Policy and Misallocation*

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Abstract

This paper investigates the effect of industrial policies on resource misallocation with a rich set of data on Chinese firms. Using a difference-in-difference approach, we provide evidence that government policies favoring particular industries lead to increased resource misallocation (i.e., an increase in the dispersion of revenue productivity across firms in four-digit industries). Moreover, the differential changes between supported and not supported industries are quantitatively large (over seven percent) and indicative of a substantial negative impact on aggregate TFP. Using a changes-in-changes model, we find evidence that the Five-Year Plan had a heterogeneous impact across the productivity distribution of firms in supported industries. Further analysis suggests that the increased misallocation is related to the way in which the Chinese government doled out support through subsidies and improved credit conditions 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 lead to resource misallocation. In particular, we estimate the effect of China's Five-Year Plans using micro-level data on Chinese firms. The misallocation of resources within industries supported by the 10th 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 10th Five-Year Plan, and it also includes industries that were neither targeted by this plan, nor by the 9th Five-Year Plan. Hence, the data is well-suited to our needs, as it allows us to identify the effects of the 10th Five-Year Plan by comparing differences in resource misallocation between supported and not supported industries.

Our work is closely related to that of Hsieh and Klenow (2009) who use the same data

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

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 9th and the 10th Five-Year Plans enable us to distinguish which four-digit industries each plan supported. Our empirical approach, then, is to use a 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 10th Five-Year Plan and those industries receiving no support in either the 9th or 10th Five-Year Plan. This industry-level DID approach fits well with the data. We can directly account for 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 interpret the resulting regression 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 over 10 percent; thus, lowering aggregate TFP by approximately 7 percent within the supported industries. 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, as to the underlying components of TFPR, we show that the policies led to higher dispersion in the marginal revenue product of capital, but the impact on the marginal revenue product of labor was small.

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, by inducing a larger capital wedge. However, 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. The results indicate that the Five-Year Plan had a positive and significant effect on most of the TFPR distribution, although the treatment effect was larger for the extreme right tail. As for the TFPQ distribution, the effect was negative and significant for the lower quintile (the marginally least productive firms), positive and significant for the highest quintile, and insignificant for the middle of the distribution. In

short, while the implemented industrial policies caused the marginally most productive firms to become more productive, firms in the extreme left tail of the distribution became even less productive.[2] These two sets of results are consistent with the idea that the Five-Year Plan tended to support low productivity firms, reducing their marginal productivity even further.

Our fifth and final set of results have 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 and improved credit conditions. 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, the marginally least productive firms received larger subsidies. Again, this evidence suggests that the 10th Five-Year Plan diverted resources away from high productivity firms in supported industries and towards low productive firms, causing the increase in 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 profitability. 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

[2] 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.

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). 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. 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, presents our main empirical results, and then documents the impact on the dispersion of the marginal products of capital and labor. 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.

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 (hereafter misallocation). Finally, we detail the firm-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 Communist 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 10th 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 10th Five-Year Plan for National Economic and Social Development (2001), were as follows. First, achieve an average economic growth rate of about 7%. 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 10th 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 10th 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 10th Five-Year Plan cover a large number of

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, a large number of industries such as chemicals, rubber and plastics, and motor vehicles received no support.[3]

We conclude this section by noting that we are not able to infer all the reasons why some industries are featured in the 10th Five-Year Plan from the available documentation. The economic motivation mentioned in the official document is to increase international competitiveness of the supported industries. However, 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". Nevertheless, our hypothesis is that the resources used to support firms within an industry (however 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. In particular, as we will show, there appears to be a tendency for low productivity 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

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

misallocation of resources.[4]

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

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

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:

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

We take Equation (1) as the definition of firm specific TFPR, and we use the dispersion or variance of logged TFPR across firms in an industry as a measure of misallocation. Again, theoretically, there should be no dispersion in TFPR in the absence of distortions.[5]

Furthermore, Hsieh and Klenow (2009) show that industry specific total factor productivity

[4] 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.

[5] 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.

(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.[6] 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 manifest itself, an increase in misallocation will result in larger dispersion in TFPR.[7]

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. 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 number of observations (firms) 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.

[6] 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.

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

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.[8] We then map 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.[9] After obtaining TFPR for each firm, we calculate the mean and the variance of TFPR for each four-digit industry (separately for each year). Recall that the latter corresponds to our measure of resource misallocation.

To further explore how total factor productivity is affected by the 10th Five-Year Plan we compute annual TFPQ for each firm i in the following manner. Given that data on firm-level output, Y_{si}, is 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}. 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 10th Five-Year Plan, our sample spans some of the years covered by the 9th Five-Year Plan. Of the 425 four-digit industries included in the Chinese Industrial Classification code, 111 were supported by the 9th Five-Year Plan. We exclude these industries in order to avoid confounding the effect of the 10th Five-Year Plan with that of its predecessor.[10] 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 942,934 establishment / year observations. We group these into 302 industries (each observed for the full eight years). Of these industries, 93 were supported by the 10th 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

[8] The Appendix shows that the results are robust to other ways of calculating dispersion, including directly measuring labor costs by the wage bill (see Gopinath et al., 2017).

[9] Following Hsieh and Klenow (2009), we scale up the labor share by 3/2.

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

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.

3 The Effects of Industrial Policy on Resource Misallocation

This section provides descriptive evidence showing the effect of the 10th Five-Year Plan on the variance of TFPR, explicitly details our difference-in-difference regression approach, and then presents our main results.

3.1 Descriptive Evidence

The evolution of the variance of the logarithm of TFPR ($var\,(\log TFPR)$) provides preliminary evidence indicating that Chinese industrial policies lead to an increase in resource misallocation. Panel A in Figure 1 plots the average $var\,(\log TFPR)$ for supported (solid line) and not supported (dashed line) industries for each year in our sample (Panels B and C show the mean of TFPR and TFPQ, which we discuss below). In the figure, we normalize our measure of misallocation to be 1 in 1998 (the Appendix contains the un-normalized version). Both groups had similar downward trends in resource misallocation prior to the enactment of the 10th Five-Year Plan in 2001. After 2001, misallocation increased for both groups.[11] However, the increase was much larger for the supported industries. Relative to its nadir in 2001, misallocation in supported industries increased 20 percent by 2005, about a 16.4 percent increase relative to 1998. For industries not supported by the 10th Five-Year Plan, misallocation increased by only 5.2 percent relative to 1998. This pattern suggests that the 10th Five-Year Plan had a differential, and very large, impact on misallocation within supported industries. Since the average $var\,(\log TFPR)$ increased for both groups, it is also consistent with the notion that the 10th Five-Year Plan increased misallocation overall for this set of industries.

