight in $t+1$, and so forth. In other words, the negative effect on capital persists over time.

To illustrate the second and the third channels at time t, I regress capital in the following periods $logk_{i,t+\Delta}, \Delta \geq 1$, on a dummy of inadequate intermediate goods, Dummy$(m_t < m_{static})$ in t, controlling for starting state variables of productivity z_{it}, capital $logk_{i,t}$, and debt/saving level $b_{i,t}$:

$$\text{log}k_{i,t+\Delta} = \beta_0 + \beta_1 z_{i,t} + \beta_2 logk_{i,t} + \beta_2 b_{i,t} + \beta_3 \text{Dummy}(m_t < m_{static})_{i,t} + residual \quad (32)$$

among the top 20% simulated firms in the benchmark model and in Exp. 1. The idea is that

Table 14: Effect of Inadequate Intermediate Goods β_3 on Future Capital, Benchmark vs Exp. 1

	Benchmark	Exp. 1
$t+1$	-0.5722	-0.3196
$t+2$	-0.5389	-0.0012
$t+3$	-0.4331	0.0222
$t+4$	-0.3270	0.0241
$t+5$	-0.2727	-0.0073

Benchmark includes all four frictions. Exp. 1 removes borrowing constraints on intermediate Goods.

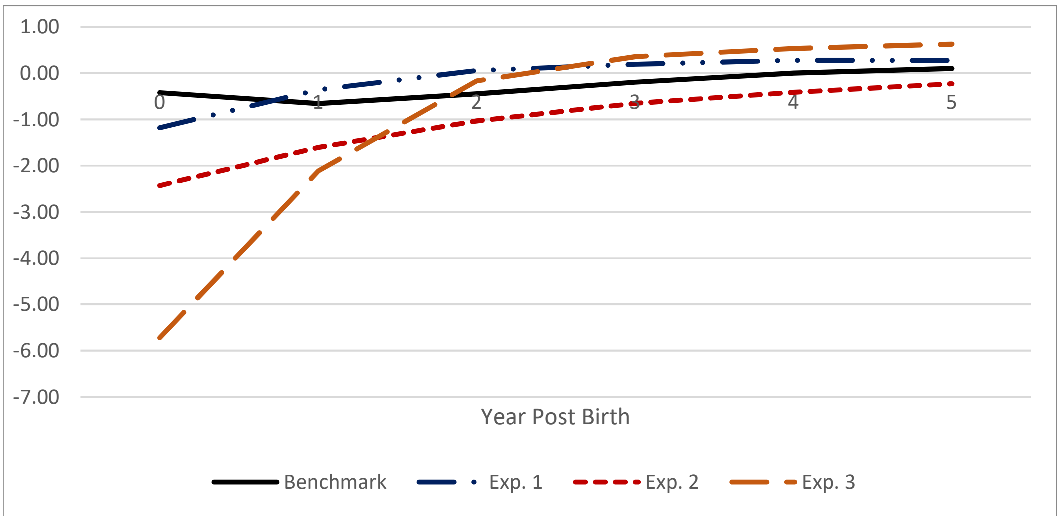
without intermediate goods frictions, firms with the same state variables (z_t, b_t, k_t) choose the same capital k_{t+1} in $t+1$. With intermediate goods frictions, a firm that has a lower productivity z_{t-1} and capital k_{t-1} in $t-1$, and chooses a lower intermediate goods m_t is in a disadvantage situation in choosing capital k_{t+1}. Equation (32) quantifies the impact of such a disadvantage on future capital.

Table 14 gives estimates of β_3 in both Benchmark and Exp. 1. In the benchmark model, the impact of inadequate intermediate goods lowers next period capital by 57%, 25 percentage points higher than in Exp.1 due to the second channel. The negative effect in Benchmark prolongs to time $t+5$ with a negative impact of 27%, due to the third channel. In contrast, next period capital only decreases by 32% in Exp. 1 and such a negative effect almost vanishes in one period.

Because of the three channels, the capital accumulation process is consequently slower when borrowing constraints on intermediate goods are on. In Figure 5, average log capital for a birth cohort takes 6 years to converge to the average of all top 20% firms in the benchmark model, and only 3 years in the Exp. 1. The resulting firm size distribution also differs. Table 15 illustrates that compared to Exp. 1, the benchmark has uniformly lower log capital on all percentiles with 145% lower average capital. Consequently, average sales is 52% lower in the benchmark model than in Exp. 1.

