Policy and Misallocation: Evidence from Chinese Firm-Level Data*

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Abstract

Using a rich dataset of Chinese firms, we investigate the effect of industrial policies on resource misallocation. Our difference-in-difference model estimates provide evidence that government policies increased the dispersion of revenue productivity across firms in four-digit industries targeted for support relative to other industries, suggesting a negative impact on aggregate TFP. Estimates of a changes-in-changes model reveal that the policies had a heterogeneous impact across the productivity distribution of firms in supported industries. Furthermore, we show that the heightened misallocation is related to the way in which the Chinese government doled out support through subsidies for a subset of firms.

Keywords: Misallocation; Total Factor Productivity; China

JEL Codes: D24, L25, O47

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1 Introduction

A large and growing literature has argued that resource misallocation contributes substantially to the differences in living standards between rich and poor countries.[1] When labor and capital are not put to their best or most efficient use, total production is, quite obviously, lower. Misallocation can happen for a variety reasons including constraints on factor mobility from financial frictions or employment restrictions, taxes or trade policy, or the government explicitly fostering certain industries for political or other reasons. Our analysis concerns the last of these: direct government intervention.

We provide evidence that government policies favoring particular industries or firms may lead to resource misallocation. We estimate the effect of China's Five-Year Plans using micro-level data on Chinese firms.[2] The misallocation of resources within industries supported by the 10^{th} Five-Year Plan increased relative to not supported industries. We measure misallocation as the dispersion of revenue productivity across firms in an industry; the differential changes in this dispersion for supported industries versus not supported industries is quantitatively large, indicating that this type of misallocation is important for understanding productivity differences both within and across countries.

Since the foundation of the People's Republic of China, the central government has controlled economic activity by making explicit policies to direct the deployment of resources. The plans are usually updated every five years. Although almost all countries have some policies favoring certain firms or industries, China's economy-wide re-shuffling of economic priorities makes for a poignant case study. We use information from the Annual Survey of Industrial Production, which contains data on Chinese firms from 1998 to 2005, to estimate resource misallocation due to the centralized planning in China. The survey covers a large sample of the firms included in the manufacturing industries that were the target of the 10^{th} Five-Year Plan, and it also includes industries that were neither targeted by this plan, nor by the 9^{th} Five-Year Plan. Hence, the data is well-suited to our needs, as it allows us to identify the effects of the 10^{th} Five-Year Plan by comparing differences in resource misallocation between supported and not supported industries.

[1] See Restuccia and Rogerson (2017) and the many papers cited within.

[2] The data is at the 'establishment' level; however, throughout, we use the terms firm and establishment interchangeably.

Our work is closely related to that of Hsieh and Klenow (2009) who use the same data to quantify productivity losses from misallocation in China (and India) relative to the United States. We build from the empirical approach developed in Hsieh and Klenow; however, our analysis is more disaggregated and seeks to answer a question only tangentially addressed in their paper. Whereas Hsieh and Klenow focus on the degree of misallocation across all manufacturing firms in China, we estimate the increase in misallocation within the specific industries supported by the Five-Year Plan. In this sense, we provide the details, or a concrete very large example (the Five-Year Plan), of how the country-wide misallocation documented by Hsieh and Klenow may result from a particular policy intervention. We also expand on their main approach by exploiting the firm-level data to investigate the distributional effects of the Five-Year Plan. We believe that tracing the effects out to the firm-level and mapping the cause to specific policies are important contributions. The literature has debated whether the type of country-wide comparisons studied in Hsieh and Klenow really measure misallocation or instead capture other differences between countries. Our empirical strategy and results are consistent with the misallocation interpretation, lending strong support to Hsieh and Klenow (2009).

To measure misallocation, we calculate revenue productivity for each firm. In the absence of firm-level distortions, according to the theory laid out in Hsieh and Klenow (2009), revenue productivity will be equated across firms in narrowly defined industries. In other words, capital and labor will be employed where their marginal value is highest. If, instead, there exists dispersion in the revenue productivity across a set of firms, then this dispersion indicates the degree to which distortions are keeping capital and labor from finding their most efficient uses. These distortions mean that resources are misallocated, which lowers both total factor productivity (TFP) and the total output produced by a given set of inputs. Thus, we use the variance of total revenue productivity (the dispersion of TFPR) across firms in an industry as our primary measure of misallocation.

The data allow us to categorize firms into industries according to the Chinese National Bureau of Statistics classification codes. We use Chinese Industry Classification codes at the finest (four-digit) level to group firms into highly disaggregated industries and calculate the variance of TFPR in each industry. Importantly, the official documents of the 9^{th} and the 10^{th} Five-Year Plans enable us to distinguish which four-digit industries each plan supported.

Our empirical approach, then, is to use a generalized difference-in-difference (DID) regression model to estimate the impact on the variance of TFPR. To identify policy effects, we compare differences in the variance of TFPR between industries newly supported by the 10^{th} Five-Year Plan and those industries receiving no support in either the 9^{th} or 10^{th} Five-Year Plan. This industry-level DID approach fits well with the data; moreover, an event study regression gives support to the use of the DID research design. In particular, it indicates the assumption of parallel trends holds.

We directly account for many observed differences across industries and over time through a series of control variables, and industry and year fixed effects allow us to control for common aggregate trends in misallocation. We also report on a series of exercises aimed at checking the validity of our empirical approach. In particular, we show that both supported and not supported industries had similar trends in misallocation prior to the 10^{th} Five-Year Plan. Also, since China joined the World Trade Organization (WTO) during the period of our study, we include variables meant to capture international trade. Our regression results are robust across the many specifications, and we interpret the estimates as evidence that the centralized plans increased resource misallocation, particularly within the supported industries.

The regression estimates indicate that the Five-Year Plan raised misallocation by about 0.03 (6 percent of the 2000 dispersion); thus, suggesting aggregate productivity gains experienced in China during this period of time would have been even greater if they had occurred in a manner that increased (or at least preserved) allocative efficiency. This large and statistically significant impact on misallocation is our main empirical finding and leads us to the second part of the paper - exploring how the policies worked to increase misallocation. We highlight five additional results.

First, we find that the plan increased correlated distortions, which suggest a more detrimental effect of the policy on growth than if it had only increased correlations not correlated with the firm's TFP. Second, we show that while the average level of TFPR for firms in supported industries increased relative to firms in not supported industries (in a similar way to TFPR dispersion), the relative average physical productivity (TFPQ) was unchanged. This finding suggests that the policies impacted prices more than productivity. Our third and fourth findings imply that the policy's impact was heterogenous across the distribution of firm productivity. To show this, we use the data at the firm level (rather than aggregating to the four-digit industry level) and estimate the quantile treatment effect of the Five-Year Plan on the supported firms. Specifically, we estimate the non-linear difference-in-difference model proposed by Athey and Imbens (2006), commonly known as the changes-in-changes (CIC) model. This approach enables us to investigate how the policies affected the full TFPR and TFPQ distributions, while also examining changes in dispersion both within and across industries. The results indicate that the Five-Year Plan had a positive and significant effect on most of the TFPR distribution, although the estimated treatment effect is considerably larger for the extreme right tail. A similar pattern is observed for the effect of the policy on the TFPQ distribution. In short, the implemented industrial policies led to an increase in (marginal) productivity across most of the TFPR distribution. Yet, because high TFPR firms experienced a larger increase, the variance rose.[3] These two sets of results are consistent with the idea that the Five-Year Plan tended to shift resources away from high TFPR firms, leading to losses in efficiency in the supported industries.

Our fifth and final set of results has to do with the way in which firms received preferential treatment. Specifically, we present evidence that the Chinese government doled out support to industries via direct subsidies. We show this through a series of firm-level DID regressions, with the support mechanisms as the dependent variable. We also examine whether these policies affected the ratios of taxes or subsidies to value-added, or the ratio of interest payments to debt. Finally, (in light of the documented heterogenous impact on misallocation across the productivity distribution) we show that the probability of receiving support through taxes and subsidies (as well as in the magnitude of the support) differed for different parts of the TFPR distribution. High-TFPR firms in supported industries experienced a relative increase in taxes; whereas, low-TFPR firms received larger subsidies. Again, this evidence suggests that the 10^{th} Five-Year Plan reshuffled resources in a manner that lead to higher misallocation.

Our results are in line with the theory and empirics from Restuccia and Rogerson (2008) who find that distortions at the firm level, stemming from tax and subsidy policies, reduce aggregate productivity. In addition to the Restuccia and Rogerson (2008) and Hsieh and Klenow (2009) papers, our work is related to several other studies on misallocation. Foster, Haltiwanger, and Syverson (2008) use revenue and physical productivity to measure firm prof-

[3]For simplicity, throughout the rest of the text, we refer to the marginally more productive firms as more productive and to the marginally less productive firms as less productive. However, that the difference exists on the margin is important to bear in mind.

itability. Haltiwanger et al. (2018) further decompose demand shocks from TFPR dispersion. David and Venkateswaran (2019) argue that capital misallocation in China results mainly from a component correlated with productivity and fixed effects and to a lesser degree from adjustment costs and uncertainty. Restuccia (2019) explored the relationship between misallocation and productivity across time and space. While Cusolito and Maloney (2018) argue that reallocation through reform can actually promote development, Melitz (2003), Baqaee and Farhi (2020), Huang (2019), and Newman et al. (2019) argue that resource misallocation generally results in lower total factor productivity growth. Moreover, misallocation is also found to decrease output (Song and Wu, 2015), income (Alfaro et al., 2008) and gains from trade (Chung, 2018). Buera, Moll, and Shin (2013) show how well-intended support policies aimed at fostering growth, even if successful at first, can have deleterious effects over time (we return to this point later). Aghion et al. (2008) find the effects of industrial policy reform are unequal across Indian states because the labor market environments differ. Guner et al. (2008) also find the effects of policies on productivity vary due to different firm characteristics. Bartelsman et al. (2010) argue that firm size affects firm productivity. Hsieh and Moretti (2019) show that land use restrictions increase the spatial misallocation of labor. Relatedly, Chen (2019) studies misallocation across geographic regions in China. Bai et al. (2019) argue that misallocation resulting from special deals in China has created risks for the future, and Yang and Lee (2021) document the misallocation due to centrally planned science parks. Finally, Dollar and Wei (2007) find that state-owned enterprises in China have lower efficiency.

The paper proceeds as follows. Section 2 details how we use the firm-level data to measure resource misallocation and offers a brief overview of China's Five-Year Plans. Section 3 discusses our empirical strategy and documents our main empirical results. Section 4 discusses China's admission into the World Trade Organization and firm entry and exit, along with several other robustness checks. Section 5 shows that the Five-Year Plan increased average TFPR in supported industries but not TFPQ; however, we then demonstrate that the impact varied over the TFPR distribution with the dispersion increasing further for high productivity firms. Section 6 investigates the mechanisms used by the Chinese government to provide support. Section 7 concludes. Additional results have been collected in an Online Appendix (hereafter Appendix).

2 Industrial Policy, Measurement, and Data

Our regressions exploit variation in the support given by China's Five-Year Plan across industries to estimate the policy's effect on the misallocation of resources. In this section, we first discuss the Five-Year Plans and describe which industries received support. We then review the theory on how to measure resource misallocation. Finally, we detail the firm (establishment)-level information used to compute misallocation by industry.

2.1 China's Five-Year Plans

Many countries implement industrial policies aimed at encouraging the development and growth of particular industries. In China, these policies take the form of Five-Year Plans developed by the State Council (the central government). The Chinese central government issued the first Five-Year Plan in 1953. The objective of the earlier Five-Year Plans was to establish and promote certain industries by making investments with specific growth targets for each industry. The first Five-Year Plans, in effect, created a variety of state-owned enterprises during a period when China was centrally controlled and closed. After the 1978 Reform and Opening Policy, the Five-Year Plans began establishing macroeconomic goals, while still delineating particular industries to support and strengthen. The plans also have allocated resources among private companies, especially since the 1997 policy of "grasping the large and letting go of the small" accelerated a movement towards privatization.

We focus on the 10^{th} Five-Year Plan because its onset and implementation (2001-2005) are covered by the available data, which begins in 1998. The plan's general objectives, according to the Report on the Outline of the 10^{th} Five-Year Plan for National Economic and Social Development (2001), were as follows. First, achieve an average economic growth rate of about seven percent. Second, adjust development patterns across different industries and regions, as well as between urban and rural areas. According to the report, this objective required strengthening agriculture, developing the service industry, and reinforcing infrastructure. Third, increase openness and prioritize the development of science, technology, and education. Fourth, raise living standards by creating more jobs, increasing personal income, making the income distribution more equitable, and improving the social security system. Lastly, coordinate sustainable economic, social, and environmental development.