FIGURE 1 HERE

[11] This increase in misallocation occurs in our sub-sample of firms, but, as other research has noted, it is not as apparent in the overall economy.

One of the objectives of the 10th 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. If true, then this 'reverse causality' might bias the estimates and change the interpretation of our results. However, we see no evidence that industries were targeted for support based on the resource misallocation observed prior to the 10th 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 (also see Appendix Figure A2). The average resource misallocation exhibited within supported industries (0.465) was slightly lower than the resource misallocation in not supported industries (0.490).

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 10th 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:

$$var(\log TFPR)_{st} = \alpha + \delta Post2000_t + \eta Supported_s + \beta \left(Supported \times Post2000\right)_{st} + X_{st}\gamma + \varepsilon_{st} \tag{5}$$

where $var\left(\log TFPR\right)_{st}$ is the variance of log TFPR across firms 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 10th Five-Year Plan, X_{st} is a vector of covariates, 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.[12] 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.[13]

The coefficients δ and η account for fixed differences in misallocation before and after 2000 and between supported and not supported industries, respectively. Thus, the coefficient β captures how being supported by the 10th 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.

[12] 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.

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

3.3 Estimation Results

Table 2 reports estimation results based on Equation (5). Column (1) reports OLS coefficient estimates using the variance of log TFPR as the dependent variable. Column (2) reports on the same regression, except we have replaced the $Post2000$ and $Supported$ dummy variables with a full set of year and industry fixed effects.[14] In Columns (3) and (4), we replace the dependent variable with the interdecile and interquartile range.[15] Columns (5) and (6) examine the components of TFPR, which we discuss in the next sub-section. Each regression is based on the full panel of eight yearly observations on the 302 industries in our sample, or 2,416 observations in total. The parentheses contain the robust standard errors clustered by 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 10th 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 (1), the estimate of β equals 0.052. Recall that the variance of TFPR for the supported industries averaged 0.465 in 2000 (see Table 1). Thus, the Five-Year Plan lead to an increase in misallocation of about 11.2 percent for the supported industries (relative to the not supported group). This 11 percent increase accounts for a large portion of the overall increase in misallocation over time (about 16.4 percent in Figure 1) and for nearly all the difference between supported and not supported industries.

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. Clearly, the

[14] Throughout the rest of the paper, we report this 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.

[15] 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.

exact magnitude depends on the parameter σ; yet, even at moderate values of σ (e.g. 3), the effect is substantial. When the variance of TFPR increases by 0.052, aggregate TFP decreases by about 7.8%.

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 and is reflected in the positive estimate of δ on $Post2000$. The coefficient estimate η for *Supported* is negative, although not statistically significant (possibly due to the fact that misallocation actually becomes largest in supported industries after 2001). 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 firms in the tails of the TFPR distribution, a topic we return to shortly.

3.4 Industrial Policy and Dispersion in Marginal Products

We now turn our attention to the variables underlying the misallocation measure (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 firms 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., a firm-specific scale distortion), whereas $\tau_{K_{si}}$ captures a distortion in the MRPK relative to the MRPL (i.e., a firm-specific factor price wedge). Investigating whether the 10th Five-Year Plan raised the dispersion of the 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 dependent variable is the variance of $\log(MPRK)$ or $\log(MRPL)$. The results reported in columns 5 and 6 of Table 2 (again, looking at $Supported \times Post2000$) reveal a statistically significant increase in the dispersion of MRPK and MRPL, with the increase in the latter being about a third smaller.[16] Hence our findings suggest that the industrial policies implemented by the Chinese government lead to a larger increase in the firm-specific wedge, $\tau_{K_{si}}$, than in the output distortion, $\tau_{Y_{si}}$.

Recent literature has questioned whether the dispersion of MRPK (and TFPR) really 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.[17] 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 firms faced larger idiosyncratic shocks due to uncertainty regarding the policy, then it seems reasonable to interpret the increased dispersion in MRPK as indicative of misallocation.

Another example is that the increased dispersion in TFPR may have stemmed from higher markup dispersion among supported firms (see Haltiwanger, et al. 2018). We do not have access to disaggregated data on firm-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 dispersion. 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.

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

[17] 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.

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 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 10th 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 firms received support. The results of this additional analysis are consistent with the misallocation interpretation.

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 DID set-up, controlling for the variance of the control variables rather than the means, using weighted least squares, and employing alternate ways to calculate TFPR and TFPQ. Here, we highlight only a few 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. Then, we examine firm entry and exit. Finally. we present a battery of robustness checks on sample selection and model specification. Throughout, our main findings remain.

4.1 WTO Accession

China officially joined the World Trade Organization (WTO) in December of 2001, and the timing coincides with the 10th 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. 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. Indeed, Brandt et al. (2017) show that WTO accession and the consequent cut in tariffs led to increased productivity among Chinese manufacturing firms. 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.

Before investigating this channel, we note the timing of the trade liberalization (see Brandt et al. 2017 for more on this). The first large and widespread set of tariff cuts occurred between 1994 and 1997. Then, a second set of reductions took place in 2002. These subsequent cuts were considerably smaller and idiosyncratic, and while the second round of cuts had been mostly agreed upon by 1999, tariffs and tariff dispersion continued to decline thereafter. So, although the major trade liberalization preceded the 10th Five-Year Plan, tariffs did decline over the period of our study.[18]

To check whether trade liberalization impacts our results, we directly control for the maximum allowable tariff under the WTO agreement for each 4-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 policymakers lowered tariffs selectively by productivity level. Figure 2 plots the median maximum allowed tariff on inputs (Panel A) and ouputs (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 higher for the supported group, while the reverse was true for the median output tariff.

FIGURE 2 HERE

Table 3 demonstrates that our main finding is robust to controlling for maximum tariffs on inputs and outputs. TFPR dispersion among supported firms continues to exhibit a significant increase after the implementation of the 10th Five-Year Plan. The coefficient estimate for β (0.077) in column (1) remains close to the estimate (0.082) from column (2) in Table 2.

TABLE 3 HERE

Moreover, the effect still appears to be driven by firms in the tails of the distribution, as evidenced by the larger coefficient estimate on $Supported * Post2000$ for the interdecile range (column 2) relative to the interquintile range (column 3). Columns (4) and (5) show that

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

the increased TFPR dispersion remains associated with a larger dispersion in the MRPK and MRPL with the estimated increase in the latter being about a third smaller than in the former.

Two additional interesting results emerge when controlling for tariff levels. First, the coefficients on the tariffs indicate a positive correlation between misallocation in an industry and the degree of protection it received. This result is consistent with many theoretical and empirical studies that underscore the distortionary effect of tariffs on the allocation of resources among heterogeneous firms (see e.g., Restuccia and Rogerson 2017). Second, across specifications, the coefficient estimate on input tariffs is larger than for output tariffs, suggesting that reductions on the former could lead to larger efficiency gains (all else constant). Indeed, Brandt et al. (2017) find a significant impact from lower input tariffs on within-industry productivity growth during the post-WTO period (2001-2007).

