R&D Misallocation in China

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Abstract

The Chinese government plays a significant role in directing private R&D and innovative activity. This top-down intervention has the potential to distort the optimal allocation of resources. Rogerson and Restuccia (2008) and Hsieh and Klenow (2009) document that distortions in the allocation of capital and labor have large negative effects on productivity. I extend the misallocation literature by developing a model with distortions on R&D spending that alter the distribution of R&D across firm productivity. I use a Melitz model along the style of Atkeson-Burstein (2010) and Hsieh and Klenow (2014) to identify both output and R&D distortions and to estimate the effect of these distortions on aggregate productivity. I calibrate the model using firm-level data from China's Annual Survey of Industries. I find that relative to a counterfactual economy with no output distortions, adding China's distribution of R&D distortions decreases aggregate productivity and GDP by about 12 percent. However, China's R&D distortions actually increase productivity by 5 percent in the Chinese economy, because they partially cancel out the effect of output distortions.

1 Introduction

Over the past quarter century, China has become a global research powerhouse. China has the second-highest R&D spending in the world and exports multiple technologies that are at the global frontier, such as supercomputers, 5G mobile technology, drones, and solar panels. This research push has been largely instituted top-down by the government rather than taking place as a result of market forces. Due to this intervention, the allocation of R&D spending across firms is distorted from the optimal allocation.

An extensive literature on misallocation has documented that input distortions have large negative effects on aggregate productivity. Rogerson and Restuccia (2008) and Hsieh and Klenow (2009) were the first to show that implicit taxes on output in developing countries have large effects, decreasing aggregate TFP in the range of 30 to 60 percent. This article contributes to the misallocation literature by extending the Rogerson and Restuccia (2008) framework to include R&D distortions. R&D distortions are important for productivity because they affect firms' technological upgrading over the life cycle.

I use firm-level data from China's Annual Survey of Industries to discipline a model in which firms choose R&D spending in order to innovate. I find that relative to a counterfactual economy with no output distortions, adding China's distribution of R&D distortions decreases aggregate productivity and GDP by about 12 percent. However, China's R&D distortions actually increase productivity by 5 percent in the Chinese economy, because they partially cancel out the effect of output distortions.

China has a long history of state involvement in research and innovation. Under early Communist rule, industrialization and technology advancement was managed directly by the government. In the 1980s, although Deng Xiaoping was taking steps to liberalize the economy, the government opened research centers that transfered technology directly to state-owned enterprises (SOEs). The Ministry of Science and Technology was founded in 1998 to fund and support research. Within the Ministry is the State Council Steering Group for Science, Technology and Education, which sets state strategy regarding management of research and technology nationwide. In 2006, President Hu Jintao and Prime Minister Wen Jiabao announced the "Medium- and Long-Term Plan on the Development of Science & Technology." This 15-year plan states that the government will heavily subsidize and encourage R&D with the goal of "leapfrogging" to the technological frontier rather than solely importing technology from other countries. It lists specific research fields in which China hopes to reach the frontier: biotechnology, information technology, advanced materials, robotics, energy, marine technology, lasers, and aerospace. The plan states that the State Council encourages R&D both through market forces and top-down intervention, "taking full advantage of the socialist system in pooling up resources to do big things and the role of the market economy system as well."

This top-down intervention is carried out through a number of different government policies. Some of these policies are implemented at the discretion of the government, potentially favoring certain firms over others. These policies include explicit funding of certain projects, loans at favorable rates, a favorable foreign exchange environment, inclusion in national high tech industrial parks, and favorable insurance. Because these benefits are not distributed equally across firms, they have the potential to create distortions in R&D spending and innovation.

Many of the policies announced by the Chinese government function as implicit subsidies and cannot be seen directly in the data, which is why I use a model to back out estimates of implicit distortions. In the data, state-owned firms are three times as large as private firms and have twice the level of R&D intensity, despite being less productive than private firms on average. This is suggestive evidence that government intervention is affecting the distribution of R&D spending across firms. The data also shows that a ten percent increase in government subsidies leads to a 1.5% increase in R&D spending when holding productivity constant.

These stylized facts suggest that government intervention is causing misallocation in R&D spending. However, there are two forces that can distort R&D: direct distortions on R&D, and distortions on output that change the firm's optimal level of R&D indirectly. In order to distinguish between these two mechanisms, I use a model that includes both output and R&D distortions and calibrate it to the data. I use a Melitz (2003) model, with added distortions on R&D spending. I calibrate the model using three moments from the data: the relationship between R&D and productivity, life cycle growth, and total R&D spending over total sales. Under Gibrat's Law, R&D intensity should be constant with respect to productivity. The relationship between R&D and productivity in the data helps identify R&D distortions as a function of productivity.

I find that implicit R&D distortions in China favor high-productivity firms relative to low-productivity firms. This relationship is the reverse of that of output distortions; as in Hsieh and Klenow (2009), I find that there are large implicit output taxes on high-productivity firms, which decrease aggregate productivity by 62 percent when added to an economy with no distortions.