More specifically, the 10^{th} Five-Year Plan lays out the industries (or whole sectors) to be supported over the following five years. The documentation thus allows us to match narrowly defined supported industries with the corresponding four-digit industry code. For example, alumina manufacturing (3316), gas turbine manufacturing (3513), integrated circuits (4035), paper making (3641), and many others were specifically targeted for support. However, in a few cases, the 10^{th} Five-Year Plan promotes the development of more broadly defined industries, such as 'plastic manufacturing'. In these cases, we treat the corresponding two-digit industry as supported. Industries supported in the 10^{th} Five-Year Plan cover many establishments in agricultural products processing, textiles, textile products processing, leather related products manufacturing, paper and paper products, chemical products, pharmaceutical manufacturing, chemical fiber, non-metallic mineral products, ferrous and nonferrous metal smelting, transportation and electrical equipment, communications and computers, and instrumentation manufacturing. Yet, many industries such as chemicals, rubber and plastics, and motor vehicles received no support.[4]

We conclude this section with two caveats. First, we are not able to infer all the reasons why some industries are featured in the 10^{th} Five-Year Plan from the available documentation. On the one hand, the economic motivation mentioned in the official document is to increase international competitiveness of the supported industries. On the other hand, the stated justification is not only economic; the policies also were intended to "improve socialist, spiritual civilization, democracy and the legal system, balance reform, development and stability, accelerate development of various social undertakings, and ensure social stability". The data does not allow us to rule out all selection issues; however, we provide evidence against the most likely threats to our identification strategy, including differences in trade patterns, establishment size, and misallocation trends across industries.[5] Second, the official plan documents were released on March 15, 2001; however, we cannot rule out that information was available in advance. While the exact contents may not have been known, the 10^{th} Plan was not a surprise because China has been issuing Five-Year Plans since 1953. Nevertheless, we provide empirical evidence suggesting a limited role for anticipation.

Our hypothesis is that the resources used to support firms within an industry (however

[4] The Appendix contains a complete list of supported industries along with additional discussion of China's Five-Year Plans.

[5] Chen (2019) examines misallocation across geographical regions in China.

these industries were selected) are not necessarily put toward their most efficient use. Specific firms may receive support to accomplish any number of objectives and especially for political expediency. Moreover, while the policy is formulated at the national level, local party officials often decide which firms to target. As we will show, there appears to be a tendency for low TFPR firms to receive subsidies, distorting resource allocation within these industries. How much the Five-Year Plans worsen misallocation is thus an empirical question.

2.2 Measuring Resource Misallocation

We measure misallocation based on the theory developed in Hsieh and Klenow (2009). They posit that revenue productivity, the product of physical productivity and output price, should be approximately equal across firms in the absence of distortions. The intuition is as follows. If firms operating in the same industry have access to the same technology and face the same input (capital and labor) prices, then, in the absence of firm-level distortions, TFPR should be equalized across firms. Thus, the greater the dispersion in TFPR, the greater is the misallocation of resources.[6]

Following Hsieh and Klenow (2009), we consider an environment of monopolistic competition. Each specific firm i in industry s produces differentiated output Y_{si}. Total industry output Y_s is a constant elasticity of substitution (CES) aggregate of output from the M_s firms in the industry

$$Y_s = \left(\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where σ is the elasticity of substitution between varieties within the industry's CES aggregator. Each individual firm uses a Cobb-Douglas production technology

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}$$

where A_{si} is the firm specific technology level, K_{si} is capital, L_{si} is labor, and the capital and

[6] The idea of using dispersion across firms to study misallocation also can be traced to Restuccia and Rogerson (2008). Foster, Haltiwanger, and Syverson (2008) first used physical productivity (TFPQ) and revenue productivity (TFPR) to study firm profitability. Other measures of misallocation have been proposed, but given our data (which lacks price information), we believe that the dispersion of TFPR is the best available statistic for our analysis.

labor shares $(1-\alpha_s)$ are allowed to vary across industries. An individual firm's TFPR is

$$TFPR_{si} = P_{si}A_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s}\left(wL_{si}\right)^{1-\alpha_s}} \tag{1}$$

where firm i sets price P_{si} and all firms face wage w. Hsieh and Klenow (2009) provide further details on the model's economic environment and for the derivation of TFPR. We also examine total factor physical productivity. TFPR equals P_{si} times TFPQ:

$$TFPQ_{si} = A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s}\left(wL_{si}\right)^{1-\alpha_s}}. \tag{2}$$

We take Equation (1) as the definition of firm specific TFPR, and we use the dispersion or variance of logged TFPR across firms (establishments) in an industry as a measure of misallocation. Again, theoretically, there should be no dispersion in TFPR in the absence of distortions.[7]

Furthermore, Hsieh and Klenow (2009) show that industry specific total factor productivity (TFP_s) can be written as

$$\log TFP_s = \frac{1}{1-\sigma}\log\left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1}\right) - \frac{\sigma}{2} var\left(\log TFPR_{si}\right) \tag{3}$$

where the summation is over the M_s firms in industry s, σ is the elasticity of substitution, and var takes the variance across the logged TFPR of firms in the industry.[8] Note that, in this framework, the variance of logged TFPR is a sufficient statistic to measure the decrease in TFP due to the dispersion in TFPR. The larger an industry's TFPR dispersion, the lower the industry's aggregate total factor productivity. If resources could be reshuffled to firms with a higher marginal productivity, then the dispersion of TFPR would decrease and output would be higher. Thus, the dispersion in TFPR constitutes a suitable way to measure resource misallocation. Moreover, although there are many mechanisms by which misallocation could

[7] As mentioned in the Introduction, the literature has suggested other factors that could impact the dispersion of TFPR, which are not captured by this model and are not necessarily misallocation. See Feng (2018) and the citations within. However, in our empirical approach below, we rely on differential *changes* in the dispersion of TFPR that are unlikely to affected by any factor other than the misallocation of resources. We return to this issue below.

[8] Technically, TFPR and TFPQ must be jointly log-normally distributed to arrive at this equation. Following Hsieh and Klenow (2009), we assume σ is the same for all sectors.

manifest itself, an increase in misallocation will result in larger dispersion in TFPR.[9]

2.3 Data

To calculate the degree of resource misallocation within each industry, we use repeated cross-sections of firm-level data from the Annual Survey of Industrial Production, which was collected by China's National Bureau of Statistics from 1998 to 2005.[10] The survey includes non-state-owned firms with nominal revenues exceeding 5 million yuan (around $700,000) and all state-owned enterprises (SOEs). The non-state-owned firms contain private, foreign and hybrid firms (local collectives, local government-private, etc.). The unit of observation in the survey is the establishment; thus, companies with multiple establishments that operate in different industries do not pose a problem as each establishment is assigned to the primary industry in which it operates. The number of observations (establishments) ranges from about 165,000 in 1998 to about 269,000 in 2005. The data set includes information on the firm's industry (at the four-digit level), value-added, export revenues, capital stock, the number of employees, wage payments, ownership, age, interest payment, liabilities, taxes paid, and subsidies received.

We compute TFPR for each firm-level observation from Equation (1) using data on value-added, wage payments, and the firm's capital stock. The survey does not include prices P_{si} or non-wage compensation; so, we follow Hsieh and Klenow (2009) and compute them as follows. First, we equate $P_{si}Y_{si}$ to the firm's value-added. Second, we define K_{si} as the book value of fixed capital net of depreciation. Third, we assume that the sum of the imputed benefits and wages –the non-wage compensation absent from the survey– equals 50% of the value-added.[11] Then, as in Hsieh and Klenow (2009), we map yearly industry specific labor shares, $1 - \alpha_s$, obtained from the NBER Productivity Database for the United States (based on the Census and Annual Survey of Manufacturers), into our data set.[12] After obtaining TFPR for each firm, we calculate the mean and the variance of TFPR for each four-digit industry (separately

[9] See Hopehayn and Rogerson (1993), Lagos (2006), Caselli and Gennaioli (2013), Buera and Shin (2009), and Guner, Ventura, and Xu (2008) for examples.

[10] Again, note that we use the terms firm and establishment interchangeably. The data does not allow us to link establishments in the same firm.

[11] Our results are robust to other ways of calculating dispersion, including directly measuring labor costs by the wage bill (see Bento and Restuccia, 2017; Gopinath et al., 2017).

[12] Following Hsieh and Klenow (2009), we scale up the labor share by 3/2 and employ US labor shares. Estimation results using labor shares computed from the Chinese data -which, as Hsieh and Klenow note, are presumably more distorted than the US- are consistent with the results in this paper. Similarly, our results are robust to using a fixed labor share of 0.65 across industries and time as in Gopinath et al. (2017).

for each year). Recall that the latter corresponds to our measure of resource misallocation. For the main estimation results, we exclude the firms in the bottom and top one percent of the TFPR distribution, relative to the average TFPR of each industry, $TFPR_{is}/\overline{TFPR}_s$. We discuss the results when the tails are not trimmed in the robustness section.

To further explore how total factor productivity is affected by the 10^{th} Five-Year Plan we compute annual TFPQ for each firm i in the following manner. Given that data on firm-level output, Y_{si}, or prices, P_{si}, are not available from the survey, we follow Hsieh and Klenow (2009) and raise the firm's value-added, $P_{si}Y_{si}$, to the power $\sigma/(\sigma-1)$ to obtain an estimate of Y_{si}.[13] Replacing this estimate in Equation (2) we obtain

$$TFPQ_{si} = A_{si} = \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s}(wL_{si})^{1-\alpha_s}}, \tag{4}$$

where σ is the elasticity of substitution as defined above. We also follow Hsieh and Klenow in setting σ equal to three to compute TFPQ.

In addition to the 10^{th} Five-Year Plan, our sample spans some of the years covered by the 9^{th} Five-Year Plan. Of the 425 four-digit industries included in the Chinese Industrial Classification code, 111 were supported by the 9^{th} Five-Year Plan. We exclude these industries in order to avoid confounding the effect of the 10^{th} Five-Year Plan with that of its predecessor.[14] We also exclude a few industries where the number of firms is too small (less than 10) to obtain a meaningful measure of resource misallocation. The resulting sample is based on 1,092,488 establishment / year observations. We group these into 308 industries (each observed for the full eight years). Of these industries, 93 were supported by the 10^{th} Five-Year Plan. This group of industries constitutes our "treatment" group and we will refer to it as the supported group. The remaining 70% of the industries in the sample comprise our "control" or not supported group. The regressions below exploit the differential changes in the variance of TFPR across supported and not supported industries in order to estimate the impact of China's Five-Year Plan on resource misallocation.

[13] The lack of firm-level data on price and output precludes the computation of direct measures of factor productivity.

[14] Below, we show that including these firms does somewhat reduce the estimated impact of the 10^{th} Five-Year Plan, possibly because these industries had already been distorted.

3 The Effects of Industrial Policy on Resource Misallocation

This section presents an 'event study' depicting the effect of the 10^{th} Five-Year Plan on the variance of TFPR within supported industries, explicitly details our difference-in-difference regression approach, and then presents our main results.

3.1 Event Study and Descriptive Evidence

The 10^{th} Five-Year Plan implemented a major shift in the groups of industries supported by China's industrial policies. Many more firms became eligible for support, even though the majority of industries were still not explicitly targeted. To estimate the causal effect on resource misallocation, our research design exploits this policy distinction using a difference-in-difference strategy that compares the change in the variance of logged $TFPR$ in supported industries versus not supported industries following the plan's inception.[15]

To gather intuition and as a test of our research design, we first estimate a reduced-form event-study model. The estimated event study equation is given by

$$var(\log TFPR)_{s,t} = \alpha_s + \rho_t + \sum_{m=-4}^{3} \beta_m Supported_{s,t-m} + u_{st}.$$

where $var\left(\log TFPR\right)_{st}$ is the variance of the logarithm of TFPR across firms in industry s in year t, $Supported_s$ is a dummy equal to 1 if the industry was supported by the 10^{th} Five-Year Plan, α_s and ρ_t are industry and time fixed effects, respectively, and u_{st} represents the error term. The term $\sum_{m=-4}^{3} \beta_m Supported_{s,t-m}$ allows the policy to have dynamic effects. The values of the lags, 3, and leads, 4, are determined by data availability (i.e. $m = 3$ corresponds to 1998 and $m = -4$ corresponds to 2005). The coefficients $\{\beta_m\}_{m=-4}^{3}$ trace out the changes in the relationship between the dispersion in $\log TFPR$ and $Supported$ across the event industries (supported) relative to the not supported.

To estimate the coefficients of interest we follow Bhuller et al. (2013) and Goodman-Bacon (2021a, 2021b) in employing a two-step pre-trend adjusted estimator. More specifically, we estimate pre-trends by group (i.e., supported and not supported) in the years before the adoption of the 10^{th} Five-Year Plan and partial them out from the $var\left(\log TFPR\right)$ in all

[15] As in Hsieh and Klenow (2009) the variance is computed relative to the industry mean.

periods. We then estimate an uncontrolled regression of the transformed $var\,(\log TFPR)$ on the interaction terms between year and support dummies. As is common in the literature on event studies, we normalize the coefficient in the year prior to the inception of the plan, 2000, to zero. The event study specification allows for dynamic policy effects (see Freyaldenhoven et al. 2021).

Figure 1 reports the estimated coefficients, $\{\beta_m\}_{m=-4}^{3}$, and corresponding 90% confidence bands. The 1998 and 1999 terms are basically zero, which constitutes strong evidence in favor of the parallel trends assumption. While the coefficient estimate for 2001 is statistically insignificant, the event-time path exhibits an increasing trend after that, with some tapering in the last year of the plan. The insignificant estimate for 2001 suggests the plan's negative influence on resource allocation may not have been immediate, or the support may have taken time to roll out. We return to the topic of timing in the robustness checks.