To summarize, our regression estimates indicate that WTO accession had a positive effect on productivity via a reduction in misallocation (consistent with previous research). However, our main finding (that the 10th Five-Year Plan increased misallocation in supported industries) is robust to controlling for the tariff reductions associated with joining the WTO.

4.2 Firm Entry and Exit

In China, new firms tend to exhibit higher revenue productivity, while productivity tends to be lower for exiting firms (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, firms newly entering into our data set after the first year exhibit higher TFPR than incumbents (see Table A1 in the Appendix); the opposite holds for firms that exit the data set.[19]

Our data does not identify why firms enter or exit (i.e., whether they 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 firms. That is, while the previous sections used an unbalanced panel of firms (to constitute the balanced panel of industries), this section exploits the panel nature of the firm-level data to reduce the impact from the extensive margin. To construct the panel, we follow Brandt, et al. (2012)

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

and match firm observations across years based on their unique ID, as well as information on their address, name, phone number, and CEO's name.[20] After matching, we follow the same procedure as before to construct an industry panel. Note, some industries fall out of the sample. So, for comparison, we also construct a sample based on all firms (including those entering and exiting) with this same reduced set of industries.

TABLE 4 HERE

Comparing the estimates for continuing firms (column 1) and all firms (column 6) in Table 4 reveals that the increase in TFPR dispersion brought about by the 10th Five-Year Plan is roughly the same (0.071) in both data sets. In other words, dropping firms that enter or exit the survey has almost no impact on the estimate for β. The same holds for columns (2) through (10); our previous estimates (i.e., the quantile ranges and marginal revenue products of capital and labor) remain roughly the same. In summary, the heightened resource misallocation induced by the 10th Five-Year Plan was not solely driven by firms directly entering and exiting certain industries.[21]

4.3 Further Robustness Checks

Table 5 presents a battery of robustness checks. Column (1) reports estimation results from a regression that includes 2-digit industry-year fixed effects. The estimated effect of the 10th Five-Year plan remains positive and statistically significant. In fact, the magnitude of the estimated effect on misallocation is larger. Broad industry categories do not drive our results.

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 9th Five-Year Plan. Thus, the analysis to this point has excluded the 95 industries supported by the 9th Five-Year Plan. Column (2) shows that the estimate of β remains large and statistically significant when we include these 95 industries, although the estimate is smaller.[22] Possibly, the effect

[20] 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.

[21] 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 firms. 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.

[22] For this regression, we continue to group industries according to whether they received support in the 10th

on misallocation from continued support (in industries receiving support from both the 9th and 10th) is smaller because the misallocation already occurred, or, similarly, the impact on misallocation could remain for firms supported by the 9th but not the 10th. Either way, the estimated impact would be reduced.

TABLE 5 HERE

Column (3) includes industries that were previously dropped because they contain fewer than 10 firms.[23] Column (4) reports the estimates when we include the top and bottom firms in the TFPR distribution, which were dropped in the main sample. Column (5) drops industries that have the largest changes in the variance of TFPR before and after the 10th Five-Year Plan (such as industries 1510, 1690, and 3513, as shown in Appendix Figures A2 and A3). Finally, column (6) reports results where we calculate industry-specific labor and capital shares with Chinese data (rather than using US values as in Hsieh and Klenow (2009)). In all cases the results remain close to our baseline findings in Table 2. We conclude that the misallocation of resources increased in industries receiving support from the 10th Five-Year Plan.

5 Digging Deeper into the Distributional Effects of the 10th 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 10th Five-Year Plan increased average TFPR for the supported firms 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 firms in the top quintiles of the productivity distribution.

Five-Year Plan, regardless of whether the industry was supported in the 9th.

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

5.1 The Effect of the 10th Five-Year Plan on Average TFPR and TFPQ

The results presented thus far revealed that the 10th 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 10th Five-Year Plan tended to increase TFPR for firms in supported industries. These firms became modestly more profitable relative to firms in not supported industries.

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 firms experienced an increase in their average physical productivity or technology level. Recall from Equations (1) and (2), TFPR equals TFPQ times price.[24] Thus, at a first pass, the support obtained through the 10th Five-Year Plan appears to have primarily increased the price that firms in supported industries charged, rather than their average productivity.

In brief, while we find evidence that the policies implemented by the Chinese government increased the variance and mean of TFPR, our results suggest the impact on the average TFPQ was negligible. It should be noted, however, that the standard linear DID estimates recover only the average effect of the policy on the supported industries (i.e., the average treatment effect on the treated). The 10th Five-Year Plan may have had heterogenous effects on firms with different levels of productivity - a possibility we explore next.

[24] 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.

5.2 The Heterogeneous Effects of the 10th 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.[25] 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? Afterall, 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 *firms* 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 and TFPQ. 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 firms with differing TFPR. Thus, in the following section, we also use the firm-level data to document what support methods were deployed following the 10th Five-Year Plan.

To estimate the quantile treatment effects, we apply the changes-in-changes (CIC) method proposed by Athey and Imbens (2006). First, the entire TFPR distribution - before and after the implementation of the 10th Five-Year Plan - is used to recover the change over time among the not supported firms. 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 firms under the period of the 10th Five-Year Plan. The quantile treatment effect of the policy on the supported firms at each quantile is estimated as the horizontal distance between the observed TFPR distribution for the supported firms and the counterfactual TFPR distribution.

We first estimate a CIC regression without including the covariates (Figure 4, Panel A).

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

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).[26]

FIGURE 4 HERE

Figure 4 plots the quantile treatment effects for supported firms, 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, albeit small (≤ 0.1 standard deviation). The extreme right tail has the largest point estimates, which 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 firms.[27] The point estimates in Panel A of Figure 5 are negative and significant, yet small (≤ 0.1 standard deviation), for the bottom quartile. The estimates are positive and significant for the top quartile and insignificant for the rest of the distribution. The largest increase is observed in the extreme right tail where the point estimates exceed a 0.1 standard deviation. Moreover, when we adjust for the covariates (Panel B of Figure 5) we find a small but negative effect of the policy for most of the TFPQ distribution and a significant increase for the highest quintile. 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 10th Five-Year Plan on the bottom and top tails of the TFPQ distribution. The insignificant average effect of the support on TFPQ found with the difference-in-difference model masks a negative effect on the physical productivity of the least productive firms and a positive effect for highly productive firms.

[26] The Appendix reports the CDF of the counterfactual TFPR distribution.
[27] The Appendix reports the CDF of the counterfactual TFPQ distribution.