Relative to a counterfactual economy with no output distortions, adding China's distribution of R&D distortions decreases aggregate TFP by 12 percent. However, adding the R&D distortions to an economy with only output distortions actually increases TFP by 5 percent, because they partially cancel out the effect of output distortions. These results are surprising: distortionary government intervention in R&D and innovation policy can help the economy in certain cases. Specifically, in developing countries where unproductive firms face implicit output subsidies, an R&D subsidy on productive firms can increase TFP. However, the optimal policy is to remove both output and R&D distortions.

The paper is organized as follows. Section II presents the model. Section III describes the firm-level dataset. Section IV details the estimation of the model. Section V concludes.

2 Model

I use a Melitz (2003) model, following the modeling choices of Atkeson and Burstein (2010) and Hsieh and Klenow (2014). The model is a closed economy GE model with monopolistic competitors whose productivities vary over the life cycle. As shown in Atkeson and Burstein (2010), there exists a steady state with a stationary distribution of firm size and a balanced growth path for aggregate variables. I focus on this steady state equilibrium. I drop time subscripts when convenient.

2.1 Base Model

I first present the base model with no R&D or output distortions.

The representative household has preferences

$$\sum_{t=0}^{\infty} \beta^t \log(C_t)$$

subject to the budget constraint

$$P_0 C_0 - W_0 L + \sum_{i=1}^{\infty} \left(\prod_{j=1}^{t} \frac{1}{R_j} \right) (P_t C_t - W_t L) \leq 0,$$

where L is inelastically supplied labor. The wage W in every period is set as the numeraire.

Final good firms exist in perfect competition. They aggregate intermediate goods $y(A_i)$ using the following technology:

$$Y = \left(\sum_{i=1}^{m} y(A_i)^{\frac{\sigma-1}{\sigma}} M(A_i) \right)^{\frac{\sigma}{\sigma-1}}$$

where $M(A_i)$ is the mass of firms with productivity A_i.

So intermediate firms face the following demand:

$$\frac{y}{Y} = \left(\frac{p}{P} \right)^{-\sigma},$$

where

$$P = \left(\sum_{i=1}^{m} p(A_i)^{1-\sigma} M(A_i) \right)^{\frac{1}{1-\sigma}}.$$

As in the Hsieh and Klenow (2014) life cycle model, there is a mass of intermediate firms at each time period t that are heterogeneous with respect to their productivity A and age a.

Intermediate firms are heterogeneous in productivity A with linear technology

$$y = Al,$$

where l is their choice of production labor.

A key feature of the model is that the evolution of productivity over the life cycle is endogenous and depends on the amount of resources that a firm devotes to innovation.

An intermediate firm's productivity either increases or decreases by one step s at each age. The firm chooses innovation $q \in [0,1]$, where the probability of productivity increasing from A to sA is q and the probability of falling to $\frac{A}{s}$ is $1-q$.

The cost of innovation without distortions is

$$C(q, A) = hA^{\sigma-1}e^{bq},$$

denominated in research labor. As in Atkeson-Burstein (2010), the elasticity of cost with respect to productivity is set equal to $\sigma - 1$. This is determined by the assumption that Gibrat's Law holds, i.e. the growth rate of a firm is independent of its size. A result of this assumption is that in an economy without distortions, R&D over sales is constant across size and productivity.

Exit is exogenous; the probability of exit at each age is δ, and all firms exit at age T. Firms face entry costs n_e, denominated in research labor. Firms enter without knowledge of their productivity.

2.2 Distortions

I introduce two distortions into this framework: R&D distortions and output distortions.

As in the original misallocation framework of Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), output distortions are represented as implicit taxes on output that decrease revenue. Distortions are a function of productivity,

$$\tau_Y(A) = 1 - Ce^{-\epsilon \ln A}$$

Revenues with output distortions are

$$(1 - \tau_Y(A))py.$$

Firms face implicit taxes on R&D that increase the cost of R&D. R&D distortions are a function of productivity.

$$\tau_C(A) = \left(\frac{A}{\gamma}\right)^{\eta} - 1.$$

The total cost of innovation is

$$(1 + \tau_C)C(q, A).$$

3 Equilibrium

A steady state equilibrium consists of $\{R, P_t, p(A), Y_t, C_t, L_{Rt}, y(A), M_t\}$ such that households maximize utility subject to the budget constraint, final goods firms maximize profits, intermediate good firms maximize profits, the feasibility constraints are satisfied, and productivity distributions evolve as described. As stated previously, the distribution of firm size is stationary and aggregate variables P_t, Y_t, C_t, L_{Rt} follow a balanced growth path. The real interest rate R is constant over time, as are the policy functions $p(A)$ and $y(A)$. The expression $\Pi_d = \frac{P^\sigma Y}{\sigma^\sigma(\sigma-1)^{1-\sigma}}$ is constant over time.