Time-to-Order on Intermediate Goods Exp. 2 further removes the real friction of time-to-order on intermediate goods. Table 13 shows that if firms in the CIES data behaved as in the model of Exp. 2, the potential output gain would be 0.49 times the actual output Y, which accounts for 35.62% of measured misallocation in the CIES. The difference of 11.07% between Exp. 1 and Exp. 2 is therefore attributed to time-to-order on intermediate goods.

Figure 5: Diff. in Log Capital of A Birth Cohort Compared to All Firms above Threshold Sales, Benchmark vs Counterfactuals



Benchmark includes all four frictions. Exp. 1 removes borrowing constraints on intermediate Goods. Exp. 2 further removes time-to-order on intermediate goods. Exp. 3 lastly removes borrowing constraints on capital.

Table 15: Log Gross Output and Log Capital Distributions, Benchmark vs Counterfactuals

Percentile	Model Specifications							
	Benchmark		Exp. 1		Exp. 2		Exp. 3	
	log y	log k	log y	log k	log y	log k	log y	log k
10%	6.27	4.06	6.92	6.02	7.36	5.04	7.64	6.50
25%	6.40	5.53	7.51	6.34	7.70	6.34	8.20	7.80
50%	7.29	6.34	8.20	7.15	8.70	8.45	9.18	9.27
75%	8.14	6.50	9.74	8.94	9.74	9.27	10.00	9.92
90%	9.24	7.48	10.85	9.75	11.24	9.92	11.37	9.92
Mean	7.46	6.04	7.98	7.49	9.04	7.84	9.33	8.83

Distribution for each specification is within the subgroup of top 20% firms. Benchmark includes all four frictions. Exp. 1 removes borrowing constraints on intermediate Goods. Exp. 2 further removes time-to-order on intermediate goods. Exp. 3 lastly removes borrowing constraints on capital.

In Exp. 1, since firms cannot purchase intermediate goods above the pre-ordered level, there exists a pre-cautionary motive for investment in intermediate goods. Consequently, the pre-ordered level of intermediate goods m' is on average 16 times of that used in the production.

Despite the pre-cautionary motive, the choice of next period intermediate goods m' is influenced by an expected return that is determined by the distribution of future productivity, and capital stock in the next period. Therefore, firms may have a pre-ordered level of intermediate goods lower than the static optimal level after high productivity shocks are realized. Table 16 shows that there are 31.12% of these firms among the top 20% group, and 16.57% among all simulated firms. These firms have a unsurprisingly higher productivity, 42.7% higher among the top 20% firms and 10.42% higher among all simulated firms. They also tend to have a lower capital stock, 86.86% lower among top 20% firms and 42.19% lower among all simulated firms, which rationalizes a lower marginal return and a lower option value of ordering intermediate goods a period ahead.

Table 16: Intermediate Goods Usage Compared to the Static Optimal, Simulated Exp. 2

	Frac. of	Average Log Productivity		Average Log Capital	
	Smaller	Equal	Smaller	Equal	Smaller
Top 20% Firms	31.12%	1.7474	2.1744	7.7653	6.8967
All Firms	16.57%	0.8838	0.9880	6.1316	5.7097

Subgroup Smaller (Equal): firms with intermediate goods usage in Exp. 2 smaller than (equal) the static optimal level. Exp 2 removes borrowing constraints and real frictions on intermediate goods.

Real frictions also lowers the capital investment through a lower current profit. However, as shown in Table 14, this effect is short-lived. This is because firms react to the high productivity by investing a high level of next period intermediate goods, which soon increases the next period profit and capital investment. As a result, the average capital in Exp. 1 is 35% lower than in Exp. 2, smaller than the difference of 145% between Benchmark and Exp. 1.

Borrowing Constraints on Capital Exp. 3 further removes borrowing constraints on capital. Table 13 presents that in a model with only one-period time-to-build and capital adjustment costs, the gross output gain is 0.48 of actual gross output Y, if marginal products of capital, labor and intermediate goods were equalized across firms. This is close to the 0.49 in Exp. 2, and suggests that borrowing constraints on capital only account for 0.87% of measured misallocation in the CIES data.