Figures 4 and 5 point towards three important distributional effects due to the Chinese government's policies. First, the 10th Five-Year Plan appears to have increased revenue productivity for the supported firms over most of the TFPR distribution and, especially, for those in the top quintile. Second, for most of the supported firms ($20^{th} - 80^{th}$ quantile) physical productivity slightly declined or remained unchanged. Third, TFPQ dispersion increased over parts of the distribution, reflecting a particularly positive effect of the policy on the highest quintile of the TFPQ distribution.[28]

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 firm-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 firms. 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) 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 firms and the counterfactual TFPR (TFPQ) in the absence of the support. On the one hand, the mean and variance of TFPR are somewhat higher for the observed than the counterfactual distribution. The support provided by the 10th Five-Year Plan increased the mean of TFPR by about 2.2% and the variance by approximately 2.6% for the supported firms. 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 essentially identical under the observed and under the

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

counterfactual distribution. The variance of TFPQ is approximately 9.7% higher. The support doled out by the 10th Five-Year Plan thus appears to have left the mean of TFPQ unchanged while increasing the dispersion of TFPQ for the supported firms. This increase in dispersion is reflective of the negative effect of the support on the lower quintile and the positive effect on the upper quintile. The CIC estimates suggest industrial policies implemented by the Chinese government resulted in greater dispersion on the physical productivity among supported firms. These findings are consistent with the idea that the policies disproportionately moved resources to (some, large) low-productivity firms and away from some high-productivity firms.

6 Mechanism: Taxes, Subsidies, and Access to Credit

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

6.1 Average Effects on Preferential Supports

Our inquiry into the possible mechanisms employed to support firms 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 a firm pays taxes:

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

where $Y_{ist} = 1$ if firm 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 a firm 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 firms. 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 firms during the 10th 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.[29] The 10th Five-Year Plan increased the probability of receiving subsidies as well as the expected 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 firm received interest payments, one if the firm did not receive or pay interest, and two if the firm paid interest. Column (6) reports the OLS results for the ratio of interest to debt. The estimates in column (5) suggest that the 10th Five-Year Plan reduced the probability of paying interest for supported firms, possibly reflecting an improvement in credit conditions. However, the impact on the average interest to debt ratio is not significant.

To summarize, the 10th 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 firms.

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

6.2 Are All Firms Treated Equally under the 10th Five-Year Plan?

The heterogeneity documented in Section 4.2 suggests that the support mechanisms did not impact all firms equally. Recall, the CIC model indicated that the plan increased TFPR for most firms; 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 33rd and 67th quantiles of the pre-plan TFPR distribution. We then classify each firm-year observation into the bottom, middle, or top tier of the pre-plan TFPR distribution by the firm's industry. Then, we re-estimate the DID models of the previous section on the bottom and top tier subsamples.[30]

Tables 9 through 11 report the estimation results using each support mechanism (tax 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 firms. That is, the coefficient estimate on the interaction term is positive and statistically significant for both tiers in Table 9.

TABLES 9-11 HERE

Second, the estimates in Table 10 indicate that the least productive firms 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 10th Five-Year Plan on the most productive firms was insignificant. Third, the estimates in Table 11 show that the *most* productive firms actually became *less* likely to get credit (column 3). The plan had no significant impact for the least productive firms. 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.

[30] 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.

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

7 Conclusions

This paper presents evidence that 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 10th 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 firms. Our central finding is that the 10th 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 10th Five-Year Plan increased the profitability (mean TFPR) for the supported industries and increased dispersion over much of the TFPR distribution. The impact was particularly high for firms with the highest productivity. The 10th Five-Year Plan did not increase the mean of physical productivity (TFPQ) in supported industries; however, the impact over the TFPR distribution was heterogenous. TFPQ declined for the least productive firms in supported industries, but it increased for high-productivity firms. Furthermore, we found that the methods used to support firms were applied unevenly. For example, firms in the supported industries were more likely to receive subsidies (and gain access to more credit), but these supports were not doled out homogeneously across firms.

Overall, the empirical findings show that the resources going to supported industries were not deployed efficiently. Indeed, our results are consistent with a pattern of resources being moved from firms with high marginal productivity toward low productivity firms, over much of the productivity distribution. Moreover, low productivity firms 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: Characteristics of Supported and Not Supported Industries in 2000

Type of Industry	Supported	Not supported
V[log(TFPR)]	.4645 (.3089)	.4897 (.3468)
M[log(TFPR)]	1.5776 (.3181)	1.6310 (.2984)
M[log(TFPQ)]	5.7728 (.3875)	5.7523 (.4316)
Age	15.3911 (7.0214)	14.2042 (5.2286)
Export/VA	.8477 (.9118)	1.2404 (2.6716)
Ownership	.2236 (.1790)	.1964 (.1638)
Log(TFPR) interdecile range (90th-10th)	1.5792 (.5691)	1.6327 (.5964)
Log(TFPR) interquartile range (75th-25th)	.7708 (.2903)	.8007 (.2982)
V[log(MRPK)]	1.9014 (.6898)	1.8989 (.6243)
V[log(MRPL)]	1.1028 (.3360)	1.1625 (.4575)
N(Industries)	93	209

Notes: V[log(TFPR)] denotes the average variance of logged TFPR across four-digit industries. M[log(TFPR)] and M[log(TFPQ)] denote the mean values of log(TFPR) and log(TFPQ) respectively. V[log(MRPK)] and V[log(MRPL)] refer to the variance of logged MRPK and logged MRPL. 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. Standard errors are in parenthesis.

Table 2: Estimates of the 10th Five-Year Plan's Effect on TFPR Dispersion

	V[log(TFPR)]		90th-10th	75th-25th	V[log(MRPK)]	V[log(MRPL)]
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Supported*Post2000	0.0524**	0.0826**	0.168**	0.0780**	0.161**	0.103**
	(0.0219)	(0.0323)	(0.0714)	(0.0368)	(0.0764)	(0.0432)
Post2000	0.0592***					
	(0.0215)					
Supported	-0.0467					
	(0.0351)					
Age	-0.0259***	0.00845	0.0210	0.00940	0.0208	0.0115
	(0.00460)	(0.0113)	(0.0256)	(0.0135)	(0.0247)	(0.0151)
Export/VA	0.0004***	0.000528***	0.000852***	0.000287**	0.00170***	0.00180***
	(8.49e-05)	(0.000130)	(0.000255)	(0.000119)	(0.000268)	(0.000225)
Ownership	1.089***	0.119	0.492	0.220	0.594	0.770**
	(0.182)	(0.213)	(0.416)	(0.222)	(0.494)	(0.318)
R-squared	0.075	0.935	0.974	0.971	0.954	0.948
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	Yes	Yes	Yes	Yes