FIGURE 1 HERE

The increased misallocation from 2001 to 2005 suggests a shifting in resources from not supported to supported industries. This shift appears to have been caused by the 10^{th} Five-Year Plan. However, other forces may have contributed. These other factors do not necessarily pose a threat to our estimation approach, unless they cannot be accounted for and they affected the two groups differentially around or just before 2001. The research design thus includes additional variables (concerning trade, in particular) as controls in this regard. As we will show in the following sections, the estimated increase in the dispersion of TFPR is robust to including additional controls. Thus, we believe it is unlikely that anything outside the 10^{th} Five-Year Plan differentially impacted the somewhat disparate group of supported industries over the time period of our study; of course, we cannot completely rule it out.

Finally, 'reverse causality' could bias the estimates and change the interpretation of our results. After all, one of the objectives of the 10^{th} Five-Year Plan was to adjust development patterns across different industries. This goal suggests the possibility that the Chinese government decided to support particular industries because it prioritized industries where resource misallocation was greater. However, we see no evidence that industries were targeted for support based on the resource misallocation observed prior to the 10^{th} Five-Year Plan. Table 1 reports the average variance of TFPR, the mean of TFPR, and the mean of TFPQ broken down by supported and not supported industries in 2000. The average resource misallocation exhibited within supported industries (0.430) was slightly lower than the resource misallocation in non-supported industries (0.439).

TABLE 1 HERE

3.2 Estimation Strategy

Our generalized difference-in-difference (DID) regression approach allows us to adjust the raw comparison in Figure 1 by other covariates that could affect resource misallocation. This estimation strategy fits well with the fact that the data consists of repeated cross-sections of firms sampled from the same aggregate industries, s. Misallocation within industries selected for support could differ from those industries not selected, and the period following the 10^{th} Five-Year Plan (after 2000) could have had a different level of misallocation for all industries. The DID lets us directly control for both of these concerns. We estimate the following regression:

$$var(\log TFPR)_{st} = \alpha_s + \rho_t + \beta\left(Supported \times Post2000\right)_{st} + X_{st}\gamma + \varepsilon_{st} \qquad (5)$$

where $var\left(\log TFPR\right)_{st}$ is the variance of log TFPR across establishments in industry s in year t, $Post2000_t$ is a dummy variable equal to 1 if the year is after 2000, $Supported_s$ is a dummy equal to 1 if the industry was supported by the 10^{th} Five-Year Plan, X_{st} is a vector of covariates, α_s and ρ_t are industry and time fixed effects, respectively, and ε_{st} represents the error term.

The covariates X_{st} include variables that vary by industry and year: the average age of the firms in the industry, the ratio of exports to value-added, and the proportion of SOEs in the industry. The motivation for including these controls is as follows. Several studies have documented a relationship between productivity and observable characteristics of the firm such as their age (see, e.g. Doms, Dunne, and Roberts 1995; Jensen, McGuckin, and Stiroh 2001; Hsieh and Klenow 2014). Thus, age is commonly used to capture differences in efficiency that stem from different levels of experience, managerial ability, and production technologies.

Here, because we use a measure of volatility at the industry level, we control for the average age in the industry. As for exports, empirical evidence from firm-level data suggests a positive relationship between the share of exporting firms and productivity. For instance, Wagner's (2007) survey of micro-economic studies finds that exporting firms are more productive than non-exporters and "more productive firms self-select into export markets". Hence, we include the control for exporting. The exporting ratio is also intended to control for the increased participation of China in world trade.[16] Finally, starting in 1996 the Chinese government implemented a series of industrial policies known as "grasping the large and letting go of the small" intended to privatize and reduce the size of the state sector. Curtis (2016) suggests that total factor productivity increased with the growth of the private sector and the closing of the least productive SOEs. Hence, the dispersion of TFPR may vary across industries depending on the share of SOEs. Table 1 summarizes the control variables.[17]

The coefficient β captures how being supported by the 10^{th} Five-Year Plan affects misallocation. This is the key parameter of interest. It compares $var\left(\log TFPR\right)$, our measure of resource misallocation, in the supported industries, before and after the plan was put in place, with $var\left(\log TFPR\right)$ of the not supported group over the same period. In this manner we are able to exploit cross-section and time series variation in the data while avoiding confounding the effect of the policy with that of unobserved variables that could have affected all industries at the same time.

Before we discuss the results, recall that we construct an industry-level binary variable that identifies whether a firm belongs to an industry targeted by the 10^{th} Five-Year Plan by reading the official documentation and matching industries explicitly mentioned in the documents with the corresponding four-digit industries. We do not have information on the amount of discretionary funds allocated to specific firms by the plan (e.g., subsidies, tax credits, lower interest rates). Thus, we cannot rule out that some industries in the supported group received little or no support (indeed, we believe this is the case) or that some firms in the not supported industries nevertheless received support. Hence, our estimates should be interpreted

[16] China joined the World Trade Organization (WTO) in 2001. However, China's government implemented policies aimed at opening the economy well in advance of joining the WTO. For example, Brandt et al. (2017) state that China's government began lowering tariff rates in 1992 and most tariff rates in the WTO accession agreement were fixed before 1999. We examine tariffs more directly below.

[17] The firms supported by the 10^{th} Five-Year Plan were, on average, marginally older and less export oriented and had greater government ownership.

as an intention to treat; that is, the effect of being made eligible to receive support. In other words, we estimate the average impact on TFPR dispersion of being assigned to the group of industries supported by the industrial policy.

3.3 Estimation Results

Table 2 reports estimation results based on Equation (5). Column (1) reports the coefficient estimates using the variance of log TFPR as the dependent variable, without including the control variables.[18] Column (2) includes the control variables of ownership, export to value-added and age. In Columns (3) and (4), we replace the dependent variable with the interdecile and interquartile range.[19] Each regression is based on the full panel of eight yearly observations on the 308 industries in our sample, or 2,464 observations in total. The parentheses contain the robust standard errors clustered by four-digit industry.

TABLE 2 HERE

The estimate of β (on $Supported \times Post2000$) is statistically different from zero (at usual significance levels) in all specifications. This estimate represents our main empirical finding. Supported industries experienced a greater increase in misallocation than industries that were not supported by the 10^{th} Five-Year Plan. We take this as strong evidence that the process used to carry out China's centralized industrial plan did not deliver more resources to the firms in which the resources could be put to their best marginal use, at least not over the five-year time horizon included in our analysis.

Moreover, the impact on misallocation is quantitatively large. Consider the more conservative result; in column (2), the estimate of β equals 0.029. Recall that the variance of TFPR for the supported industries averaged 0.430 in 2000 (see Table 1). Thus, the Five-Year Plan lead to an increase in misallocation of about 6.7 percent for the supported industries (relative to the not supported group). This 6.7 percent increase is close in magnitude to the difference observed in the variance of TFPR between supported and not supported industries after

[18] Throughout the rest of the paper, we report the more general fixed effects version of the DID model. The DID results without the broader set of controls are similar, except where noted. See the Appendix.

[19] While the use of the variance of TFPR to measure resource misallocation follows naturally from the work of Hsieh and Klenow (2009), other measures of dispersion provide useful information regarding the effect of industrial policies on the allocation of resources and provide an insightful robustness check.

2001.[20]

Another way to interpret β is to look back at Equation (3) and calculate the reduction in overall TFP, within supported firms, due to the increase in the variance of TFPR. Note, the formula for aggregate TFP only holds with joint log-normal distribution and the exact magnitude depends on the parameter σ; yet, even at moderate values of σ (e.g. 3), the effect appears to be substantial. When the variance of TFPR increases by 0.029, aggregate TFP decreases by about 4.5%.

It is also worth noting that misallocation increased over time for both the supported and not supported industries, on average within our sample. This pattern can be seen in Figure 1. Looking at columns (3) and (4) of Table 2, the effect on the interdecile range is larger than on the interquartile range, which may indicate that the impact of the policy was larger for establishments in the tails of the TFPR distribution, a topic we return to shortly.

4 Robustness Checks

The key finding, that misallocation increased in supported industries, is robust to alternative specifications. The Appendix includes many additional pieces of analysis, including further estimates using the generalized DID set-up, using weighted least squares, as well as additional results using the panel of continuing establishments (which we discuss further below). Here, we highlight the regressions of particular interest. First, we present several regressions that control for the change in tariffs associated with China's joining the World Trade Organization (WTO). Then, we examine establishment entry and exit. Then, we present a battery of robustness checks on sample selection and model specification. Finally, we provide evidence of a correlation between the distortions and firm-level TFP. Throughout, our main findings remain largely unchanged.

[20] We do not know for certain which establishments actually experienced a change in support (i.e., supported or not supported industries). Thus, as mentioned above, it might be more precise to interpret our estimate as measuring the differential impact on misallocation for the industries that were intended to receive treatment versus those industries that were not intended for treatment.

4.1 WTO Accession

China officially joined the World Trade Organization in December of 2001, and the timing coincides with the 10^{th} Five-Year Plan. Thus, fore-knowledge of the WTO agreement may have informed which industries received support, possibly biasing our regression estimates (in either direction) or altering their interpretation.[21] For example, the documented increase in TFPR dispersion in supported industries could be a side-product of trade liberalization and its heterogeneous effect within and across sectors of the economy.[22] Indeed, Brandt et al. (2017) show that WTO accession and the consequent cut in tariffs led to increased productivity among Chinese manufacturing establishments. Moreover, Brandt et al. provide evidence indicating that reduced output tariffs led to lower markups among (mainly) incumbent firms, while lower input tariffs led to efficiency gains among new entrants.

We recognize that WTO accession poses a challenge to our identification strategy. However, the largest and most widespread tariff cuts occurred between 1992 and 1997 (see Figure 2). A second round of reductions took place in 2002, but these subsequent cuts were considerably smaller and idiosyncratic. Also, this next set of cuts had been mostly agreed upon by 1999; although, tariffs and tariff dispersion did continue to decline thereafter. So, even though the major trade liberalization preceded the 10^{th} Five-Year Plan, tariffs did decline over the period of our study.[23]

To check whether trade liberalization impacts our results, we directly control for the maximum allowable tariff under the WTO agreement for each four-digit industry. Brandt et al. (2017) show that maximum allowable tariffs proxy well for actual tariffs imposed, and China often implemented these tariff levels earlier than mandated, with little concern that policy makers lowered tariffs selectively by productivity level. Figure 2 plots the median maximum allowed tariff on inputs (Panel A) and outputs (Panel B) in supported and not supported industries over time. Clearly, the largest declines in tariffs occur before 1998, during the first set of cuts. Notice that the median input tariff was slightly higher for the supported group, while

[21] Basu and Matray (2020) show that some forms of opening to international markets reduce misallocation across establishments within Indian industries. Pavncnik (2002) documents trade liberalization's effect on productivity across Chilean establishments.

[22] Uncertainty may have changed, too. See Pierce and Schott (2016).

[23] Note, the tariff cuts of the supported and not supported industries are quite similar. For example, the median tariff on inputs are around 10% (15% on output) for both the supported and not supported industries after 1997.

the reverse was true for the median output tariff. Yet, the magnitude of the tariff reduction on the supported and not supported group was similar. And, again, the subsequent cuts were considerably smaller, idiosyncratic and had been negotiated by 1999.

FIGURE 2 HERE

Column (5) of Table 2 demonstrates that our main finding is robust to controlling for maximum tariffs on inputs and outputs. TFPR dispersion among supported establishments continues to exhibit a significant increase after the implementation of the 10^{th} Five-Year Plan. The coefficient estimate for β (0.032) in column (5) is slightly larger than the estimate (0.030) from column (1) in Table 2. Moreover, the effect still appears to be driven by establishments in the tails of the distribution, as evidenced by the larger coefficient estimate on $Supported \times Post2000$ for the interdecile range (column 6) relative to the interquintile range (column 7).

Despite the robustness to controlling for tariffs, other aspects of the accession to WTO could have affected TFPR dispersion. Clearly our investigation is not exhaustive; however, estimation results reported in the Appendix (see Table A.3) suggest that the estimated increase in TFPR dispersion for the supported industries (relative to not supported) is robust to controlling for industry-level restrictions on foreign direct investment (FDI) and non-tariff barriers.[24] To summarize, our main finding (that the 10^{th} Five-Year Plan increased misallocation in supported industries relative to the not supported industries) is robust to controlling for various aspects associated with joining the WTO and suggests that aggregate productivity gains experienced by China during the span of the 10^{th}Five-Year plan could have been even greater had they occurred in a manner that preserved or increased allocative efficiency.

4.2 Entry and Exit

The previous section analyzed a panel of industries in which each industry was composed of a repeated cross-section of establishment-level data. Thus, observations for a given industry

[24] We use data from Brandt et al. (2017), who record whether an industry faced restrictions to FDI or non-tariff barriers during the period under analysis. Changes in access to FDI took place only in 2002 for both supported and not supported industries. In contrast, both for the supported and not supported group, the share of industries that experienced non-tariff barriers was constant between 1998 and 1999 and increased in 2000. It declined gradually from 2001 onwards, while for the not supported group the share increased slightly in 2001, declined sharply in 2002 and remained almost unchanged for the rest of the sample.

are potentially based on different sets of establishments in different years. In China, new establishments tend to exhibit higher revenue productivity, while productivity tends to be lower for exiting establishments (Hsieh and Klenow, 2009; Brandt et al. 2012); hence, our estimated increase in the variance of revenue productivity among supported industries could be partially driven by entry and exit dynamics. Indeed, establishments newly entering into our data set after the first year exhibit significantly higher TFPR than incumbents (see Table A1 in the Appendix).[25]

Our data does not identify why establishments enter or exit (i.e., whether firms enter/exit the market or just the survey), and we do not attempt to directly estimate the likelihood of entry and exit. Instead, we re-estimate our regression model with a panel of continuing establishments. That is, while the previous sections used an unbalanced panel of establishments (to constitute the balanced panel of industries), this section exploits the panel nature of the establishment-level data to reduce the impact from the extensive margin. To construct the panel, we follow Brandt, et al. (2012) and match establishment observations across years based on their unique ID, as well as information on their address, name, phone number, and CEO's name.[26] After matching, we follow the same procedure as before to construct an industry panel. Because some industries are discarded, for comparison, we also construct a sample based on all establishments (including those entering and exiting) with this same reduced set of industries .