One may argue that the small output loss is driven by restricting attention to firms in the top

20% of sales distribution, as these firms are relatively unconstrained. There may still exist many firms that are constrained and below the threshold sales such that removing borrowing constraints on capital increases output significantly among all firms. Yet if I calculate measured misallocation among all simulated firms in Exp. 2 and Exp. 3, the results are similar to that in Table 13. The potential output gain is 0.52 in Exp. 2, and 0.51 in Exp. 3.

The small output loss from borrowing constraints on capital, however, does not indicate firms are unconstrained. In Figure 5, capital accumulation with the constraint takes more than 5 years to converge to the average log capital among top 20% firms, slower than the case without the constraint. As a result, percentiles of log capital distribution in Table 15 with the constraint are lower than those without the constraint, except for the 90 percentile. The seeming contradiction of a small output loss and a lower average capital stock is reconciled by the fact that the most productive firms have high capital stocks with and without the constraint. Since most output is produced by these top productive firms,[35] reallocating inputs does not increase more output gain despite an average lower capital with the constraint. Table 17 illustrates this point. If I calculate the fraction of capital stock owned by firms above log productivity 2.25 (75 percentile of the productivity distribution), the number is 53% in Exp. 2 with borrowing constraints on capital, and a similar fraction 57% in Exp. 3 without. In terms of output, they produce a very similar fraction of aggregate output at 97% in Exp. 2 and Exp. 3. A qualitatively similar result holds for the 99 percentile of productivity 3.15.

Table 17: Fraction of Gross Output Produced and Owned by Top Productive Firms, Top 20% Simulated Firms

		Exp. 2		Exp. 3	
Log Productivity Above	Productivity Percentile	Frac. of Agg. Output	Frac. of Agg. Capital	Frac. Of Agg. Output	Frac. Of Agg. Capital
3.15	99%	71.3%	14.5%	71.3%	11.5%
2.25	75%	97.1%	53.4%	97.4%	56.7%

Exp 2 removes borrowing constraints and real frictions on intermediate goods. Exp 3 further removes borrowing constraints on capital.

Compared to the literature, this finding of a small output loss from borrowing constraints on capital is unsurprising. Midrigan and Xu (2014) and Moll (2014) address that self-financing can undo misallocation caused by borrowing constraints on capital, which is also true in this paper as

[35] This property is called granularity, see Xavier (2011).

firms can save and productivities are persistent. As Hopenhayn (2014) points out, the impact of financial constraints on misallocation may be larger, given a high entry with young and constrained firms. However, this paper shows that with capital adjustment costs slowing down the growth of firms, a high entry rate of 17% in China, about two times in Midrigan and Xu (2014), does not magnify the role of borrowing constraints on capital in accounting for misallocation. Unless there are other frictions that further slow down the growth of firms, it could be hard to get a sizable misallocation by simply feeding in more entrants.

Real Frictions on Capital The remained frictions in Exp. 3 are one-period time-to-build and adjustment costs for capital. The channels of these two frictions are well addressed in the investment literature, e.g. Cooper and Haltiwanger (2006) and Khan and Thomas (2008), and in the misallocation literature, e.g. Asker et al. (2014). First, because of one-period time-to-build, capital stock determined a period ahead is not static optimal after stochastic productivity shocks. Second, due to the fixed and convex adjustment costs, firms that would like to adjust capital to a certain level may find it too costly to do.

Table 13 presents that in Exp. 3, gross output gain is 0.48 if marginal products of capital, labor and intermediate goods were equalized across firms, which accounts for about 35% of measured misallocation in the CIES data. Without frictions on intermediate goods and borrowing constraints on capital, the capital threshold for top 20% firms in sales are effectively lower, and capital accumulation is pretty fast. In Figure 5, a birth cohort starts from an average capital much lower than the mean of all firms in the top 20% group, and converges to the mean in 3 years. This accumulation speed is much faster than that in the CIES data in Figure 3.