3.1 Static Decision

Intermediate firms choose labor inputs to maximize the following static problem:

$$\max_{l}(1-\tau_Y)p(l)y(l) - Wl.$$

The solution to the static problem is

$$p(A) = \frac{\sigma}{\sigma-1}\frac{1}{A}\frac{1}{1-\tau_Y(A)}$$

$$y(A|P,Y) = \left(\frac{\sigma}{\sigma-1}\frac{1}{A}\right)^{-\sigma} P^{\sigma}Y(1-\tau_Y(A))^{\sigma}$$

$$l(A|P,Y) = \left(\frac{\sigma}{\sigma-1}\frac{1}{A}\right)^{-\sigma} \frac{1}{A}P^{\sigma}Y(1-\tau_Y(A))^{\sigma}$$

Profits can be expressed as

$$\Pi(A) = \Pi_d A^{\sigma-1}(1-\tau_Y(A))^{\sigma}$$

where as above,

$$\Pi_d = \frac{P^{\sigma}Y}{\sigma^{\sigma}(\sigma-1)^{1-\sigma}}$$

3.2 Dynamic Decision

The value of a firm of age a and productivity A at time t is as follows:

$$V_t^a(A) = \max\Bigg\{ \max_{q\in[0,1]} \Pi_{dt}A^{\sigma-1}(1-\tau_Y(A))^{\sigma} - (1+\tau_C)hA^{\sigma-1}e^{bq}$$
$$+(1-\delta)\frac{1}{R_t}\left(qV_{t+1}^{a+1}(sA) + (1-q)V_{t+1}^{a+1}\left(\frac{A}{s}\right)\right), 0\Bigg\}$$

Implicit taxes on output, τ_Y, and on R&D, τ_C, decrease the expected value of the firm. We can drop time subscripts in the steady state.

First order conditions give the optimal level of q as

$$q^a(A) = \frac{1}{b}\log\left[\frac{(1-\delta)\frac{1}{R}[V^{a+1}(sA) - V^{a+1}(\frac{A}{s})]}{(1+\tau_C(A))hA^{\sigma-1}b}\right]$$

when q has an interior solution in $[0,1]$.

So when q has an interior solution, pre-tax R&D spending is

$$C^a(A) = \frac{(1-\delta)\frac{1}{R}[V^{a+1}(sA) - V^{a+1}(\frac{A}{s})]}{b(1+\tau_C(A))}$$

R&D taxes act through the denominator, directly decreasing R&D spending, and by lowering the future expected value of the firm, indirectly decreasing R&D spending. Output distortions also lower the future expected value of the firm, indirectly decreasing R&D spending. This model will distinguish between the effects of output and R&D distortions.

At the boundary solution $q = 0$, we have

$$C^a(A) = hA^{\sigma-1}.$$

At the boundary solution $q = 1$, we have

$$C^a(A) = hA^{\sigma-1}e^b.$$

3.3 Productivity Over the Life Cycle

The entrant productivity distribution is exogenous. The distribution over the life cycle can be found by using $q(A)$ as follows:

$$M_a(A_i) = (1-\delta)q(A_{i-1})M_{a-1}(A_{i-1}) + (1-\delta)(1-q(A_{i+1}))M_{a-1}(A_{i+1})$$

where $a \in \{2, 3, .., T\}$ is the age of the firm.

Then the distribution of all firms is given by

$$M(A_i) = \sum_{a=1}^{T} M_a(A_i).$$

As stated before, since $\delta = 0$, the total mass of firms of age a is

$$N_a = \sum_{i=1}^{m} M_a(A_i) = (1-\delta)^a N_1.$$

3.4 Free Entry Condition

Firms face entry costs n_e. Firms enter without knowledge of their productivity, so entry costs are equal to the weighted average of the value function of entering firms.

$$n_e = \frac{1}{R}\sum_{i=1}^{m} \frac{V_1(A_i)M_1(A_i)}{N_1}$$

3.5 Feasibility Constraints

Consumption is equal to output:

$$C = Y$$

Entry costs and research costs use research labor L_R, so

$$N_1 n_e + \sum_{i=1}^{m} C(q, A_i)M(A_i) = L_R$$

Output labor is defined as:

$$L_Y = \sum_{i=1}^{m} l(A_i)M(A_i)$$

Labor feasibility constraint: Labor used for output plus research labor equals total inelastic labor supply.

$$L_Y + L_R = L$$

4 Data

I use firm-level data from the Annual Survey of Industries, conducted by China's National Bureau of Statistics, in years 2001 and 2005-2007. The survey is restricted to industrial firms with sales above 5 million RMB (755,000 USD). I further restrict the data to manufacturing firms. I use data on R&D spending, value-added, sales, total capital stock, and total wage bill. I define capital stock as fixed capital net of depreciation. The survey does not include data on nonwage compensation. I estimate compensation by multiplying the wage bill by a constant factor that brings the aggregate labor share to 50%, the value reported in Chinese national accounts.

10 percent of firms report positive R&D spending. The R&D spending in the data sums to match OECD aggregates. R&D spending by industry is shown in Table 1. Characteristics of R&D and non-R&D firms are shown in Table 2. The distribution of R&D of firms with positive R&D is shown in Figure 1.