TABLE 3 HERE

Comparing the estimates for continuing establishments (column 1) and all establishments (column 4) in Table 3 reveals that the increase in TFPR dispersion brought about by the 10^{th} Five-Year Plan remains large in both data sets. In other words, dropping establishments that enter or exit the survey has little impact on the estimate for β.[27] The same holds for columns (2) through (6); our previous estimates (e.g., the quantile ranges) remain roughly the same.

[25] Midrigan and Xu (2014) examine resource misallocation and the relationship between financial frictions and entry and exit. We further explore access to credit below.

[26] Overall, about 96% of all year-to-year matches are constructed using firm IDs, and only the remaining 4% are matched using the other information.

[27] For the sake of brevity, we collect estimation results obtained using this panel in the Appendix. Estimates for all specifications are robust, albeit estimated with a lower degree of precision in some cases.

In summary, the heightened resource misallocation induced by the 10^{th} Five-Year Plan was not solely driven by establishments directly entering and exiting certain industries.[28]

4.3 Mismeasurement and Sample Selection

Measurement error is a potential concern when using indirect measures of TFPR. Sources of 'mismeasurement' could be linked to the use of the NBER Productivity Database to compute the industry-specific labor shares, poor measurement of costs or revenue in the survey, or heterogeneity of factor intensity across establishments in particular industries. To address these issues, we run a series of robustness checks and report the estimated coefficient on $Supported \times Post2000$ in Table 4. For brevity, and to ease comparison across specifications, we do not report the coefficients on the remaining covariates.[29]

First, in the previous section we presented the results obtained when we re-estimate the main empirical model using the industry-level data set constituted from a panel of establishments. Exploiting the panel dimension has one advantage: it ameliorates concerns regarding the impact of poorly measured costs or revenues (see Bils, Klenow and Ruane, 2020). Yet, a drawback to using only the establishments that appear in all the survey years to compute measures of TFPR dispersion is that the number of establishment-year level observations falls by roughly 80%. The smaller sample could introduce noise when using detailed industry classifications. To further tackle this issue, we computed the variance of TFPR in each industry using a panel of establishments that appear in at least three consecutive years and re-estimated the generalized DID specification. As column (1) of Table 4 illustrates, with this set of establishments, the estimated effect of the 10^{th} Five-Year plan on TFPR dispersion remains positive and significant.

Second, while our use of the NBER database is intended to make the TFPR measure directly comparable to Hsieh and Klenow (2009),[30] China's production technology likely differed from that of the US and was possibly affected by the 10^{th} Five-Year plan. Hence, we repeat

[28] We concede that our exercise does not allow us to completely rule out entry and exit. For example, supported industries may have experienced more entry (or exits), which could have impacted dispersion among the continuing supported establishments. This channel, though, could also be a form of misallocation. Given our data limitations, we leave further investigation of this important issue to future research.

[29] All equations include year and industry fixed effects as well as the covariates included in the regressions reported in Tables 2 and 3.

[30] Using the Chinese survey to compute the labor share leads to the same qualitative results: the plan led to an increase in TFPR dispersion.

our estimation after computing TFPR using the capital and labor shares from Gopinath et al. (2017). That is, we set the share of labor equal to 0.65 across sectors, eliminating dispersion in TFPR that stems from variation in the labor and capital shares. The results are qualitatively unchanged; the 10^{th} Five-Year plan increased TFPR dispersion in the targeted industries (see column (2) of Table 4).

Concerns regarding the impact of sample selection and mismeasurement naturally arise when using survey data. For instance, the survey includes all SOEs but restricts non-SOEs to establishments whose nominal revenues exceed 5 million Yuan. Given that the threshold is constant across industries, differences in the size distribution could matter. In addition, if preferential treatment (e.g., subsidies) is given to establishments that are more politically connected, then the inclusion of all SOEs (and truncation of the non-SOEs) could bias the estimates towards finding an increase in misallocation. To address these concerns, we re-estimate our model on the subsample of non-SOEs and on a subsample of non-SOEs with revenues exceeding 6 million Yuan.[31] The estimation results reported in columns (3) to (5) of Table 4 lessen any worries about selection. Even though these estimates are slightly less precise, we still find an increase in misallocation.

TABLE 4 HERE

4.4 Further Robustness Checks

Table 4 presents a battery of additional robustness checks. Column (6) reports estimation results from a regression that includes 2-digit industry-year fixed effects. The estimated effect of the 10^{th} Five-Year plan remains positive and statistically significant. In fact, the magnitude of the estimated effect on misallocation is larger, thus suggesting that broad industry categories do not drive our results. Column (7) reports estimation results obtained via weighted least squares where we use the value-added for each four-digit industry in each year as weight. The coefficient of interest is about the same as that in column (2) of Table 2.

As mentioned earlier, a possible confounding factor when drawing inferences about the effect of the policy is the fact that some industries were supported by the 9^{th} Five-Year Plan. Thus, the analysis to this point has excluded the 95 industries supported by the 9^{th} Five-

[31] We obtain similar results if we impose a threshold of 5.5 or 7 million Yuan .

Year Plan.[32] Column (8) shows that the estimate of β is smaller when we include these 95 industries.[33] Possibly, the effect on misallocation from continued support (in industries receiving support from both the 9^{th} and 10^{th}) is smaller because the misallocation already occurred, or, similarly, the impact on misallocation could remain for establishments supported by the 9^{th} but not the 10^{th}. Either way, the estimated impact would be reduced.

Column (9) includes industries that were previously dropped because they contain fewer than 10 establishments.[34] Column (10) reports the estimates when we include the top and bottom establishments in the TFPR distribution, which were dropped in the main sample. Column (11) drops industries that have the largest and smallest changes in the variance of TFPR before and after the 10^{th} Five-Year Plan (such as industries 1510, 1690, and 3513, as shown in Figures A1 and A2 of the online Appendix).

As discussed above, a possible threat to our empirical approach is the validity of the parallel trends assumption (i.e. whether supported and not supported industries had different pre-trends in misallocation prior to the plan). To further address this concern, we conduct a placebo test. We 'assume' the plan was implemented in 2000, the year prior to the actual inception of the $10th$ Five-Year Plan. Estimation results reported in column (12) of Table 4 reveal an insignificant effect. Similar results are obtained when we assume the plan was implemented in the two years preceding the inception, 1999 and 2000 (see column (7) of Table A3 in the Appendix). These results, in conjunction with the event study estimates in Figure 1, suggest the parallel trends assumption is valid. Similarly, column (13) of Table 4 introduces two interactions between supported industries and the years before the implementation of the 10^{th} Five-Year Plan to capture possible anticipation effects. The coefficient of interest is larger than the baseline estimate.

If anything, in Figure 1, the impact of the policy appears to be delayed. One possibility is that the actual treatment (receiving support) took time to occur or to effect the allocation of resources. We have redone all of our main regressions using 2002 as the treatment year instead of 2001. The central implications of the regressions remain unchanged. Column (14) reports the main estimate, and the coefficient increases to 0.042 (relative to the baseline estimate of

[32] Industries with less than ten firms in a year are not included.

[33] For this regression, we continue to group industries according to whether they received support in the 10^{th} Five-Year Plan, regardless of whether the industry was supported in the 9^{th}.

[34] Some of these industries have no firms in some years, leading to an unbalanced panel in terms of industries.

0.029). A second possibility is that the policy was not distortionary - at first. However, as mentioned in the Introduction, Buera, Moll, and Shin (2013) show how even well-targeted supports can lead to misallocation due to policy inertia. Thus, the misallocation due to the policy may have taken time to manifest, but then it persisted into the future (also see Banerjee and Moll (2010)).

A concern with the controls is that they could have responded endogenously to the Five-Year Plan. To address this, column (15) of Table 4 reports the estimates obtained when we interact the "post" dummy with the value of the covariates in 1998 - well before the 10^{th} Five-Year Plan. The coefficient on the variable of interest remains positive and statistically significant, indicating that TFPR dispersion in the supported industries increased relative to the not supported industries.[35]

We also have examined whether our results are robust to using the wage bill to measure productivity (abstracting from capital), as in Bento and Restuccia (2017, 2021). Column 16 reports the estimated coefficient (0.041), and it remains statistically significant.[36] That is, we still find evidence of an increase in misallocation in the supported industries relative to not supported industries. Throughout the many robustness checks the results remain close to (or larger than) our baseline findings in Table 2 (with the singular exception of including industries supported by the 9^{th} Five-Year Plan). We conclude that the misallocation of resources increased in industries receiving support from the 10^{th} Five-Year Plan.

4.5 Policy and Distortions

A key insight from Restuccia and Rogerson (2008), Hsieh and Klenow (2009, 2014), Restuccia (2019), and Bento and Restuccia (2017, 2021) is that distortions that are correlated with establishment-level TFP have the potential to do more damage than distortions not systematically related to TFP. The policies implemented by the 10^{th} Five-Year Plan could have led to an increase not only in random distortions –those not systematically related to establishment TFP– but to 'correlated distortions', with more detrimental effects. For instance, the plan may have doled out large subsidies to establishments with low TFP and provided less (or no)

[35] Qualitatively similar results are obtained when we use the value of the covariates in 1999 as the initial year (see column (8) of Table A.3 in the Appendix).

[36] Given that Chinese establishments report only wage payments, we follow Hsieh and Klenow (2009) and assume that the non-wage benefits are a fraction of the total wage compensation reported by the establishment.

subsidies to establishments with high TFP.

The next section digs deeper into the distributional effects. Here, though, we look directly at the effect of the plan on correlated distortions.[37] To do so we use establishment-level data to compute two measures of correlated distortions and productivity for each year-industry. First, we follow the same model structure as in Bento and Restuccia (2017) to compute a measure of correlated output distortions. Second, following Hsieh and Klenow (2009, 2014), we use a composite distortion measure that includes output and capital distortions. That is, we measure distortions as the elasticity of the wedge to TFPQ. We then employ our difference-in-difference framework to estimate the effect of the 10^{th} Five-Year Plan on the industry-level distortions. Neither measure is perfect; each relies on the structure imposed on the data by the model. However, using these statistics to evaluate the policy allows us to gauge whether the Five-Year Plan had a negative impact that goes beyond the increase in random distortions.

TABLE 5 HERE

The estimation results in Table 5 indicate that the Five-Year Plan increased the correlated distortions in supported industries relative to those not supported. As columns (1) and (3) illustrate, this finding is robust to using the two measures of correlated distortions. The increase in the average correlated distortions is estimated to be somewhat smaller when using a measure of correlated output distortions (column 1). When we assume a higher elasticity of substitution within industries ($\sigma = 5$ instead of 3) the increase in distortions brought about by the 10^{th} Five-Year Plan is estimated to be slightly larger (see columns 2 and 4). Our estimation results thus suggest that as correlated distortions increased in the supported industries, TFP and output likely failed to reach the levels they could have obtained in the absence of distortionary policies. This finding hints at a mechanism whereby the 10^{th} Five-Year Plan distorted resource allocation through a differential effect on low and high TFP firms within supported industries, a point we return to below.

[37] We thank an anonymous referee for suggesting that we look into the effect of the Five-Year Plan on correlated distrortions.

5 Digging Deeper into the Distributional Effects of the 10^{th} Five-Year Plan

We have shown that industrial policies increased the dispersion in the ratio of revenues to input costs across Chinese industries. This section furthers our investigation by examining how these policies impacted average revenue (or quantity) productivity. Section 5.1 presents evidence that the 10^{th} Five-Year Plan increased average TFPR for the supported establishments but had little effect on average TFPQ. Then, in Section 5.2, we employ the methodology developed by Athey and Imbens (2006) to estimate the quantile treatment effects of the policy, which allows us to document the heterogeneous effects across the TFPR and TFPQ distributions. We conclude that on average the policy's effect on TFPR was positive, but at the cost of inefficiently shuffling resources between establishments in the top quintiles of the productivity distribution.

5.1 The Effect of the 10^{th} Five-Year Plan on Average TFPR, TFPQ, MRPK, and MRPL

The results presented thus far revealed that the 10^{th} Five-Year Plan increased resource misallocation as measured by the variance of TFPR. This section examines the mean (or level) of TFPR by replacing the variance of TFPR with the industry mean and re-estimating Equation (5). Column (1) in Table 6 reports the results. Once more, we focus on the estimated coefficient for the interaction term ($Supported \times Post2000$). The estimate of β is positive and statistically significant at the 5% level; the 10^{th} Five-Year Plan tended to increase TFPR (marginal productivity) for establishments in supported industries. Along the lines of Liu (2019), which finds that sectoral interventions had positive effects, we find an increase in average TFPR for supported firms (but and increased variance).