Notes: V[log(TFPR)] is the variance of logged TFRP within a four-digit industry. 90th-10th and 75th-25th refer to differences in TFPR between the 90th and the 10th percentile, and between the 75th and the 25th 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 is the average ratio of export to value-added in the industry. A constant is kept in column (1) and the estimate is 0.623. The are 2,416 observations from 302 industries for each column. The parentheses report robust standard errors clustered by four-digit industry. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 3: Effect of the 10th Five-Year Plan's on TFPR Dispersion - Tariffs

	V[log(TFPR)]	90th-10th	75th-25th	V[log(MRPK)]	V[log(MRPL)]
VARIABLES	(1)	(2)	(3)	(4)	(5)
Supported*Post2000	0.0765***	0.155***	0.0696***	0.139**	0.0929***
	(0.0217)	(0.0418)	(0.0213)	(0.0549)	(0.0291)
Maximum Allowable	0.0418**	0.104***	0.0532***	0.0803**	0.0622***
Input Tariff	(0.0171)	(0.0343)	(0.0163)	(0.0319)	(0.0139)
Maximum Allowable	0.00252	0.00518	0.00360	0.0104	0.00454
Output Tariff	(0.00323)	(0.00568)	(0.00313)	(0.00653)	(0.00310)
Age	0.000785	0.00241	-0.000512	0.00386	-0.000242
	(0.00430)	(0.00713)	(0.00360)	(0.0125)	(0.00709)
Export/VA	0.000441***	0.000642***	0.000173***	0.00150***	0.00167***
	(8.30e-05)	(0.000113)	(2.46e-05)	(0.000170)	(0.000179)
Ownership	0.0269	0.272	0.0994	0.369	0.626***
	(0.147)	(0.232)	(0.125)	(0.379)	(0.234)
R-squared	0.940	0.978	0.976	0.956	0.951

Notes: V[log(TFPR)] is the variance of logged TFRP within a four-digit industry. 90th-10th and 75th-25th refer to differences in TFPR between the 90th and the 10th percentile, and between the 75th and the 25th. Post2000 equals 1 if it is after 2000 and 0 otherwise. Supported equals 1 if an 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 is the average ratio of export to value-added in the industry. Following Brandt et al. (2017), we use the maximum allowable tariffs from the predetermined maximum tariff rates in the WTO agreement. Each regression is based on 2,416 observations and includes a full set of year and industry fixed effects. Parentheses report robust standard errors clustered industry. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 4: Continuing vs All Firms

	Continuing Firms					All Firms				
VARIABLES	V(TFPR)	90-10	75-25	V(MRPK)	V(MRPL)	V(TFPR)	90-10	75-25	V(MRPK)	V(MRPL)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SupportedPost2000	0.0708***	0.147***	0.0580**	0.134**	0.0677**	0.0710***	0.149***	0.0709***	0.126**	0.0653**
	(0.0230)	(0.0459)	(0.0263)	(0.0530)	(0.0320)	(0.0227)	(0.0431)	(0.0208)	(0.0487)	(0.0278)
Maximum Allowable Input Tariff	0.0526***	0.124***	0.0562***	0.113***	0.0650***	0.0398**	0.0958***	0.0533***	0.0858**	0.0648***
	(0.0160)	(0.0325)	(0.0178)	(0.0303)	(0.0130)	(0.0174)	(0.0339)	(0.0158)	(0.0334)	(0.0128)
Maximum Allowable Output Tariff	-0.00381	-0.00388	0.000104	-0.00372	-0.00113	0.00227	0.00598	0.00314	0.00999	0.00324
	(0.00269)	(0.00486)	(0.00311)	(0.00490)	(0.00303)	(0.00356)	(0.00631)	(0.00346)	(0.00704)	(0.00311)
Age	0.00524	0.00800	0.00304	0.00770	-0.00418	0.00623	0.0141	0.00408	0.00571	0.00523
	(0.00631)	(0.0100)	(0.00490)	(0.0118)	(0.00703)	(0.00506)	(0.00874)	(0.00431)	(0.00981)	(0.00703)
Export/VA	0.0210**	0.0197*	0.0103	0.0498**	0.0357***	0.0004***	0.0006***	0.0002***	0.0014***	0.0016***
	(0.00842)	(0.0102)	(0.00718)	(0.0225)	(0.0137)	(2.27e-05)	(4.35e-05)	(2.29e-05)	(6.01e-05)	(4.96e-05)
Ownership	0.111	0.376	0.249	0.317	0.654***	-0.0311	0.111	0.0206	0.143	0.535***
	(0.207)	(0.301)	(0.189)	(0.365)	(0.247)	(0.175)	(0.276)	(0.153)	(0.294)	(0.185)
R-squared	0.925	0.972	0.964	0.955	0.948	0.954	0.983	0.981	0.973	0.971

Notes: This table compares regressions from a panel of 240 industries composed from the same set of firms (continuing firms) throughout the 8 years to the same panel of 240 industries in which firms enter and exit over the years. Each regression is based on 1,920 industry / year observations and includes a full set of year and industry fixed effects. Parentheses report robust standard errors clustered industry. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 5: Further Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Year 2-digit Industry FE	9th FYP	Small Industries	With 99th and 1st Percentiles	Exclude Outliers	Chinese Factor Shares
Supported*Post2000	0.122**	0.0450*	0.0813**	0.0839***	0.0845***	0.151**
	(0.0542)	(0.0230)	(0.0322)	(0.0318)	(0.0312)	(0.0675)
Age	0.00377	0.00779	0.00851	0.0106	0.0107	0.0149
	(0.00780)	(0.00952)	(0.00883)	(0.0122)	(0.0115)	(0.0227)
Export/VA	0.0005***	0.0005***	0.0005***	0.0004**	0.0005***	0.0017***
	(8.98e-05)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0003)
Ownership	0.363	0.106	0.117	0.282	0.0830	0.446
	(0.270)	(0.194)	(0.196)	(0.270)	(0.140)	(0.429)
Observations	2,416	3,176	2,529	2,416	2,384	2,416
R-squared	0.945	0.935	0.927	0.940	0.940	0.949
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year*2-digit Industry FE	Yes	No	No	No	No	No

Notes: Column (1) controls for two-digit industry fixed effects. Column (2) includes the industries that were supported by the 9th Five Year Plan. Column (3) includes the industries that had less than 10 firms. Column (4) includes firms whose TFPR is larger than the 99th or smaller than the 1st percentiles. In column (5), industries whose change in variance of TFPR is the largest before and after the 10th Five Year Plan, such as industry 1510 and 1690, were dropped. Column (6) uses labor and capital shares for each industry based on our calculations from Chinese data (rather than relying on US data for the shares) to arrive at TFPR for each firm. Robust standard errors clustered by four-digit industry are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 6: Mean of TFPR and TFPQ