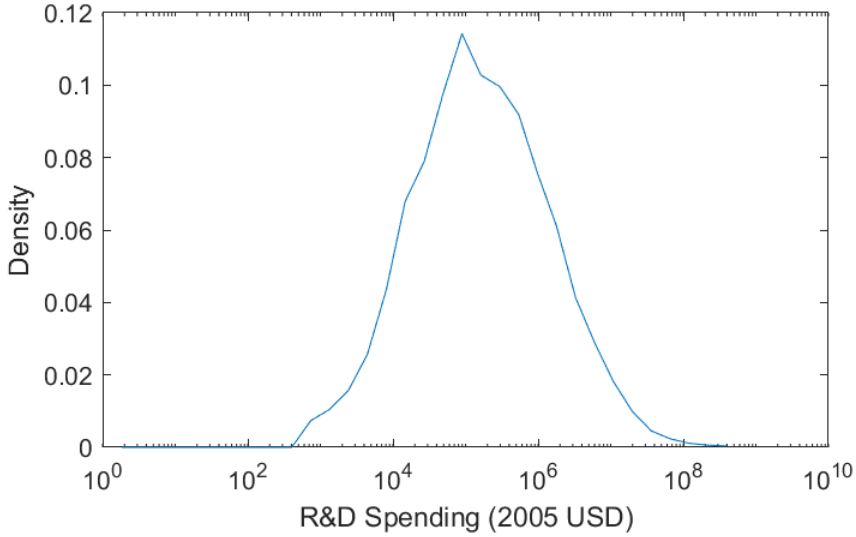
Table 1: 2005 China NBS Survey Data

Industry	# Firms	Fraction R&D Firms	Average $\frac{\text{R\&D}}{\text{Sales}}$ of R&D Firms	Average $\frac{\text{R\&D}}{\text{Sales}}$ of All Firms
Cars/Transport Equipment	6167	.20	.014	.0027
Chemicals/Rubber/Minerals/Metals	69676	.10	.014	.0014
Coke/Refined Petroleum/Nuclear Fuel	1845	.08	.005	.0004
Metal Products/Machinery/Equipment	64878	.15	.022	.0033
Food/Tobacco	21986	.09	.007	.0007
Textiles/Fur/Leather	40617	.05	.007	.0004
Wood/Paper	12613	.04	.005	.0002
Other	16837	.09	.013	.0012
Total	234619	.10	.016	.0016

Table 2: 2005 Characteristics of Firms by R&D

	Non-R&D Firms	R&D Firms
# Firms	210301	24318
Mean Value Added (million 2005 USD)	2.1	10.9
Mean Employment	202	627
Fraction State-Owned	.03	.08

Figure 1: Distribution of R&D Spending of R&D Firms



The data includes value-added but not output. Since plant-specific deflators are not available, some structure must be placed on the data in order to calculate firm productivity. I briefly describe the model that I use to calculate productivity, which is slightly different from the model above in order to account for both capital and labor inputs. The model follows the methodology of Hsieh and Klenow (2009).

Final good firms exist in perfect competition. They aggregate intermediate goods $y(A_i)$ using the following technology:

$$Y = \left(\sum_{i=1}^{m} y_i^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}.$$

So intermediate firms face the following demand:

$$\frac{y}{Y} = \left(\frac{p}{P} \right)^{-\sigma},$$

where

$$P = \left(\sum_{i=1}^{m} p_i^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

Firms produce output using capital and labor as follows:

$$y = Ak^{\alpha} l^{1-\alpha}.$$

Firms make profits

$$\pi = (1-\tau_Y)py - wl - Rk,$$

where τ_Y represents output distortions. The resulting firm-level value added is

$$py \propto A^{\sigma-1}(1-\tau_Y)^{\sigma-1}$$

and inputs are

$$k^{\alpha} l^{1-\alpha} \propto A^{\sigma-1}(1-\tau_Y)^{\sigma}.$$

So

$$A \propto \frac{(py)^{\frac{\sigma}{\sigma-1}}}{k^{\alpha} l^{1-\alpha}}.$$

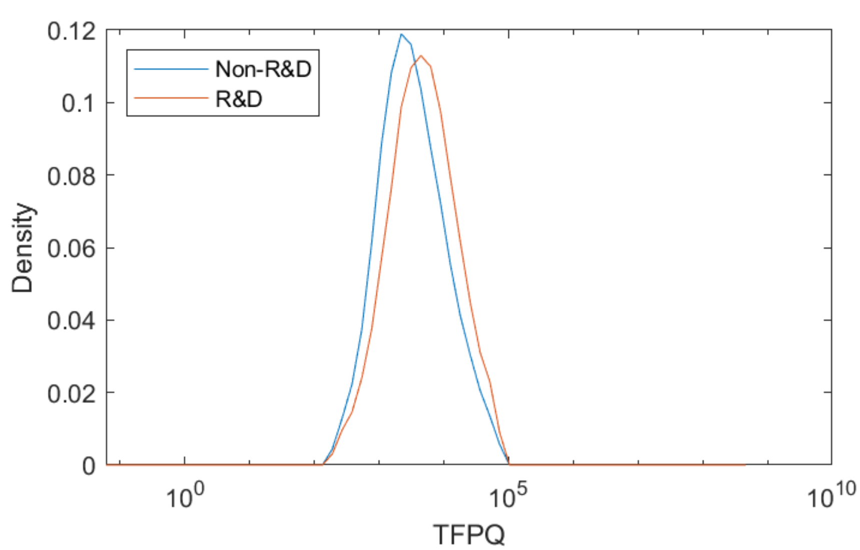
In order to account for differences in effective labor, I use total wages instead of hours worked. So productivity is calculated as

$$A_{si} = \kappa_s \frac{(p_{si} y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s} (w L_{si})^{1-\alpha_s}}$$

Capital shares α_s are taken from U.S. data as in Hsieh and Klenow (2009).