TABLE 6 HERE

Column (2) reports the regression estimates using mean log TFPQ as the dependent variable. The null of no average treatment effect ($\beta = 0$) cannot be rejected. Moreover, the estimate is quantitatively small relative to average TFPQ. We find no evidence that supported establishments experienced an increase in their average physical productivity or technology level. Recall from Equations (1) and (2), TFPR equals TFPQ times price.[38] Thus, at a first pass, the support obtained through the 10^{th} Five-Year Plan appears to have primarily increased the price that establishments in supported industries charged.

In brief, we find evidence that the policies implemented by the Chinese government increased the variance and mean of TFPR, but our estimated impact on average TFPQ is negligible. However, since we compute TFPQ indirectly – due to the lack of price and quantity data in the survey – the latter result should be taken with a grain of salt.

We now turn our attention to the variables underlying the productivity measures (i.e., the marginal revenue products of capital and labor, MRPK and MRPL respectively). Following the insights of Hsieh and Klenow (2009) and Gopinath et al. (2017), an increase in the dispersion of a factor's return across establishments in a supported industry could reflect increasing frictions/barriers to the allocation of the production factors. In their framework, the marginal revenue products are given by

$$MRPL_{si} := (1-\alpha_s)\frac{\sigma-1}{\sigma}\frac{P_{si}Y_{si}}{L_{si}} = w\frac{1}{1-\tau_{Y_{si}}} \tag{6}$$

and

$$MRPK_{si} := \alpha_s\frac{\sigma-1}{\sigma}\frac{P_{si}Y_{si}}{K_{si}} = R\frac{1+\tau_{K_{si}}}{1-\tau_{Y_{si}}} \tag{7}$$

where w denotes the wage, R denotes the interest rate, τ_Y denotes the output distortion and τ_K denotes a capital distortion. As equations (6) and (7) illustrate, τ_Y constitutes a distortion that increases the MRPK and MRPL proportionally (i.e., an establishment-specific scale distortion), whereas $\tau_{K_{si}}$ captures a distortion in the MRPK relative to the MRPL (i.e., an establishment-specific factor price wedge). Investigating whether the 10^{th} Five-Year Plan affected MRPK and/or the MRPL provides additional insights into the effect of the policy on the labor and capital wedges. In turn, inquiring into the effect of China's industrial policies on these wedges allows us to take a first stab at understanding the mechanisms at play.

For this inquiry, we again use a generalized DID estimation strategy, where now the depen-

[38] The calculation of TFPQ depends on σ. Therefore, we have re-run these regressions using alternate values of σ. The point estimate remains quantitatively small at larger values, but if σ gets large enough the effect becomes statistically significant. See the Online Appendix.

dent variable is the mean of $\log(MPRK)$ or $\log(MRPL)$. The results reported in columns (3) and (4) of Table 6 (again, looking at $Supported \times Post2000$) reveal a statistically significant increase in average MRPK and no significant change in MRPL.[39] Hence our findings suggest that the industrial policies implemented by the Chinese government lead to a larger increase in the establishment-specific wedge, $\tau_{K_{si}}$, than in the output distortion, $\tau_{Y_{si}}$.

Recent literature has questioned whether the dispersion of TFPR reflects only misallocation. Asker, et al. (2014) and Haltiwanger, Kulick and Syverson (2018), among others, caution about the drawbacks of using the indirect approach pioneered by Hsieh and Klenow (2009) for measuring misallocation.[40] For example, differences in adjustment costs on capital combined with more variable idiosyncratic shocks in the supported industries could result in a larger dispersion of marginal revenue products (see Asker et al., 2014). Although David and Venkateswaran (2019) argue that adjustment costs account only for about a 1% of the variance of MRPK in China; whereas distortionary factors explain more than 40% of the MRPK dispersion. Moreover, if –despite being similar along the observable characteristics- the supported establishments faced larger idiosyncratic shocks due to uncertainty regarding the policy, then it seems reasonable to interpret the increased in MRPK for the supported industries as indicative of misallocation.

Another example is that the increased dispersion in TFPR may have stemmed from higher markup dispersion among supported establishments (see Haltiwanger, et al. 2018). We do not have access to disaggregated data on establishment-level quantities and prices to directly test this hypothesis; yet, our results do provide indirect evidence that channels other than markup dispersion play a role in explaining the increase in TFPR dispersion observed among supported industries. Indeed, the markup channel likely would have led to similar increases in MRPK and MRPL among supported industries. We also show below that the effects across the distribution are consistent with a change in misallocation that does not solely come from markup dispersion.

Finally, it has been argued that the variance of TFPR is not a sufficient statistic for misallocation when some of the assumptions in Hsieh and Klenow (2009) are relaxed. While

[39] Whereas the increase in the dispersion of MRPK is robust across specifications, that of MRPL is positive but not statistically significant.

[40] Also, see Asker et al. (2019), Bils et al. (2020), and de Nicola et al. (2020). Acemoglu et al. (2013), Jones (2011), and Hang et al. (2020) consider input-output linkages among firms.

obtaining a sharper measure of misallocation lies beyond the scope of our paper (in part due to the lack of price and quantity data), in the next two sections we dig deeper into the effects of the 10^{th} Five-Year Plan on the productivity and efficiency of the Chinese economy by examining other moments of the TFPR distribution and by looking into the ways establishments received support. The results of this additional analysis are consistent with the misallocation interpretation. It should also be noted that the generalized DID estimates recover only the average effect of the policy on the supported industries (i.e., the average treatment effect on the treated). The 10^{th} Five-Year Plan may have had heterogenous effects on establishments with different levels of productivity - a possibility we explore next.

5.2 The Heterogeneous Effects of the 10^{th} Five-Year Plan

Figure 3 contains a scatter plot of industries depicting their change in misallocation after 2001. The vast majority of supported industries experienced an increase in the variance of TFPR.[41] The worsening within-industry resource allocation is the key finding of the previous sections. However, does this imply an increase in resource misallocation across industries? After all, the TFP loss in one industry could be offset by gains in other industries, increasing overall productivity. Moreover, Figure 3 shows that the effect was heterogenous across the (industry) productivity distribution, suggesting differential treatment across establishments with different marginal productivity levels.

FIGURE 3 HERE

We next investigate this heterogeneity by estimating the quantile treatment effects using a nonlinear difference-in-difference model, revealing how the treatment affected the full distribution of TFPR. This analysis considers the distribution across all industries rather than relying on industry-specific measures of dispersion. Policies such as tax cuts, subsidies, or easy access to credit are bound to have heterogenous effects across establishments with differing TFPR. Thus, in the following section, we also use the establishment-level data to document what support methods were deployed following the 10^{th} Five-Year Plan.

To estimate the quantile treatment effects, we apply the changes-in-changes (CIC) method

[41] Figure A2 in the Online Appendix further illustrates that only a few supported industries (e.g., industry 1931, 2920, and 3010) experienced a decrease in TFPR dispersion during the period spanned by the plan.

proposed by Athey and Imbens (2006). First, the entire TFPR distribution - before and after the implementation of the 10^{th} Five-Year Plan - is used to recover the change over time among the not supported establishments. Then, under the assumption that the TFPR distribution in the supported group would have exhibited the same change as the not supported group in the absence of the policy, we estimate the counterfactual distribution for the supported establishments under the period of the 10^{th} Five-Year Plan. The quantile treatment effect of the policy on the supported establishments at each quantile is estimated as the horizontal distance between the observed TFPR distribution for the supported establishments and the counterfactual TFPR distribution.

We first estimate a CIC regression without including the covariates (Figure 4, Panel A). Then, we follow Garlick's (2018) methodology and redo the computation controlling for the same covariates as in Section 3.3 (Figure 4, Panel B).[42]

FIGURE 4 HERE

Figure 4 plots the quantile treatment effects for supported establishments, without and with adjustment for covariates, along with the 95% confidence intervals constructed using a percentile bootstrap. Regardless of the adjustment, the point estimates are small and statistically insignificant for the lowest percentile. For most of the distribution the point estimates are positive and significant. In fact, they are increasing in the level of TFPR with the difference between the observed and counterfactual TFPR increasing from 41% for the 60th percentile to 58% at the 90th. This larger increase at the extreme tail of the TFPR distribution is consistent with other findings in the literature (see, for example, De Loecker et al. (2020)). These results indicate that the increase in average TFPR was largest in the upper tail of the distribution and that this heterogeneity played a role in increasing TFPR dispersion.

FIGURE 5 HERE

We also estimate the quantile treatment effect of the policy on the TFPQ distribution for supported establishments.[43] The point estimates in Panel A of Figure 5 are positive but

[42] The Appendix reports the CDF of the counterfactual TFPR distribution.
[43] The Appendix reports the CDF of the counterfactual TFPQ distribution.

insignificant for the bottom quartile; yet, for most of the distribution we estimate a significant increase. Indeed, as it is the case for TFPR, the largest differences between the observed and the counterfactual distribution are observed for the extreme right tail where the difference between the observed and counterfactual distributions exceed 20% (e.g., 20.2% and 25.6% for the 80th and 90th percentiles, respectively). These results reinforce our conclusion that, on average, industrial policies in China increased misallocation. Moreover, the CIC estimates reveal significant heterogeneity in the effects of the 10^{th} Five-Year Plan on the bottom and top tails of the TFPQ distribution.

Figures 4 and 5 point towards three important distributional effects due to the Chinese government's policies. First, the 10^{th} Five-Year Plan appears to have increased revenue productivity for the supported establishments over most of the TFPR distribution and, especially, for those in the top quartile. Second, for most of the supported establishments ($20^{th} - 80^{th}$ quantile) physical productivity increased slightly, but less than TFPR. Third, TFPQ increased over parts of the distribution, which we interpret as suggestive evidence –due to the indirect computation of TFPQ– that the policy did have an effect on the physical productivity of some establishments.[44]

While the nonlinear model provides more information than the DID model, it requires stronger identification assumptions. The quantile treatment effects are only identified if the distribution of the unobserved establishment-level TFPR (or $TFPQ$) determinants do not change over time. Both the policy of "grasp the large and let go of the small" and the increased participation of China in world trade may well have altered the distribution for the covariates. However, the quantile estimates above are similar with and without the controls; thus, quantitatively, this does not appear to be a great concern.

TABLE 7 HERE

Finally, Table 7 reports summary statistics for the observed and counterfactual TFPR and TFPQ distributions. These summary statistics are computed across all the establishments. Therefore, the reported change in the variance does not equal the change in the variance by industry reported in Section 3, and, hence, does not correspond to Hsieh and Klenow's (2009)

[44] Estimation results including firm and year fixed effects -available from the authors upon request- are almost identical.

measure of misallocation. Instead, it captures the variability of TFPR in the economy as a whole. The table reports measures of TFPR (TFPQ) dispersion for the observed distribution of supported establishments and the counterfactual TFPR (TFPQ) in the absence of the support. On the one hand, the mean and variance of TFPR are higher for the observed than the counterfactual distribution. The support provided by the 10^{th} Five-Year Plan increased the mean of TFPR by about 23% and the aggregate variance by approximately 180% for the supported establishments. The increase in the mean is a result of the positive effect of the support on most quantiles of the TFPR, while the increase in the variance is mostly due to the large positive effect on the top tail. On the other hand, the mean of TFPQ is somewhat larger under the observed and under the counterfactual distribution, whereas the variance of TFPQ is approximately 110% higher. The support doled out by the 10^{th} Five-Year Plan thus appears to have increased the mean of TFPQ slightly while increasing the dispersion of TFPQ for the supported establishments. This increase in dispersion is reflective of the positive effect over all the distribution but the bottom quartile. The CIC estimates suggest industrial policies implemented by the Chinese government resulted in greater dispersion on the physical and revenue productivity among supported establishments, but also lead to an increase in TFPQ. These findings are consistent with the idea that, while the policies had the intended effect to boost productivity for some establishments, they disproportionately moved resources to (some, large) low-productivity establishments and away from some high-productivity establishments.

6 Mechanism: Taxes, Subsidies, and Access to Credit

Three of the most common ways the Chinese government supports establishments are tax breaks, direct subsidies, and access to credit. Each of these, when handed out to only a subset of establishments, can distort the allocation of resources. The official documentation on the 10^{th} Five-Year Plan does not contain information regarding the mechanism used to support establishments. So, we turn to the data to learn about the instruments used by the Chinese government, and then we investigate whether these had a heterogenous impact for establishments with different initial levels of marginal revenue productivity. Throughout this section, we use the data at the establishment level (rather than aggregating into industries) because this allows us to show that establishments within the same industry received different treatment.

6.1 Average Effects on Preferential Supports

Our inquiry into the possible mechanisms employed to support establishments follows a two-pronged approach. First, we use a probit difference-in-difference model to estimate the effect of the plan on the probability that an establishment pays taxes:

$$\Pr(Y_{ist} = 1) = \phi \left[\alpha + \beta \left(Supported \times Post2000\right)_{ist} + \delta_t + \eta_s + \varepsilon_{ist}\right] \quad (8)$$

where $Y_{ist} = 1$ if establishment i in industry s paid taxes at time t. We use a similar regression to estimate the impact of the Five-Year Plan on the probability that an establishment receives subsidies and an ordered probit regression to model the probability of receiving or paying interest.

Second, we inquire into the effect of these industrial policies on the expected ratio of the latent taxes (subsidies) to value-added, which we interpret as a proxy for the impact on the average tax (subsidy) rate faced by the supported establishments. For this, we employ a Tobit model with the same control variables as before.