Summary This section decomposes the model simulated misallocation in Section 4.2 into contributions by borrowing constraints and real frictions on intermediate goods and capital. Out of 69% CIES measured misallocation by the model, I find that real frictions on capital and borrowing constraints on intermediate goods account for the most measured misallocation in the CIES data by 34.75% and 22.65%, respectively. Real frictions on intermediate goods account for another 11.07% while borrowing constraints on capital account for a negligible 0.87%. In other words, new frictions proposed in this paper on intermediate goods can account for an extra 33.72% of misallocation in China, on top of the misallocation caused by capital frictions that has been well studied in the literature.

5 Conclusion

This paper introduces borrowing constraints and time-to-order on intermediate goods and quantifies their role in accounting for measured misallocation in the CIES data. Although intermediate goods have been largely ignored in the misallocation literature, I find that reallocating intermediate goods alone generates the most gross output gain than reallocating capital or labor alone. Consistent with the borrowing constraints story, the dispersion of marginal products in intermediate goods is observed to be larger among firms with low net worth.

I incorporate borrowing constraints and time-to-order on intermediate goods, as well as borrowing constraints on capital, into a standard firm investment model Cooper and Haltiwanger (2006) with entry and exit. When calibrated to key moments in China, I find that the model generates substantial misallocation, and accounts for 69% of that in the CIES data. A further decomposition shows that frictions on intermediate goods are quantitatively important. They account for about a half of the model generated misallocation, and about 34% of misallocation in the CIES data. In particular, borrowing constraints account for a third and around a quarter of misallocation in the model and in the CIES data, respectively. Real frictions on capital are also important and account for a similar magnitude of misallocation as intermediate goods frictions. Consistent with the literature, I find that borrowing constraints on capital generate little misallocation.

There are several future extensions for this project. First, in the current paper, costs in intermediate goods and capital are in one borrowing constraint. It can be, however, separated into two with one working capital constraint on current period intermediate goods, and one borrowing constraints on capital. This alternative setting will keep the negative effect of borrowings for intermediate goods on capital, as long as competitive lenders observe both types of borrowings. An upper limit for the current period intermediate goods would be the result of the working capital constraint. This benefits in relaxing the assumption that firms cannot buy intermediate goods above the pre-ordered level in the current paper. Second, the partial equilibrium stand on intermediate goods, labor and output markets can be extended into a general equilibrium analysis. Output of each firm can be used as final goods consumed by households, and also intermediate goods for other firms, as in Basu (1995). If inputs are misallocated at the first place by mechanisms studied in this paper, most productive firms cannot produce and supply a large amount of output in the intermediate goods market. The extra effect, studied by Jones (2011), could increase prices of intermediate goods, which could further create misallocation by worsening the financing problem for productive constrained firms.

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Appendix

Table A1: Variable Definitions in China Industrial Enterprise Survey (CIES)

Variable	Definition
Registration ID	Unique 9-digit identifying number for each firm
Ownership (SOE)	Firms with Registration Classification 110,120,141,143,145,151(see Holz, 2013)
Ownership (NonSOE)	Firms with Registration Classification 130,142,149,159,160,171,172,173, 174,190,219,220,230,240,310,320,330,340 (see Holz, 2013)
Birth year	The first year firms operate. It could be earlier than the year when firms get registered. If a firm switches from state-owned to non-state owned, the birth year is that of the old firm.
Industry	4-digit China Industrial Classification code GB/T 4754-1994 before 2003, GB/T 4754-2002 between 2003 and 2011, and GB/T 4754-2011 since 2012
Gross Output	Market value of finished products and semi-finished products that are produced in the calendar year
Book Value of Capital	The value at which the asset is carried on a balance sheet and calculated by taking the cost of an asset minus the accumulated depreciation.
Employment	Average employment over the calender year; includes both full-time and part-time employment
Total Wage Payable	Total wage bill for all workers, including full-time and part-time. This does not include benefits.
Intermediate Inputs	Raw materials, energy and semi-finished products that are purchased from all sources *and* used in producing gross output in the calendar year.
Inventory	The value of raw materials, semi-finished products and finished products.
Account Receivables	The value of sales (not restricted to sales in the calendar year) that have not been collected from buyers.