Figure 2 shows productivity distributions of non-R&D firms and R&D firms. Firms that do R&D have higher productivity at every percentile than firms that do not do R&D.

Figure 2: Productivity Distributions of Non-R&D and R&D Firms



5 Calibration

5.1 Parametrization

I use the following parameters.

- Innovation step size $s = e^{0.35}$ set to match the 35 percent standard deviation of employment growth of large plants
- Entrant productivity distribution $M_1(A)$ on grid, taken from data
- Wage W=1 is numeraire
- Exogenous exit $\delta = .16$, taken from data

- $\sigma = 3$
- All firms exit at age group $T = 20$, corresponding to 100 years
- Number of entrant firms set to match the data. Mass of firms of age a is $N_a = \sum_{i=1}^{m} M_a(A_i) = (1-\delta)^a N_1$
- β set such that annual interest rate is 5%
- Entry cost n_e, calibrated under assumption that there are 45 workers per firm

I select four additional moments from the data to identify key relationships in the model. As in Hsieh and Klenow (2009), I calibrate output distortions using the elasticity of average products with respect to productivity in the data. The elasticity of R&D spending with respect to productivity from the data helps to identify implicit R&D taxes and subsidies as a function of productivity. In order to deal with firms with zero R&D, I take average R&D over productivity bins, then regress log R&D spending against log productivity. Firm life cycle growth from the data and total R&D over total sales helps to calibrate the R&D cost function.

There are three functions that must be calibrated.

Implicit output taxes:

$$1 - \tau_Y(A) = Ce^{-\epsilon \ln A}$$

R&D cost function:

$$C(q, A) = hA^{\sigma-1}e^{bq}$$

Implicit R&D taxes:

$$1 + \tau_C(A) = \left(\frac{A}{\gamma}\right)^{\eta}.$$

Table 3: Function parametrization

Param.	Function	Target	Value
ϵ	Implicit output tax	China elasticity of average products w.r.t. productivity	.54
C	Implicit output tax	$C = \frac{\sigma}{\sigma-1}\frac{1}{1-\bar{\alpha_S}}$ †	3
η	Implicit R&D tax	Three moments*	-.55
γ	Implicit R&D tax	Three moments*	54.6
h	R&D cost	Three moments*	exp(-32)
b	R&D cost	Three moments*	30

† $\bar{\alpha_S}$ is the aggregate capital share

* These four parameters target three moments: (1) elasticity of R&D spending with respect to productivity, (2) Firm life cycle growth, (3) total R&D over total sales

$\epsilon > 0$ implies that more productive firms are more highly taxed, while $\eta < 0$ implies that more productive firms are more highly subsidized. Thus, R&D distortions partially cancel out the distorting effects of output misallocation.

5.2 Model fit

I calibrate the model by minimizing the squared distance between the moments in the data and those in the model. The model matches the data well. The elasticity of R&D to productivity is .84 in the model and .93 in the data. Total R&D divided by total value added is .0036 in the model and .0035 in the data.

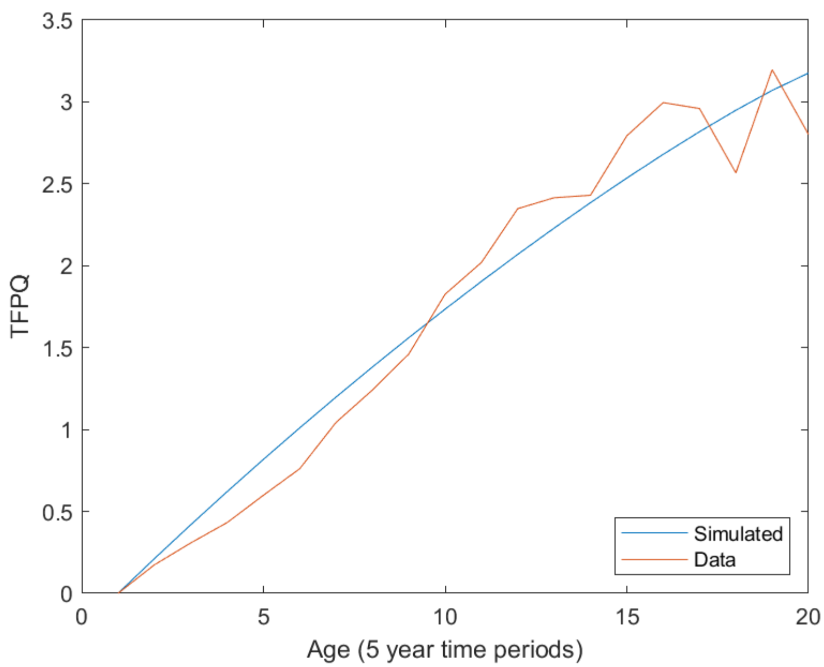
Life cycle growth is matched as follows:

Let A_a^{sim} be average productivity of firms of age a in the model and let A_a^{data} be the corresponding value from the data. Calculate the sum of squared deviations between the logs of the two,

$$SS = \sum_{a=1}^{T} \left(\frac{\log(A_a^{\text{sim}}) - \log(A_a^{\text{data}})}{\text{mean}\{\log(A_a^{\text{data}})\}} \right)^2 .$$

Life cycle growth in the model matches that of the data well, as shown below in Figure 3.