TABLE 8 HERE

Column (1) of Table 8 reports the estimation results for the probability of paying taxes, and Column (2) reports the Tobit. While the coefficient on the interaction term in a probit/Tobit model does not equal the treatment effect, the sign of the treatment does equal the sign of the interaction term (see Puhani, 2012). Thus, the statistically significant and positive coefficient estimate on the interaction term $Supported \times Post2000$ suggests that both the probability of paying taxes and the tax rate increased for supported establishments during the 10^{th} Five-Year Plan. At a first glance, on average, tax breaks do not appear to have been heavily used to provide support to the targeted industries.

Columns (3) and (4) of Table 8 show that support was doled out in the form of subsidies.[45] The 10^{th} Five-Year Plan increased the probability of receiving subsidies as well as the expected

[45] See Fakos (2019) for a related analysis of firm level subsidies in Greece.

ratio of subsidies to value-added in supported industries.

Column (5) reports the estimation results for an ordered probit model where the dependent variable takes a value of zero if the establishment received interest payments, one if the establishment did not receive or pay interest, and two if the establishment paid interest. Column (6) reports the OLS results for the ratio of interest to debt. The estimates in column (5) suggest that the 10^{th} Five-Year Plan reduced the probability of paying interest for supported establishments, possibly reflecting an improvement in credit conditions. However, the impact on the average interest to debt ratio is not significant.

To summarize, the 10^{th} Five-Year Plan led to an increase in average subsidies and a decrease in the probability of paying interest, but also an increase in taxes, for the supported establishments. We would like to know more about the nature of the support. For example, if the subsidies targeted capital expenditures (rather than hiring labor), then it might help explain the TFPQ results above, which, in turn, could have strong policy implications. However, the data does not contain such information, and we must leave this to future research.

6.2 Are All Establishments Treated Equally under the 10^{th} Five-Year Plan?

The heterogeneity documented in Section 4.2 suggests that the support mechanisms did not impact all establishments equally. Recall, the CIC model indicated that the plan increased TFPR for most establishments; yet the increase was greater for the right tail of the TFPR distribution. The effect on TFPQ was even more uneven - negative for the lower quintile and positive for the upper quintile.

To investigate whether the three key government support methods were applied unequally across the TFPR distribution, we partition the sample in the following manner. For each industry, we obtain the TFPR values that correspond to the 33^{rd} and 67^{th} quantiles of the pre-plan TFPR distribution. We then classify each establishment-year observation into the bottom, middle, or top tier of the pre-plan TFPR distribution by the establishment's industry. Then, we re-estimate the DID models of the previous section on the bottom and top tier subsamples.[46]

Tables 9 through 11 report the estimation results using each support mechanism (tax

[46] Qualitatively, the results obtained by using the top and bottom quartile or the top and bottom quintile are similar. We opt for using tiers so as to have more representative subsamples.

payments, subsidies, and interest payments, as previously defined) as the dependent variable for the bottom and top tier subsamples. We arrive at three insights. First, as noted above, the industrial policies implemented by the Chinese government increased the probability of paying taxes and the tax to value-added ratio for all establishments. That is, the coefficient estimate on the interaction term is positive and statistically significant for both tiers in Table 9. Both low and high-TFPR establishments paid higher taxes and the differences between them were statistically insignificant, indicating that taxes are not the main support mechanism behind our results.

TABLES 9-11 HERE

Second, the estimates in Table 10 indicate that the least (marginally) productive establishments in the supported industries experienced an increase in both the probability of receiving subsidies and the ratio of subsidies to value-added, while the effect of the 10^{th} Five-Year Plan on the marginally high-TFPR establishments was insignificant. These findings point to subsidies as a channel for increased misallocation: in supported industries, low-TFPR establishments received higher subsidies than their high-TFPR counterparts.

Third, the estimates in Table 11 show that the marginally most productive establishments actually became less likely to get credit (column 3). The plan had no significant impact for the low-TFPR establishments. The sign on the interaction term in the ordered probit model is insignificant for the bottom tier of the TFPR distribution, but negative and significant for the top tier. That is, we do not find statistically significant evidence of an heterogenous effect of the Five-Year Plan on access to credit.

We started this section by asking whether establishments were treated equally under the 10^{th} Five-Year Plan. Clearly, the answer is no. Our estimation results indicate that the least productive establishments in supported industries received more subsidies (relative to their value-added). The unequal support provided to establishments in different parts of the TFPR distribution, via subsidies, helps to explain how the heterogeneity of the policies across establishments in the supported industries caused the misallocation of resources and, thus, likely had the unintended consequence of reducing TFP.

7 Conclusions

This paper presents evidence on how China's central economic plans affect the allocation of resources. We employ a difference-in-difference approach to estimate the relative change in resource misallocation within industries supported by the 10^{th} Five-Year Plan. We use the variance of TFPR as an industry-wide measure of misallocation, as calculated from rich micro-level data on manufacturing establishments. Our central finding is that the 10^{th} Five-Year Plan greatly increased misallocation within supported industries. As to the underlying components of TFPR, the plan resulted in higher dispersion for the marginal revenue product of capital.

We also show that the 10^{th} Five-Year Plan increased the mean TFPR for the supported industries and increased dispersion over much of the TFPR distribution. The impact was particularly high for establishments with the highest (marginal) productivity. The 10^{th} Five-Year Plan did not increase the mean of physical productivity (TFPQ) in supported industries; however, the impact over the distribution was heterogenous. Furthermore, we found that the methods used to support establishments were applied unevenly. For example, establishments in the supported industries were more likely to receive subsidies, but these supports were not doled out homogeneously across establishments.

Our results are consistent with a pattern of resources being moved from establishments with high marginal revenue productivity toward low revenue productivity establishments, over much of the productivity distribution. Moreover, low revenue productivity establishments seem to have simply received direct subsidies or access to easy credit - a very direct way to (mis-) allocate resources.

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Table 1. Summary Statistics

	Supported	Not Supported
V[log(TFPR)]	0.4298	0.4388
	(0.2944)	(0.3070)
M[log(TFPR)]	1.5782	1.6387
	(0.3280)	(0.2977)
M[log(TFPQ)]	5.7969	5.7771
	(0.3811)	(0.4242)
M[log(MRPK)]	1.3554	1.5038
	(0.4680)	(0.4420)
M[log(MRPL)]	0.2808	0.2421
	(0.3594)	(0.4425)
90^{th}-10^{th}	1.5479	1.5821
	(0.5817)	(0.5625)
75^{th}-25^{th}	0.7527	0.7966
	(0.2984)	(0.2943)
Age	14.84	14.92
	(7.48)	(6.11)
Ownership	0.2676	0.2415
	(0.1852)	(0.1730)
Export/VA	0.4948	0.7891
	(1.2812)	(1.1916)
Tax Dummy	0.7140	0.7302
	(0.1182)	(0.1174)
Tax/VA	0.0268	0.0550
	(0.0128)	(0.1424)
Subsidy Dummy	0.1160	0.1027
	(0.0872)	(0.0595)
Subsidy/VA	0.0121	0.0173
	(0.0313)	(0.0693)
Interest Dummy	1.7328	1.6943
	(0.1253)	(0.1308)
Interest/Debt	0.0465	0.0602
	(0.0301)	(0.1177)
Number of Industries	93	215

Notes: V[log(TFPR)] denotes the average variance of logged TFPR across four-digit industries in the year 2000. M[log(TFPR)], M[log(TFPQ)], M[log(MRPK)] and M[log(MRPL)] are the mean values of logged TFPR, TFPQ, MRPK and MRPL, respectively. 90^{th}-10^{th} and 75^{th}-25^{th} refer to the interdecile and interquartile differences in log(TFPR) of four-digit industries. Age is the average age of the firms in an industry. Export/VA is the ratio of the value of export to value/added. Ownership measures the percentage of state-owned firms in an industry. Tax dummy, subsidy dummy and interest dummy indicate the proportion of firms who paid taxes, received subsidies and paid interest. Tax/VA and subsidy/VA refer to the ratio of tax to value-added, and subsidy to value-added. Interest/Debt denotes the ratio between interest payment and total debt. Standard errors are in parenthesis.

Table 2. Estimates of the 10^{th} Five-Year Plan's Effect on TFPR Dispersion

	V[log(TFPR)]	V[log(TFPR)]	90^{th}-10^{th}	75^{th}-25^{th}	V[log(TFPR)]	90^{th}-10^{th}	75^{th}-25^{th}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Supported*Post2000	0.0302**	0.0292**	0.0649**	0.0389**	0.0318**	0.0697**	0.0411**
	(0.0142)	(0.0132)	(0.0298)	(0.0172)	(0.0136)	(0.0308)	(0.0176)
Maximum Allowable Input Tariff					0.0028	0.0088	0.0035
					(0.0063)	(0.0122)	(0.0062)
Maximum Allowable Output Tariff					-0.0017	-0.0018	-0.0009
					(0.0014)	(0.0026)	(0.0014)
Ownership		-0.0685	0.0002	-0.1335	-0.0628	0.0053	-0.1308
		(0.0694)	(0.1544)	(0.0822)	(0.0688)	(0.1537)	(0.0816)
Export/VA		0.0093	-0.0054	0.2459***	0.0065	-0.0060	0.2451***
		(0.0130)	(0.0351)	(0.0219)	(0.0138)	(0.0357)	(0.0219)
Age		-0.0004	-0.0012	0.0003	-0.0004	-0.0011	0.0003
		(0.0007)	(0.0015)	(0.0004)	(0.0007)	(0.0015)	(0.0004)
Number of Industries	2464	2464	2464	2464	2464	2464	2464
R^2	0.910	0.910	0.869	0.841	0.911	0.869	0.842

Notes: V[log(TFPR)] is the variance of logged TFRP within a four-digit industry. 90^{th}-10^{th} and 75^{th}-25^{th} refer to differences in TFPR between the 90^{th} and the 10^{th} percentile, and between the 75^{th} and the 25^{th} percentiles by industry. Post2000 equals 1 if it is after 2000 and 0 otherwise. Supported equals 1 if the four-digit industry is supported. Age denotes the average age of firms in a four-digit industry, Ownership refers to the ratio of state-owned firms, and Export/VA (rescaled by multiplying 1000) is the average ratio of export to value-added in the industry. The are 2,464 observations from 308 industries for each column. Year and four-digit industry fixed effects are controlled across columns. The parentheses report robust standard errors clustered by four-digit industry. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 3. Continuing vs All Firms

	Continuing Firms			All Firms		
	V[log(TFPR)]	90^{th}-10^{th}	75^{th}-25^{th}	V[log(TFPR)]	90^{th}-10^{th}	75^{th}-25^{th}
	(1)	(2)	(3)	(4)	(5)	(6)
Supported*Post2000	0.0390**	0.0940**	0.0552**	0.0424***	0.0869***	0.0552***
	(0.0196)	(0.0437)	(0.0241)	(0.0150)	(0.0326)	(0.0187)
Maximum Allowable	0.0035	0.0237*	0.0045	0.0085*	0.0121	0.0113*
Input Tariff	(0.0066)	(0.0123)	(0.0077)	(0.0045)	(0.0096)	(0.0058)
Maximum Allowable	-0.0049**	-0.0093**	-0.0031	-0.0024	-0.0029	-0.0023
Output Tariff	(0.0021)	(0.0037)	(0.0024)	(0.0017)	(0.0030)	(0.0017)
Ownership	-0.219	-0.215	-0.267	-0.0930	-0.0946	-0.127
	(0.199)	(0.350)	(0.225)	(0.0883)	(0.192)	(0.110)
Export/VA	1.25e-07	2.15e-07	1.91e-07*	-7.28e-08	8.49e-09	1.46e-08
	(0.0000)	(0.0000)	(9.93e-08)	(0.0000)	(0.0000)	(0.0000)
Age	0.0008	0.0014	0.0006	0.0008	0.0021	0.0001
	(0.0005)	(0.0013)	(0.0007)	(0.0010)	(0.0017)	(0.0010)
Number of Industries	1864	1864	1864	1864	1864	1864
R^2	0.792	0.772	0.725	0.930	0.901	0.880

Notes: The above table compares regressions from a panel of 233 industries composed from the same set of firms (continuing firms) throughout the 8 years to the same panel of 233 industries in which firms enter and exit over the years. Each regression is based on 1,864 industry / year observations and includes a full set of year and industry fixed effects. Year and four-digit industry fixed effects are controlled across columns. Parentheses report robust standard errors clustered industry. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 4. Robustness Checks

	Using firms observed at least in three consecutive years	Assuming a capital share of 0.35	Non-SOEs	Non-SOEs (Revenue > 6 million)	SOEs & non-SOEs (Revenue > 6 million)	Year 2-digit Industry FE	WLS	Including industries supported by the 9th Five-Year Plan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Supported*Post2000	0.0362**	0.0357*	0.0276*	0.0279*	0.0309**	0.1057**	0.0284**	0.0173
	(0.0140)	(0.0195)	(0.0160)	(0.0166)	(0.0146)	(0.0417)	(0.0136)	(0.0116)
Number of Industries	2424	2456	2400	2344	2448	2464	2464	3280
Number of Firms	808,396	1,092,381	921,765	779,128	950,456	1,092,488	1,092,488	1,426,416
R^2	0.893	0.694	0.897	0.897	0.906	0.665	0.946	0.918