Sources: National Bureau of Statistics at Shanghai, http://www.stats-sh.gov.cn/, and Beijing http://www.bjstats.gov.cn/

Table A2: 2-Digit China Industrial Classification Code (CIC), Manufacturing

2-Digit	GB/T 4754-1994	Changes in GB/T 4754-2002
13	Food processing	N/A
14	Manufacture of foods	N/A
15	Manufacture of beverages	N/A
16	Manufacture of tobacco	N/A
17	Manufacture of textiles	N/A
18	Garments and other fiber products	N/A
19	Leather, furs, down and related products	N/A
20	Timber processing, bamboo, cane, palm fiber and straw products	N/A
21	Manufacture of furniture	N/A
22	Papermaking and paper products	N/A
23	Printing and recorded media	N/A
24	Cultural, educational and sports goods	N/A
25	Petroleum processing and coking	N/A
26	Raw chemical materials and chemical products	N/A
27	Medical and pharmaceutical products	N/A
28	Chemical fiber	N/A
29	Rubber products	N/A
30	Plastic products	N/A
31	Nonmetal mineral products	N/A
32	Smelting and pressing of ferrous metals	N/A
33	Smelting and pressing of nonferrous metals	N/A
34	Metal products	N/A
35	Ordinary machinery	N/A
36	Special purpose equipment	N/A
37	Transport equipment	N/A
39	Weapons and ammunition manufacturing	Merged into 36
		Relabeled: Electric equipment and machinery

Table A2: 2-Digit China Industrial Classification Code (CIC), Manufacturing(continued)

2-Digit	GB/T 4754-1994	Changes in GB/T 4754-2002
40	Electric equipment and machinery	Relabeled: Electronic and telecommunications equipment
41	Electronic and telecommunications equipment	Relabeled: Instruments, meters, cultural and office equipment
42	Instruments, meters, cultural and office equipment	Relabeled: Other manufacturing
43	Other manufacturing	New: Industrial Waste Recycling

Source: National Bureau of Statistics. There are four versions of Industrial Classification Codes. GB/T 4754-1984 was used during 1985 to 1994. GB/T 4754-1994 was used during 1995 to 2002. GB/T 4754-2002 was used during 2003 to 2011. The newest code system is GB/T 4754-2011 and has been used since 2012.

Table A3: Summary Statistics of China Industrial Enterprise Survey (CIES) Data

Year	Num.	NonSOE %	NonSOE Emp. %	NonSOE Output %	Emp. (Mean)	GrossOutput (Mean)	WageBill (Mean)	Int. Input (Mean)
1998	147,960	38%	32%	46%	308.47	39.45	2.46	30.77
1999	146,321	44%	39%	52%	321.31	43.18	2.56	33.32
2000	147,106	52%	47%	60%	309.60	50.62	2.79	38.13
2001	154,276	64%	58%	69%	283.05	53.91	2.87	40.96
2002	165,583	71%	65%	73%	276.28	59.06	2.98	45.14
2003	179,265	79%	73%	78%	269.48	70.24	3.14	52.45
2004	250,090	88%	83%	85%	224.07	66.02	2.88	48.44
2005	249,891	90%	85%	86%	235.58	80.35	3.33	56.96
2006	277,468	92%	88%	88%	227.03	89.73	3.62	62.63
2007	304,599	94%	90%	89%	221.25	101.71	4.07	70.98

Million, 1998 Constant Yuan. Source: China Industrial Survey Data 1998-2007

Table A4: Constant Shares of Intermediate Goods and Labor

Year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Labor Share (All)	6%	6%	6%	5%	5%	4%	4%	4%	4%	4%
Labor Share (State-Owned)	7%	7%	7%	7%	6%	6%	6%	5%	5%	5%
Labor Share (Private-Owned)	5%	5%	5%	5%	5%	4%	4%	4%	4%	4%
Intermediate Goods Share	78%	77%	75 %	76%	76%	75%	73%	71%	70%	70%
Intermediate Goods Share (State-Owned)	77%	76%	74%	75%	75%	74%	74%	73%	72%	73%
Intermediate Goods Share (Private-Owned)	79%	78%	76%	77%	77%	75%	73%	71%	69%	69%