Figure 3: Productivity by Age, Data vs Model



5.3 Two-Period Model

Restricting the model to two periods gives a simple analytic expression for R&D as a function of productivity, which is informative about the intuition behind the calibration of R&D distortions.

Consider a model in which firms live for two periods, t=1 and t=T. Firms choose innovation q in the first period in order to increase their productivity in the second period. When $q(A)$ has an interior solution, plugging the policy function $q(A)$ into the R&D function $C(q, A)$ gives the expression

$$C^*(A) = \frac{(1-\delta)\frac{1}{R}[V^T(sA) - V^T(\frac{A}{s})]}{b(1+\tau_C(A))}$$

where

$$V^T(A) = \Pi_d A^{\sigma-1}(1-\tau_Y(A))^{\sigma}.$$

So $\ln C$ is a linear function of $\ln A$:

$$\ln C = Z + (\sigma-1)\ln A - \epsilon\sigma \ln A - \eta \ln A + \eta \ln \gamma,$$

and log of R&D spending over total sales is given by

$$\ln \frac{C}{PY} = Z' - \eta \ln A + \eta \ln \gamma - \epsilon \ln A.$$

In an economy without output or R&D distortions,

$$\ln \frac{C}{PY} = Z',$$

so R&D spending divided by sales is constant for all firms. Introducing implicit output and R&D taxes on high productivity firms causes them to spend less on R&D.

In this model, when log of R&D spending over total sales is regressed against log productivity, the coefficient β is

$$\beta = -\eta - \epsilon.$$

So η can be identified using ϵ and $\hat{\beta}$ from the data. This example gives intuition for the calibration of η.

5.4 Counterfactuals

I produce three counterfactual economies: an economy with no distortions, an economy with only output distortions, and an economy with only R&D distortions. I consider the effects of adding distortions on aggregate productivity.

I use the calibrated values of h, b from the baseline economy. For the economy with R&D distortions, I also use the calibrated values of η and a. I add constant R&D taxes to all firms, keeping total R&D taxes the same as in the baseline economy. This isolates the effect of a change in the relationship between R&D and productivity rather than a change in the level of R&D taxes.

As in Hsieh and Klenow (2014), adding output distortions to an economy with no distortions decreases TFP significantly. Output distortions cause a 72% decrease in TFP when added to a no-distortion economy, both from direct effects on output and indirect effects on R&D. Implicit output taxes are higher for more productive firms. This hurts their expected future profits, reducing their incentive to do R&D.

In general, R&D distortions have the potential to hurt productivity by distorting the allocation of R&D spending from the optimal allocation. Adding R&D distortions to an economy with no distortions decreases TFP by 12%. However, in an economy with large output distortions as in Hsieh and Klenow, adding new distortions can offset this effect. R&D distortions subsidize more productive firms, increasing their chosen R&D spending. This cancels out a portion of the negative effects of the output distortions. Adding R&D distortions to this output-distortion economy actually increases TFP by 5%. The effects on total value added of the economy are the same as the effects on aggregate TFP, because labor supply is fixed and TFP is equal to value added over total labor.

Finally, I compare an economy with output and R&D distortions to an economy with no distortions. Adding both output and R&D distortions decreases productivity by 70 percent. Although R&D

distortions can increase TFP in an economy with output distortions, it is still optimal to remove all distortions.

Output distortions decrease total R&D by 63 percent relative to a no-distortion economy, by lowering expected future profits and lowering the incentive for productive firms to do R&D. R&D distortions cause a 3 percent increase in total R&D by incentivizing high-productivity firms to do more R&D. When R&D distortions are added to an output-distortion economy, they act against output distortions' effect on R&D, increasing total R&D by 1 percent. Both distortions decrease total R&D by 63 percent relative to a no-distortion economy.

Output distortions increase entry by 231 percent, because entrants face less competition from the distorted high-productivity firms and thus have higher expected profits. Conversely, R&D distortions decrease entry by 4 percent relative to a no-distortion economy, because high-productivity firms are subsidized and thus increase competition. When R&D distortions are added to output distortions, the change in entry is negligible. Relative to an economy with no distortions, adding both distortions increases entry 230 percent.