	Including industries with less than 10 firms	Including the 99th and 1st Percentiles	Excluding Outliers	Placebo Test	Anticipating Effects	2002 as Treated	Initial Covariates	Wage bill
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Supported*Post2000	0.0338**	0.0564**	0.0343**		0.0406**	0.0421**	0.0329**	0.0411*
	(0.0145)	(0.0231)	(0.0144)		0.0181	(0.0249)	(0.0146)	(0.0248)
Supported*Year2000				-0.0062	0.0230			
				(0.0129)	0.0183			
Number of Industries	2540	2464	2416	2464	2464	2464	2464	2464
Number of Firms	1,094,386	1,112,078	1,075,278	1,092,488	1,092,488	1,092,488	1,092,488	1,092,488
R^2	0.901	0.856	0.902	0.910	0.911	0.666	0.910	0.666

Notes: The dependent variable is the variance of log(TFPR) across columns. Column (1) includes firms that appear for at least three consecutive years. Following Gopinath et al. (2017), we assume capital and labor shares fixed values across industries and years in column (2). Column (3) includes only non-SOEs. Column (4) includes only non-SOEs too, but only the non-SOEs whose nominal revenue is larger than 6 million yuan. Column (5) includes all SOEs, and non-SOEs whose nominal revenue is larger than 6 million yuan. The interaction of year and two-digit industry is controlled in column (6). Column (7) shows the results with weighted least square method, which value-added of each industry in each year is used as the weights. Column (8) includes the industries supported by the 9th Five Year Plan. Column (9) includes the small industries with less than 10 firms in a year. Column (10) includes those firms whose TFPR is larger than the 99% percentile or smaller than the 1% percentile. Industries with the largest or smallest TFPR values are further dropped, and the results are shown in (11). A placebo check is conducted in column (12), in which the interaction between the supported industries and the year 2000 dummy is introduced. Column (13) introduces the interactions between Supported and year dummies to examine the anticipating effects. The year of 1998 was omitted as comparison. Column (14) assumes the year of 2002 is the beginning of the Five-Year Plan, instead of 2001. Column (15) includes the interactions between the supported industries and the initial values (at year 1998) of the covariates. Hsieh and Klenow (2009) assume that firm's labor compensation equals to half of value-added. Half of value-added is about 2.7 times of firm's wage bill. Results obtained when using labor compensation to compute misallocation are reported in Column (16). Control variables are maximum allowable input and output tariffs, share of SOEs in an industry, average ratio of export to value-added, and average age of firms in an industry. Year and four-digit industry fixed effects are also controlled across columns. The parentheses report robust standard errors clustered by four-digit industry. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 5. On Correlated Distortions

	BR(2017)	BR(2017)	HK(2009,2014)	HK(2009,2014)
Sigma =	3	5	3	5
	(1)	(2)	(3)	(4)
Supported*Post2000	0.0144***	0.0208***	0.0243***	0.0269**
	(0.0041)	(0.0056)	(0.0061)	(0.0105)
Maximum Allowable Input Tariff	0.0020	0.0033*	0.0037**	0.0021
	(0.0013)	(0.0017)	(0.0018)	(0.0031)
Maximum Allowable Output Tariff	0.0000	0.0000	-0.0000	0.0005
	(0.0003)	(0.0004)	(0.0004)	(0.0008)
Ownership	-0.0693***	-0.1297***	-0.1269***	-0.1418***
	(0.0243)	(0.0338)	(0.0340)	(0.0521)
Export/VA	-0.0001***	-0.0001***	-0.0000*	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age	-0.0002*	-0.0003**	-0.0003**	0.0004*
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Number of Industries	2464	2464	2464	2464
R^2	0.876	0.885	0.324	0.255

Notes: We follow Bento and Restuccia (2017) and Hsieh and Klenow (2009, 2014) to measure correlated distortions for each four-digit industry over the years and use the mean of the correlated distortions as the dependent variables across columns. Year and four-digit industry fixed effects are controlled across columns. The parentheses report robust standard errors clustered by four-digit industry. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 6. Mean of TFPR, TFPQ, MRPK and MRPL

	M[log(TFPR)]	M[log(TFPQ)]	M[log(MRPK)]	M[log(MRPL)]
	(1)	(2)	(3)	(4)
Supported*Post2000	0.0434**	0.0216	0.0743**	0.0040
	(0.0189)	(0.0215)	(0.0299)	(0.0218)
Maximum Allowable Input Tariff	-0.00001	0.0011	0.0055	0.0259***
	(0.0060)	(0.0098)	(0.0096)	(0.0086)
Maximum Allowable Output Tariff	-0.0011	-0.0025	-0.0001	0.0039*
	(0.0015)	(0.0023)	(0.0023)	(0.0021)
Ownership	-0.328***	-0.876***	-0.489***	-0.950***
	(0.0987)	(0.113)	(0.149)	(0.127)
Export/VA	4.47e-07	6.67e-07	8.72e-07	1.06e-10
	(3.91e-07)	(5.47e-07)	(7.46e-07)	(5.64e-07)
Age	-0.0007	-0.0006	-0.0008	-0.0006
	(0.0005)	(0.0006)	(0.0007)	(0.0011)
Number of Industries	2464	2464	2464	2464
R^2	0.873	0.899	0.817	0.872

Notes: M[log(TFPR)], M[log(TFPQ)], M[log(MRPK)] and M[log(MRPL)] are the mean values of logged TFPR, TFPQ, MRPK and MRPL, respectively. Year and four-digit industry fixed effects are controlled across columns. The parentheses report robust standard errors clustered by four-digit industry. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 7. Effects of the 10th Five Year Plan on TFPR Dispersions

	Observed distribution	Counterfactual distribution	Support effects
	(1)	(2)	(3)
		TFPR - Unconditional	
Mean	1.7334	1.4079	0.3256
	(0.0504)	(0.0534)	(0.0723)
Variance	0.5008	0.1773	0.3235
	(0.0736)	(0.0325)	(0.0790)
		TFPR - Residualized	
Mean	1.6505	1.3309	0.3196
	(0.0817)	(0.0914)	(0.0755)
Variance	0.4926	0.1803	0.3123
	(0.0699)	(0.0327)	(0.0751)
		TFPQ - Unconditional	
Mean	6.0201	5.6082	0.4119
	(0.0553)	(0.0626)	(0.0828)
Variance	0.9994	0.4419	0.5575
	(0.1024)	(0.0599)	(0.1168)
		TFPQ - Residualized	
Mean	5.9898	5.5979	0.3918
	(0.1064)	(0.1169)	(0.0896)
Variance	0.9946	0.4589	0.5356
	(0.1011)	(0.0572)	(0.1138)

Notes: Column (1) shows the observed distribution of firms in supported industries, and column (2) shows the distribution for the same firms in the absence of support. Column (3) shows the effects of the Five-Year Plan on firms from the supported industries. Standard errors in parentheses are from 1,000 bootstrap iterations.

Table 8. Taxes, Subsidies, and Interest Payments

	Tax Dummy	Tax /Value-added	Subsidy Dummy	Subsidy /Value-added	Interest Payment	Interest /Debt
	Probit	Tobit	Probit	Tobit	Ordered Probit	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Supported*Post2000	0.0624***	0.0100***	0.0231***	0.0364***	-0.0228***	0.0351
	(0.0063)	(0.0028)	(0.0075)	(0.0132)	(0.0065)	(0.0228)
Maximum Allowable Input Tariff	-0.0177***	-0.0065***	-0.0241***	-0.0388***	-0.0167***	0.0178*
	(0.0028)	(0.0013)	(0.0033)	(0.0058)	(0.0028)	(0.0102)
Maximum Allowable Output Tariff	-0.0004	0.0004	0.0047***	0.0083***	-0.0049***	-0.0072***
	(0.0006)	(0.0003)	(0.0008)	(0.0014)	(0.0007)	(0.0023)
Export/VA	-0.0001***	-0.112***	8.03e-05	0.0050***	-4.20e-05	-2.57e-05
	(3.34e-05)	(0.0016)	(6.32e-05)	(0.0003)	(5.60e-05)	(0.0002)
Age	0.0002***	4.05e-05***	0.0002***	0.0003***	0.0004***	-7.83e-05
	(2.76e-05)	(1.24e-05)	(3.36e-05)	(5.86e-05)	(2.80e-05)	(9.95e-05)
Ownership	0.0472***	-0.0139***	0.2330***	0.3630***	-0.2880***	-0.0667***
	(0.0045)	(0.0020)	(0.0049)	(0.0086)	(0.0042)	(0.0158)
Number of Firms	1,066,365	1,066,365	1,066,365	1,066,365	1,066,365	1,056,348

Notes: This table reports regression estimates in which the dependent variable is a method of support. Tax Dummy equals 1 if a firm pays taxes. Subsidy Dummy equals 1 if a firm receives subsidy. Interest payment takes value 1, 2, or 3, corresponding to whether a firm pays negative, zero, or a positive interest rate. Each regression includes year and four-digit industry fixed effects. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 9. Effect on Tax Payments by TFPR Tier

	Top		Bottom	
	Tax Dummy	Tax /Value-added	Tax Dummy	Tax /Value-added
	(1)	(2)	(3)	(4)
SupportedPost2000	0.0415***	0.0101*	0.0625***	0.0131***
	(0.0094)	(0.0060)	(0.0122)	(0.0027)
Maximum Allowable Input Tariff	-0.0098**	-0.0081***	-0.0096*	-0.0021
	(0.0041)	(0.0026)	(0.0057)	(0.0013)
Maximum Allowable Output Tariff	-0.0016*	0.0003	0.0002	0.0004
	(0.0009)	(0.0006)	(0.0013)	(0.0003)
Export/VA	0.0004***	-0.107***	-0.686***	-0.0043***
	(7.66e-05)	(0.0034)	(0.0063)	(0.0002)
Age	0.0001**	1.03e-05	0.0004***	3.54e-05***
	(4.27e-05)	(2.76e-05)	(4.99e-05)	(1.11e-05)
Ownership	-0.228***	-0.135***	0.299***	0.0418***
	(0.0064)	(0.0042)	(0.0087)	(0.0018)
Number of Firms	503,638	503,638	266,879	266,879

Notes: Tax Dummy equals 1 if a firm pays taxes. Each regression includes year and four-digit industry fixed effects. As firms' TFPR increases, the number of firms in the top tier is more than that in the bottom. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 10. Effect on Subsidies by TFPR Tier

	Top		Bottom	
	Subsidy Dummy	Subsidy /Value-added	Subsidy Dummy	Subsidy /Value-added
	(1)	(2)	(3)	(4)
Supported*Post2000	0.0026	-0.0042	0.0637***	0.0789***
	(0.0122)	(0.0324)	(0.0138)	(0.0185)
Maximum Allowable Input Tariff	-0.0313***	-0.0695***	-0.0129**	-0.0323***
	(0.0052)	(0.0135)	(0.0065)	(0.0087)
Maximum Allowable Output Tariff	0.0073***	0.0172***	0.0010	0.0058***
	(0.0012)	(0.0031)	(0.0015)	(0.0020)
Export/VA	-7.24e-05*	0.0049***	0.0025***	0.0033***
	(4.20e-05)	(0.0005)	(0.0004)	(0.0005)
Age	0.0001**	0.0003*	0.0003***	0.0003***
	(5.29e-05)	(0.0001)	(6.20e-05)	(8.23e-05)
Ownership	0.233***	0.384***	0.232***	0.335***
	(0.0079)	(0.0211)	(0.0087)	(0.0115)
Number of Firms	503,638	503,638	266,879	266,879

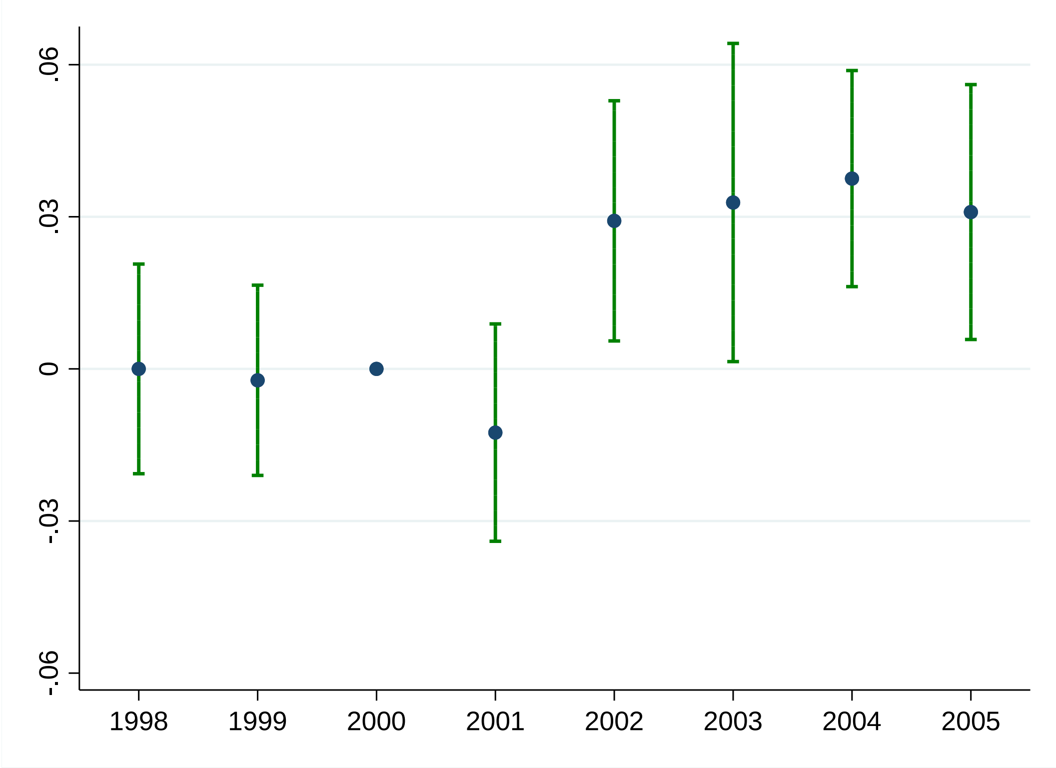
Notes: Subsidy Dummy equals 1 if a firm receives subsidy. Each regression includes year and four-digit industry fixed effects. As firms' TFPR increases, the number of firms in the top tier is more than that in the bottom. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 11. Effects on Interest Payments by TFPR Tier