Source: China Industrial Survey Data 1998-2007

Table A5: Growth in Mean Productivities in the CIES, 1998-2007

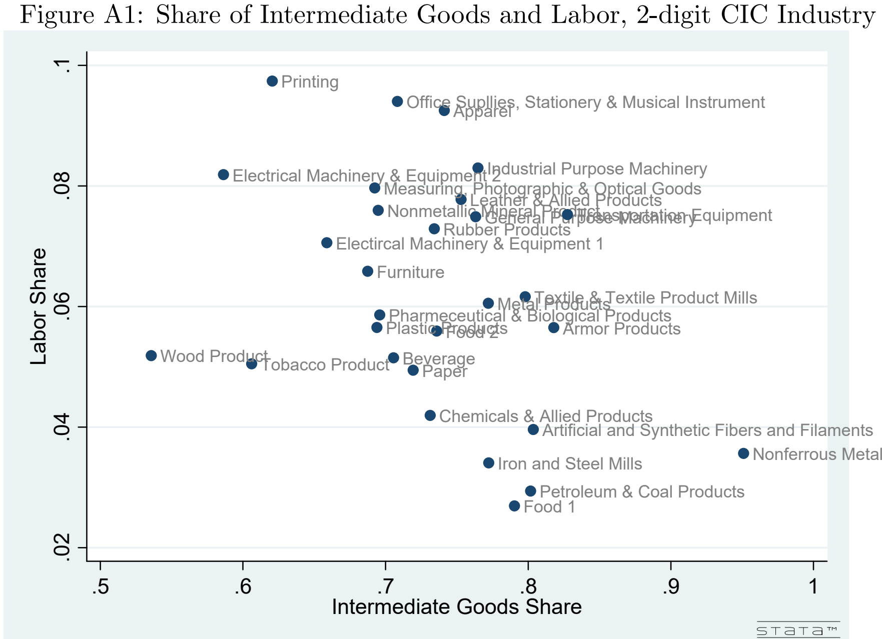
Year	Mean Productivity $\bar{z}$	Mean Productivity Relative to 1998 Δz
1998	1.82	0
1999	1.84	0.02
2000	1.89	0.07
2001	1.90	0.08
2002	1.92	0.10
2003	1.97	0.15
2004	1.98	0.16
2005	2.04	0.22
2006	2.09	0.27
2007	2.12	0.30

Source: China Industrial Survey Data 1998-2007

Table A6: Gross Output Gain in Top 20% Firms vs Simulated All Firms, Benchmark

Simulated Period	Top 20%	All	Extra TFP Gain from All Firms
0	1.01	1.09	0.08
1	0.95	1.03	0.08
2	0.94	1.02	0.08
3	0.95	1.03	0.08
4	0.95	1.02	0.08
5	0.96	1.04	0.08

Figure A1: Share of Intermediate Goods and Labor, 2-digit CIC Industry



Source: China Industrial Survey Data 1998-2007

Table A7: Data Entry and Exit in Above Threshold Sample: Simulated Data vs CIES Data

Model: Given One Birth Cohort							
Years Post Birth		No. of Firms in Data	Data Exit	Exit %	Data Enter	Enter %	Enter-Exit
0		2246					
1		3075	656	29.21%	1485	66.12%	36.91%
2		3862	860	27.97%	1647	53.56%	25.59%
3		4177	1232	31.90%	1547	40.06%	8.16%
4		4374	1264	30.26%	1461	34.98%	4.72%
5			1298	29.68%	1411	32.26%	2.58%
Data: 1998 Cohort							
Years Post Birth	Year	No. of Firms in Data	Data Exit	Exit %	Data Enter	Enter %	Enter-Exit
0	1998	5024					
1	1999	7430	801	15.94%	3038	60.47%	44.53%
2	2000	9622	1031	13.88%	2888	38.87%	24.99%
3	2001	11886	1871	19.45%	3706	38.52%	19.07%
4	2002	12870	1425	11.99%	2395	20.15%	8.16%
5	2003	13308	1736	13.49%	2079	16.15%	2.67%
6	2004	15892	3017	22.67%	5567	41.83%	19.16%
7	2005	14749	2188	13.77%	1089	6.85%	-6.92%
8	2006	14712	1238	8.39%	1183	8.02%	-0.37%
9	2007		1155	7.85%	1083	7.36%	-0.49%

Source: China Industrial Survey Data 1998-2007