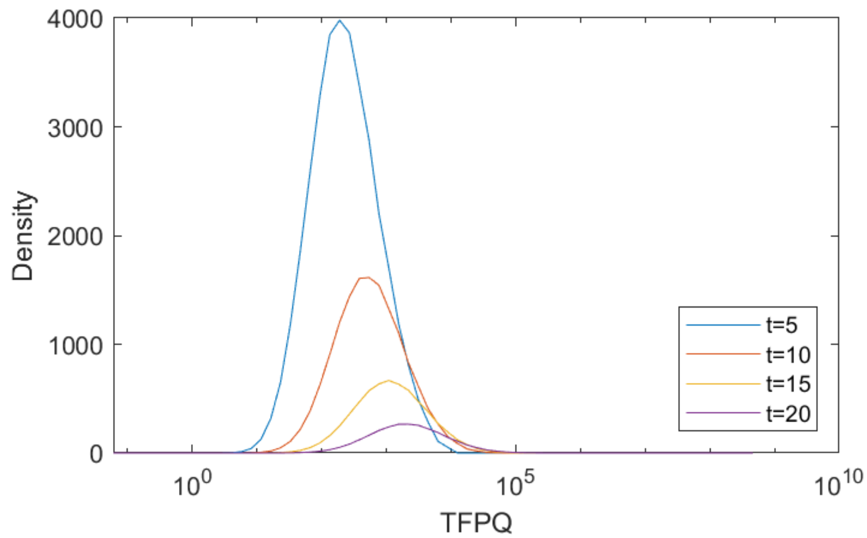
Table 4: Counterfactuals

	Output / None	R&D / None	Output and R&D / Output	Output and R&D / None
TFP	0.28	0.88	1.05	0.30
Total R&D	0.37	1.03	1.01	0.37
Number of Firms	2.31	0.96	1.00	2.30

5.5 Economy Comparisons

Each economy has the same exogenous entrant productivity distribution but different evolutions of the productivity distributions as firm age increases. As an example of how productivity distributions evolve over firm age, Figure 4 shows how the productivity distribution evolves in the economy with two distortions.

Figure 4: Productivity distribution over the life cycle



As time increases, average productivity increases and dispersion increases. Firms exit at each time period.

Figure 5 shows each economy's productivity distribution at age $a = 20$, the final age group. The distributions have been normalized so that the mass of firms is the same in each.

In general, distortions that favor low-productivity firms and hurt high-productivity firms lower dispersion in the productivity distribution, and vice versa. The productivity distribution of the economy with only output distortions has the least dispersion, because low-productivity firms are subsidized and high-productivity firms are taxed. Conversely, the economy with only R&D distortions has the most dispersion, because subsidies increase with productivity. In the economy with both distortions, R&D distortions slightly increase the dispersion relative to the economy with only output distortions.

Figure 5: Productivity distribution at age a=20

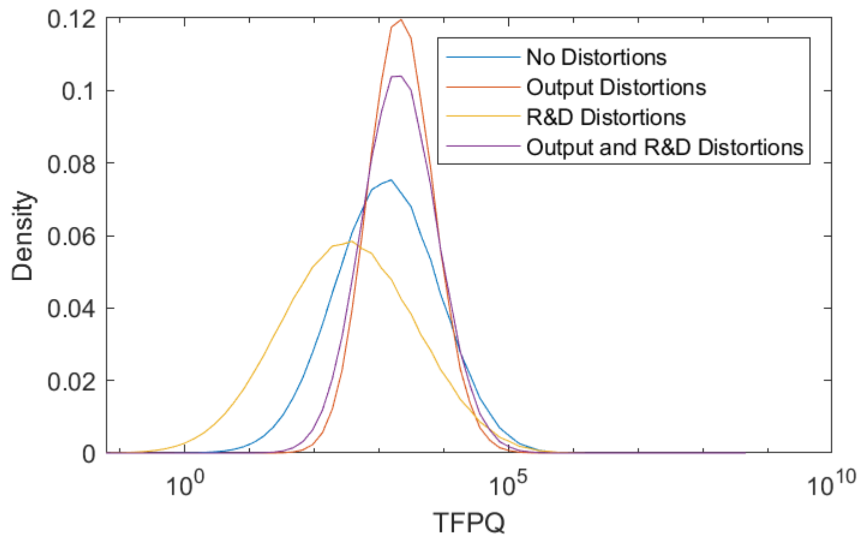


Figure 6 shows the relationship between employment and productivity in each economy. R&D distortions do not affect the static decision of firms at each productivity level; thus, they do not affect production employment. Because of this, the no-distortion and R&D-distortion economies (blue) have an identical slope of employment to productivity, as do the output-distortion and two-distortion economies (red). Implicit output taxes decrease the amount of labor used by high-productivity firms, decreasing the slope of the relationship between employment and productivity.