	Top		Bottom	
	Interest Payment	Interest /Debt	Interest Payment	Interest /Debt
	(1)	(2)	(3)	(4)
Supported*Post2000	-0.0142	0.0315	-0.0216*	0.0662
	(0.0094)	(0.0345)	(0.0130)	(0.0580)
Maximum Allowable Input Tariff	-0.0061	0.0324**	-0.0272***	0.0089
	(0.0039)	(0.0148)	(0.0059)	(0.0275)
Maximum Allowable Output Tariff	-0.0072***	-0.0145***	-0.0038***	0.0007
	(0.0009)	(0.0033)	(0.0014)	(0.0064)
Export/VA	-4.81e-05	-3.36e-06	-0.0015***	-0.0005
	(5.62e-05)	(0.0002)	(0.0004)	(0.0020)
Age	0.0004***	-5.53e-05	0.0005***	-0.0002
	(4.15e-05)	(0.0002)	(5.39e-05)	(0.0002)
Ownership	-0.371***	-0.102***	-0.183***	-0.0397
	(0.0060)	(0.0237)	(0.0082)	(0.0385)
Number of Firms	503,638	496,134	266,879	265,743

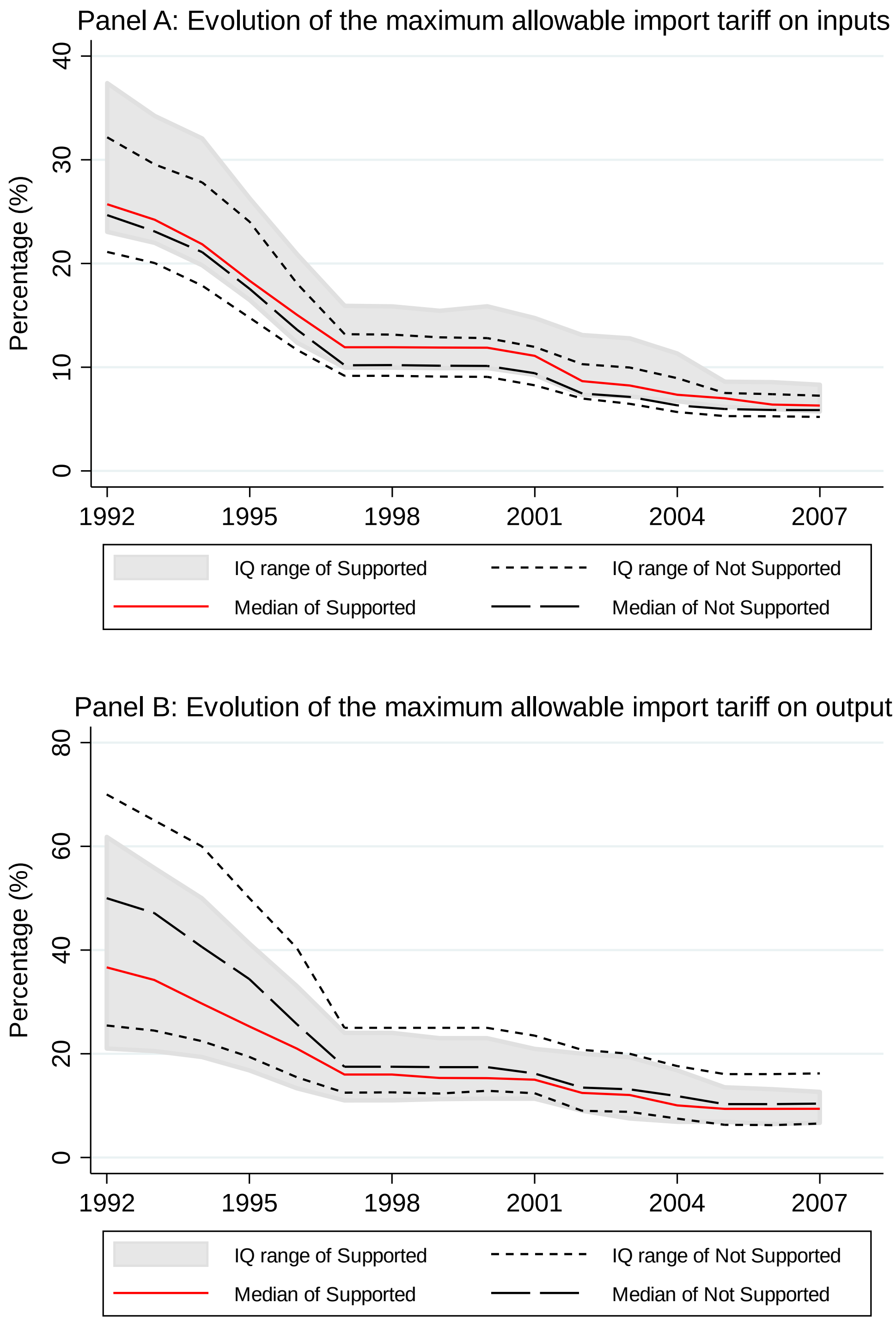
Notes: Interest payment takes value 1, 2, or 3, corresponding to whether a firm pays negative, zero, or a positive interest rate. As firms' TFPR increases, the number of firms in the top tier is more than that in the bottom. Each regression includes year and four-digit industry fixed effects. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Figure 1. Event study



Notes: The lines refer to 90% confidence intervals. The year 2000 is set to zero.

Figure 2. Maximum Allowable Import Tariff over Time

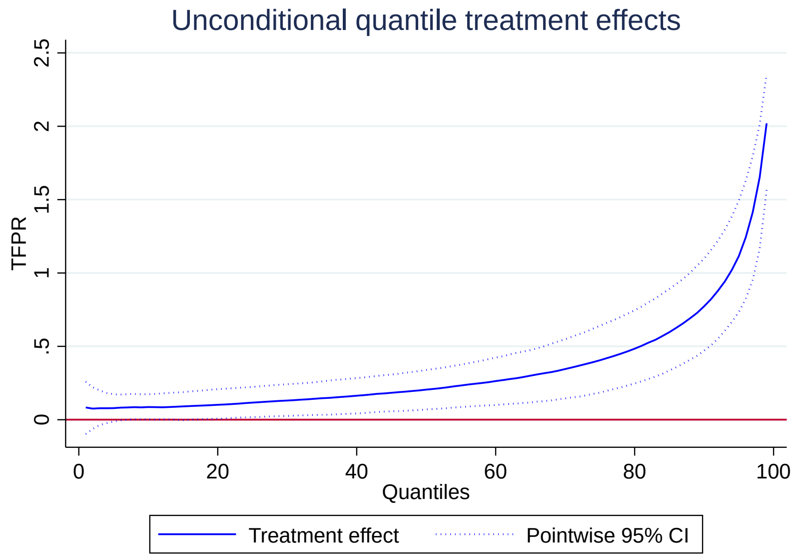


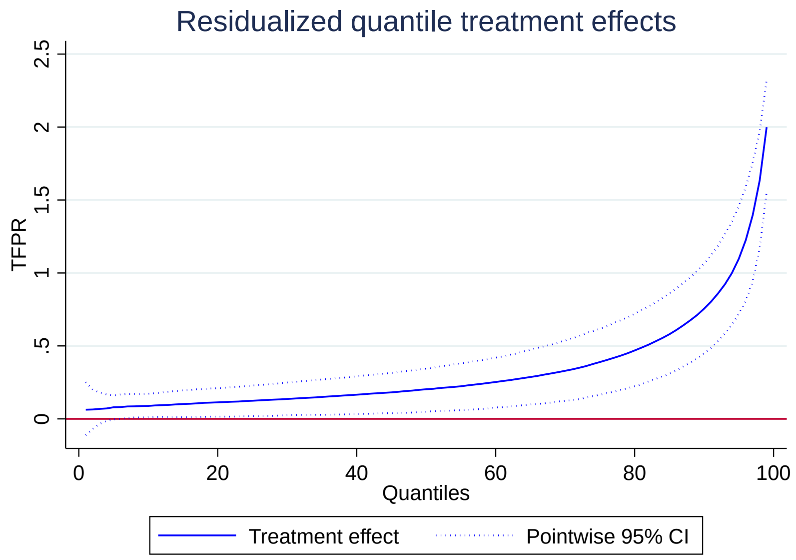
Notes: This figure depicts the evolution of the average maximum tariffs, as a percent, for the supported and not supported industries over time. IQ range is the interquartile range (75th-25th).

Figure 3. Changes in Variance of TFPR before and after 2001

Notes: Horizontal axis shows the variance of TFPR of each four-digit industry in 2000, and the vertical shows the changes in average values before and after 2001.

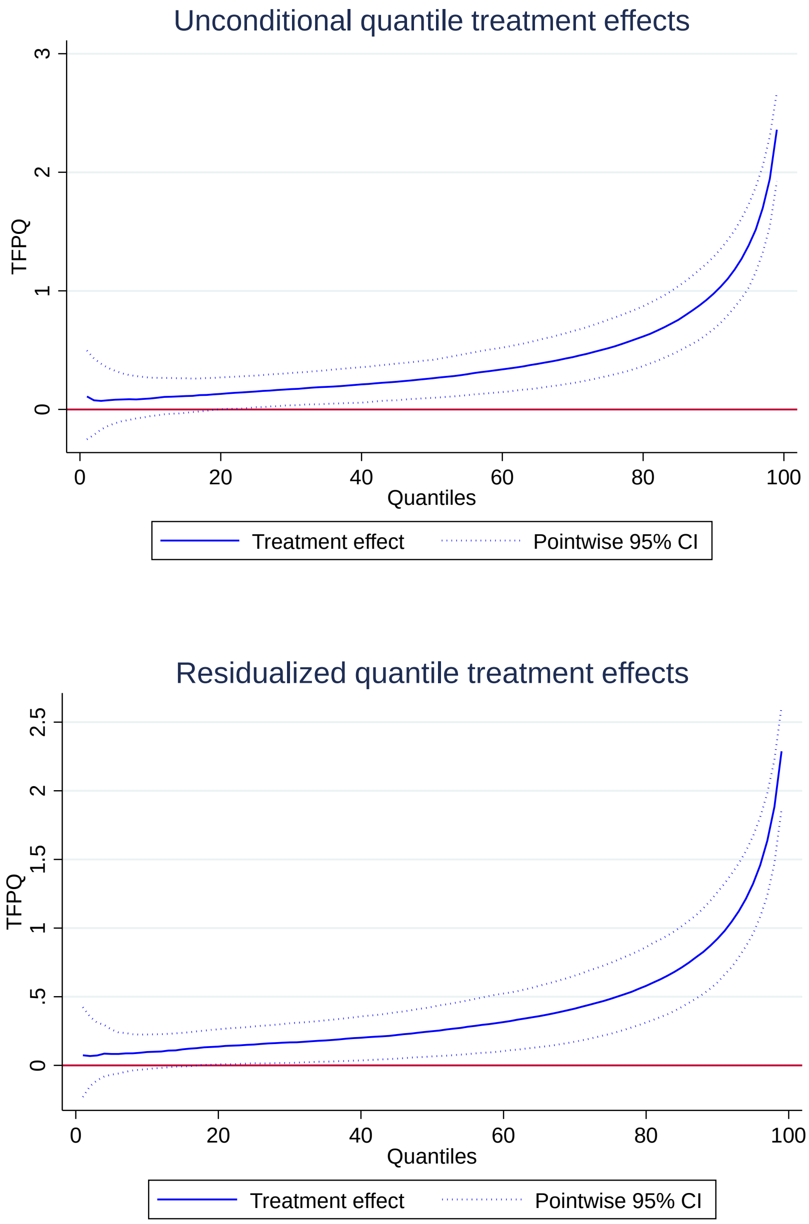
Figure 4. Quantile Treatment Effects of the 10th Five-Year Plan on Firm's TFPR





Notes: The data used is the firm level unbalanced panel data. The control variables include firm's age, export to value-added, ownership, and input and output tariffs. Solid lines denote the effects of the 10th Five-Year Plan on changes at percentiles of firms' TFPR, and dash lines are 5% confidence intervals.

Figure 5. Quantile Treatment Effects of the 10th Five-Year Plan on Firm's TFPQ



Notes: The data used is the firm level unbalanced panel data. The control variables include firm's age, export to value-added, ownership, and input and output tariffs. Solid lines denote the effects of the 10th Five-Year Plan on changes at percentiles of firms' TFPQ, and dash lines are 5% confidence intervals.