VARIABLES	M(TFPR)	M(TFPQ)
	(1)	(2)
SupportedPost2000	0.109*	0.199
	(0.0617)	(0.149)
Age	0.0226	0.0755
	(0.0221)	(0.0562)
Export/VA	0.0003*	0.0006
	(0.0002)	(0.0005)
Ownership	0.0142	-0.144
	(0.322)	(0.776)
R-squared	0.989	0.996

Notes: The dependent variable in these regressions is the mean industry TFPR in column (1) and mean TFPQ in column 2. Each regression is based on 2,416 observations and includes a full set of year and industry fixed effects. Parentheses report robust standard errors clustered industry. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 7: Effects of the 10th Five-Year Plan on TFPR and TFPQ Distributions

	Observed distribution	Counterfactual distribution	Support effect	Support effect in % terms
	(1)	(2)	(3)	(4)
		TFPR		
Mean	1.7390	1.7017	0.0373	2.192
	(0.0014)	(0.0035)	(0.0038)	
Variance	0.5098	0.4966	0.0131	2.638
	(0.0019)	(0.0044)	(0.0048)	
		TFPQ		
Mean	6. 0299	6.0227	0.0072	0.120
	(0.0020)	(0.0046)	(0.0050)	
Variance	1.0088	0.9195	0.0893	9.712
	(0.0032)	(0.0068)	(0.0074)	

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. Column (4) shows the effect of the Five-Year Plan as a percentage of the counterfactual level. 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
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Supported*Post2000	0.0599***	0.0155***	0.0372***	0.0829***	-0.0119**	0.0145
	(0.00660)	(0.00254)	(0.00774)	(0.0213)	(0.00595)	(0.0144)
Age	0.0104***	0.00104***	0.00731***	0.0166***	0.0108***	-0.000269
	(0.000158)	(5.30e-05)	(0.000151)	(0.000413)	(0.000134)	(0.000306)
Export	-0.590***	-0.0102***	1.98e-05	0.000115***	-0.00234***	-3.17e-06
	(0.00355)	(0.000216)	(1.59e-05)	(3.79e-05)	(0.000163)	(4.09e-05)
Ownership	0.00443	0.0197***	0.149***	0.410***	-0.213***	-0.0349***
	(0.00580)	(0.00205)	(0.00592)	(0.0162)	(0.00488)	(0.0118)
Observations	942,934	942,934	942,934	942,934	942,934	942,934

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

	Bottom Tier		Top Tier	
	Tax Dummy	Tax /Value-added	Tax Dummy	Tax /Value-added
	Probit	Tobit	Probit	Tobit
VARIABLES	(1)	(2)	(3)	(4)
Supported*Post2000	0.0700***	0.0322***	0.0396***	0.00424***
	(0.0117)	(0.00919)	(0.0113)	(0.000680)
Age	0.0147***	0.00355***	0.00494***	4.51e-06
	(0.000270)	(0.000181)	(0.000273)	(1.50e-05)
Export/VA	-0.696***	-0.0161***	-0.0823***	-0.00180***
	(0.00640)	(0.000537)	(0.00135)	(9.10e-05)
Ownership	0.0798***	0.0773***	-0.0613***	-0.00223***
	(0.00945)	(0.00671)	(0.0104)	(0.000601)
Observations	264,619	264,619	383,444	383,444

Notes: Tax Dummy equals 1 if a firm pays taxes. 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 10: Effect on Subsidies by TFPR Tier

	Bottom Tier		Top Tier	
	Subsidy Dummy	Subsidy /Value-added	Subsidy Dummy	Subsidy /Value-added
	Probit	Tobit	Probit	Tobit
VARIABLES	(1)	(2)	(3)	(4)
Supported*Post2000	0.0711***	0.252***	0.0224	0.00706*
	(0.0133)	(0.0624)	(0.0143)	(0.00393)
Age	0.00698***	0.0264***	0.00647***	0.00164***
	(0.000254)	(0.00118)	(0.000286)	(7.81e-05)
Export/VA	5.92e-06	0.000117	0.0448***	0.0102***
	(2.16e-05)	(7.18e-05)	(0.00142)	(0.000397)
Ownership	0.119***	0.574***	0.148***	0.0497***
	(0.00957)	(0.0445)	(0.0115)	(0.00312)
Observations	264,619	264,619	383,444	383,444

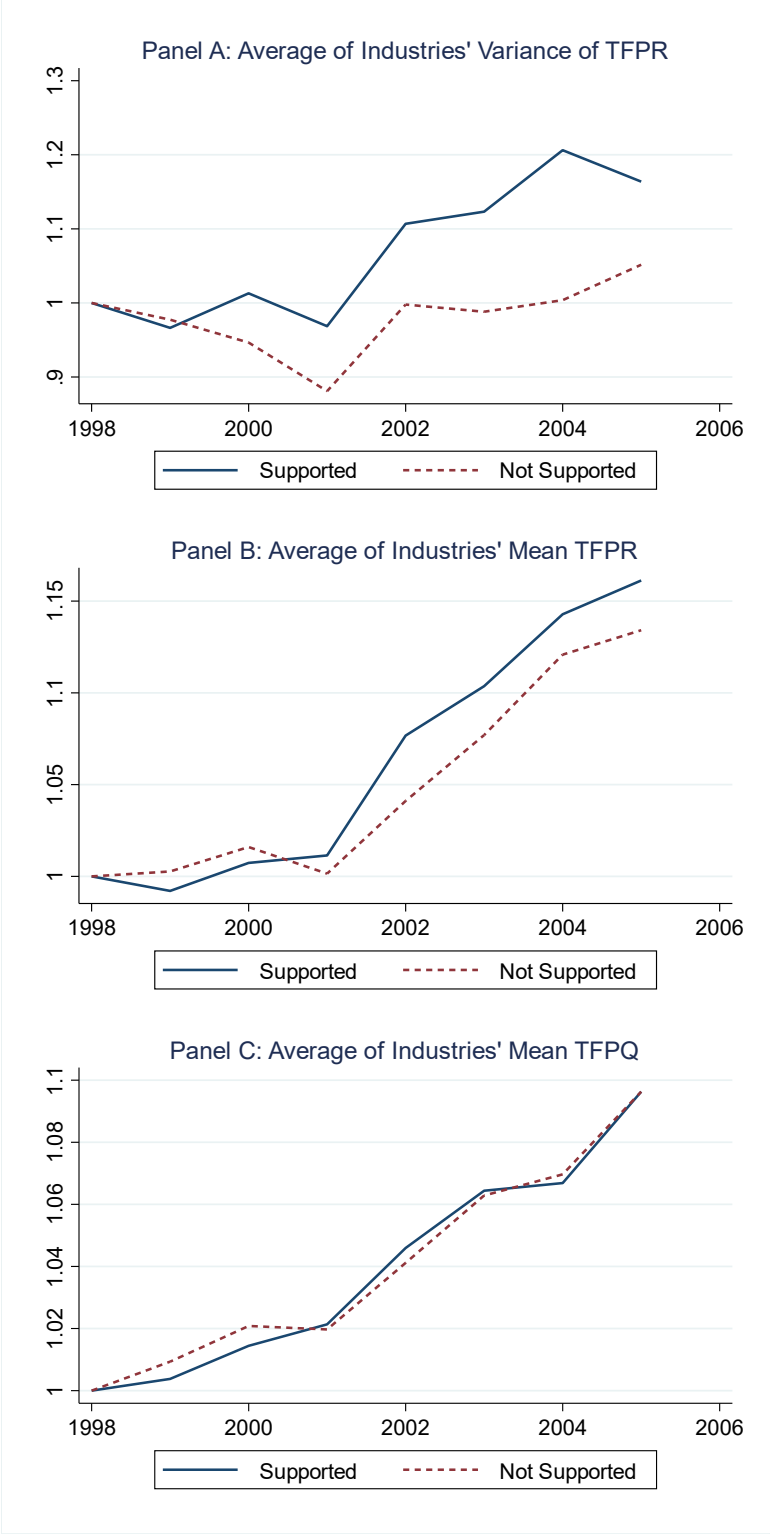
Notes: Subsidy Dummy equals 1 if a firm receives subsidy. Each regression includes year and four-digit industry fixed effects. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 11: Effects on Interest Payments by TFPR Tier