Figure 6: Production Employment

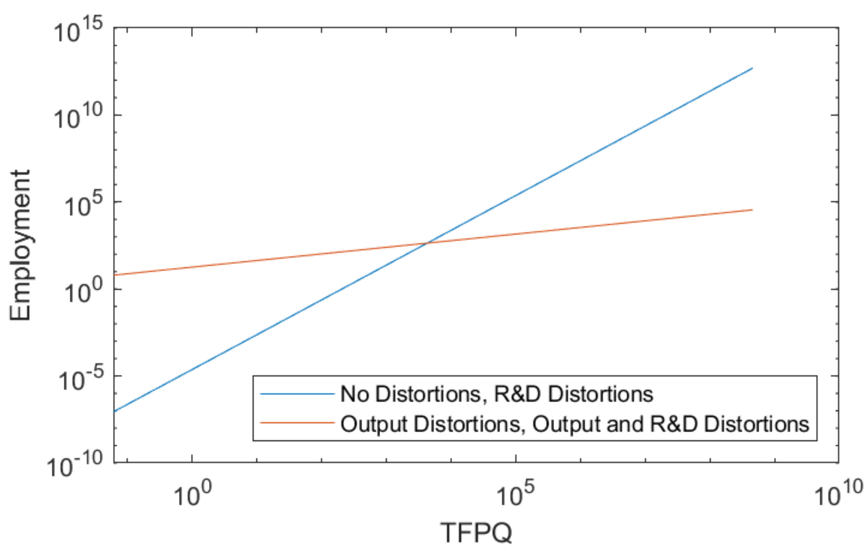


Figure 7 compares the choice of innovation q in period 1 between the different economies. In the case of a no-distortion economy, all firms choose the same amount of innovation.

Figure 7: Choice of q in period 1

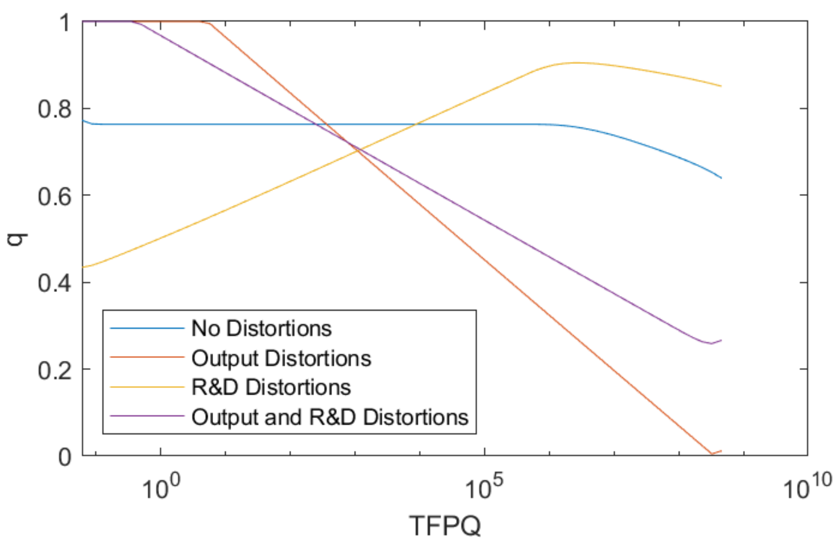
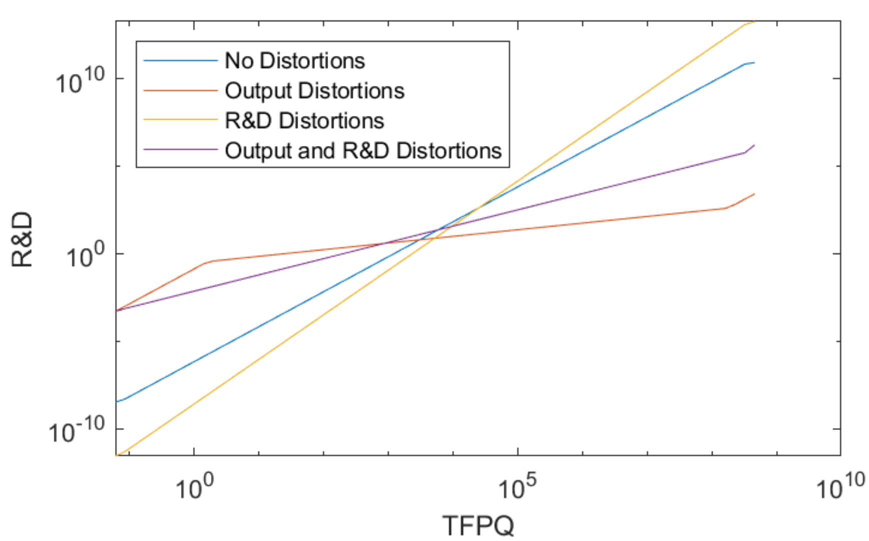


Figure 8 shows the resulting R&D spending as a function of productivity for each economy. In the model, the cost of R&D increases proportionally with productivity, in order to match Gibrat's Law. Since all firms choose the same level of innovation q, R&D spending increases proportionally with productivity as well.

Figure 8: R&D spending at t=T-1



6 Conclusion

In this article, I have estimated the effects of different distortions on the Chinese economy. My framework has allowed me to separately identify R&D distortions and output distortions and finds that R&D distortions favor productive firms, while output distortions favor unproductive firms. This analysis helps to open up the black box of opaque government policy and to inform about the nature of the Chinese government's R&D push. I have found that the net effect of all R&D distortions has been to favor productive firms. The model above shows that on their own, R&D distortions are harmful and can decrease TFP on the order of 10 percent. However, in developing countries, R&D distortions can help to counteract the negative effect of the high output distortions that have been found by the literature.