	Bottom Tier		Top Tier	
	Interest Payment	Interest /Debt	Interest Payment	Interest /Debt
	Ordered Probit	OLS	Ordered Probit	OLS
VARIABLES	(1)	(2)	(3)	(4)
Supported*Post2000	0.00656	-0.000106	-0.0305***	0.0182
	(0.0108)	(0.00409)	(0.00990)	(0.0351)
Age	0.0110***	-4.28e-05	0.0110***	-4.59e-05
	(0.000237)	(8.35e-05)	(0.000228)	(0.000783)
Export/VA	-0.00164***	-8.71e-07	-0.0154***	-0.00558
	(0.000170)	(6.43e-06)	(0.00113)	(0.00440)
Ownership	-0.166***	-0.0103***	-0.301***	-0.0611*
	(0.00825)	(0.00308)	(0.00859)	(0.0312)
Observations	264,619	264,619	383,354	383,444

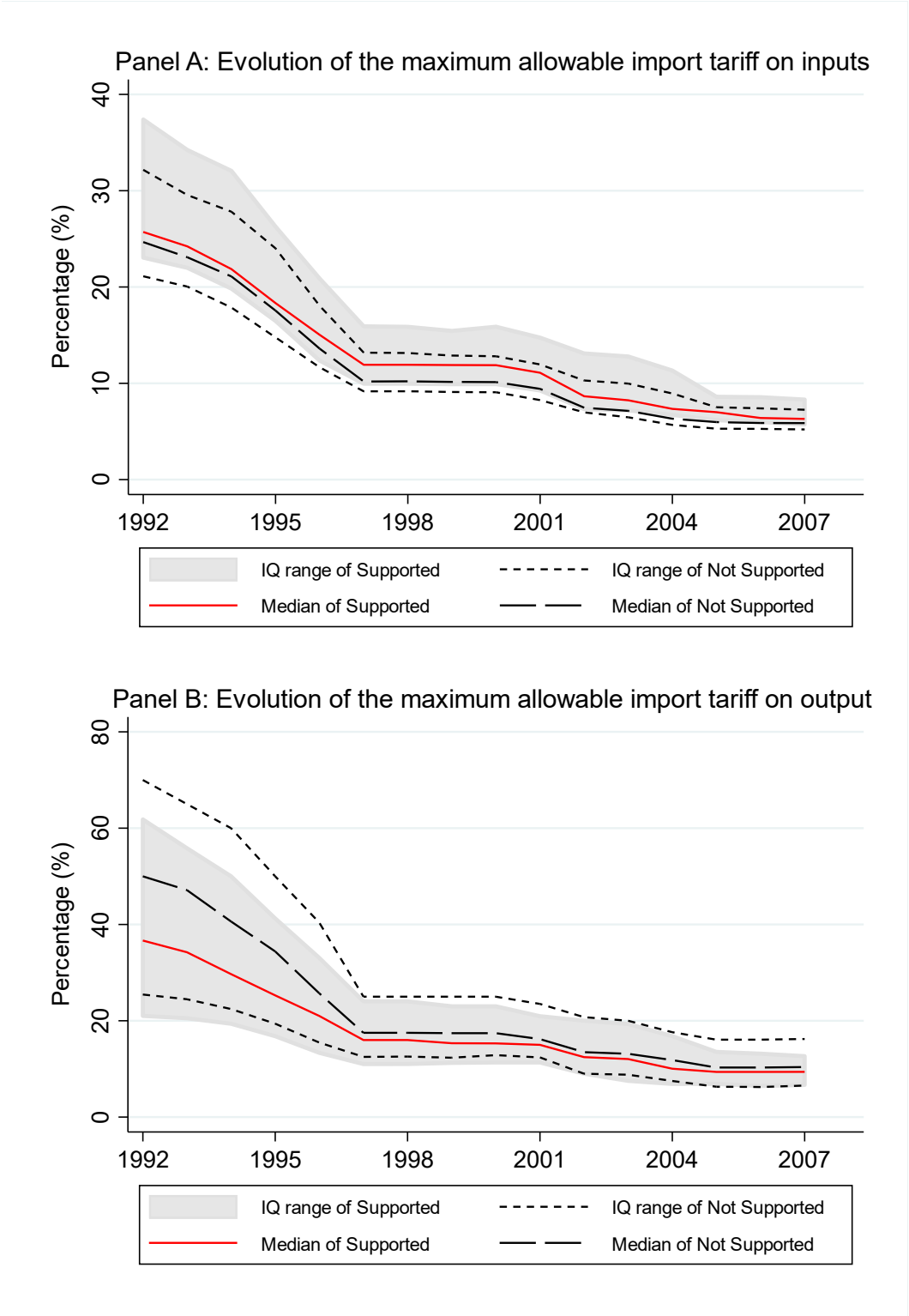
Notes: Interest payment takes value 1, 2, or 3, corresponding to whether a firm pays negative, zero, or a positive interest rate. Each regression includes year and four-digit industry fixed effects. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Figure 1 TFPR and TFPQ over Time



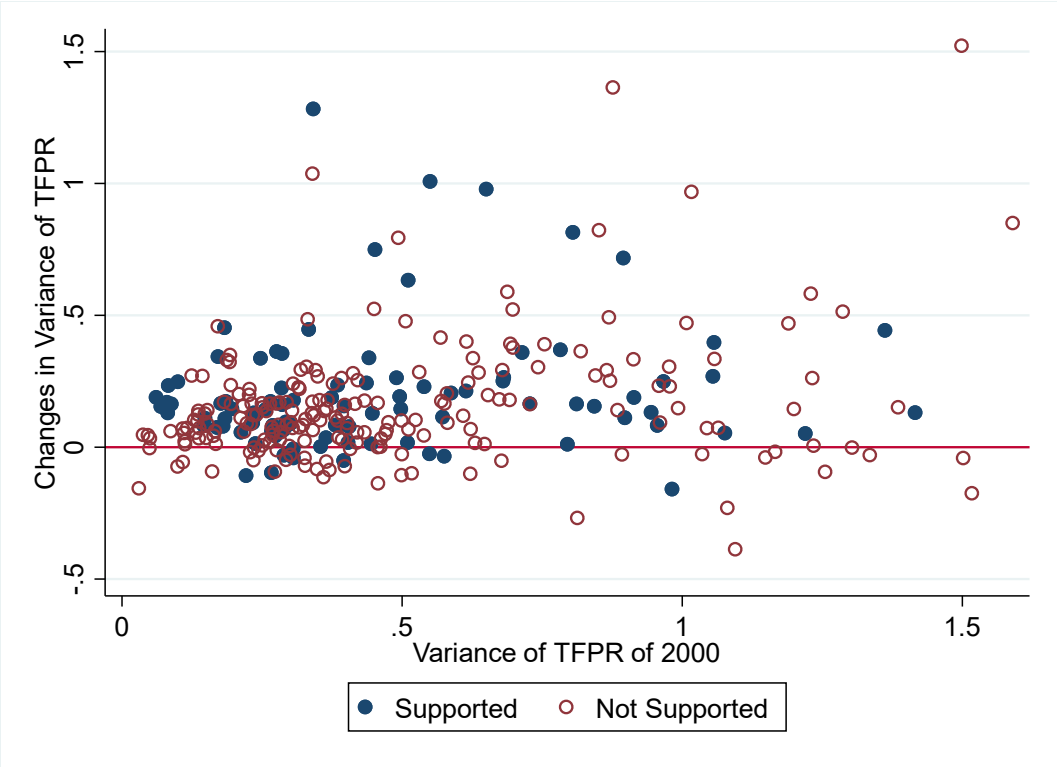
Notes: The 1998 values for each variable have been normalized to 1.

Figure 2 Maximum Allowable Import Tariffs over Time



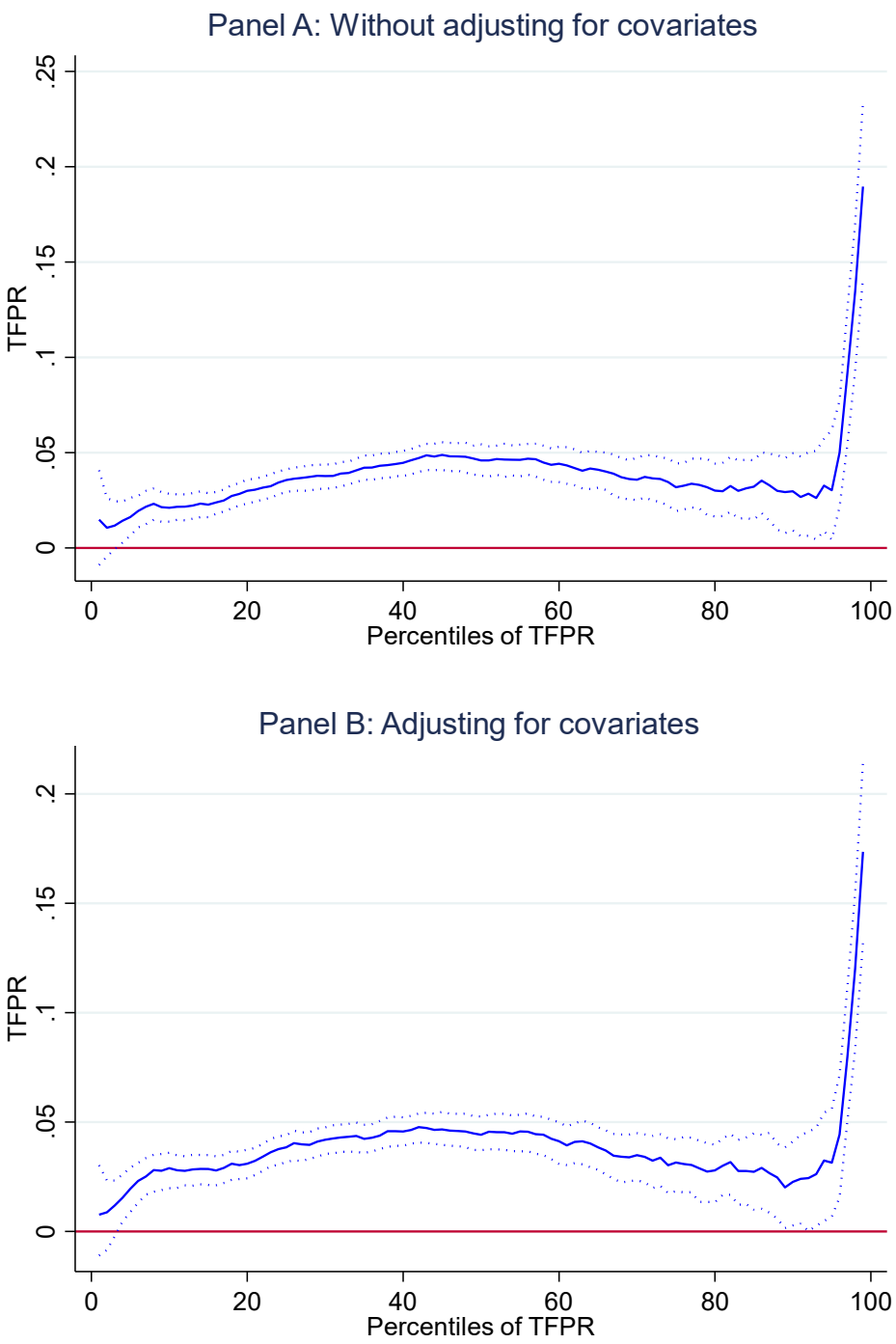
Notes: This figure depicts the evolution of the average maximum tariffs, as a percent, for supported and not supported industries over time. IQ range is the interquartile range (75th-25th).

Figure 3 Changes in Variance of TFPR before and after 2001



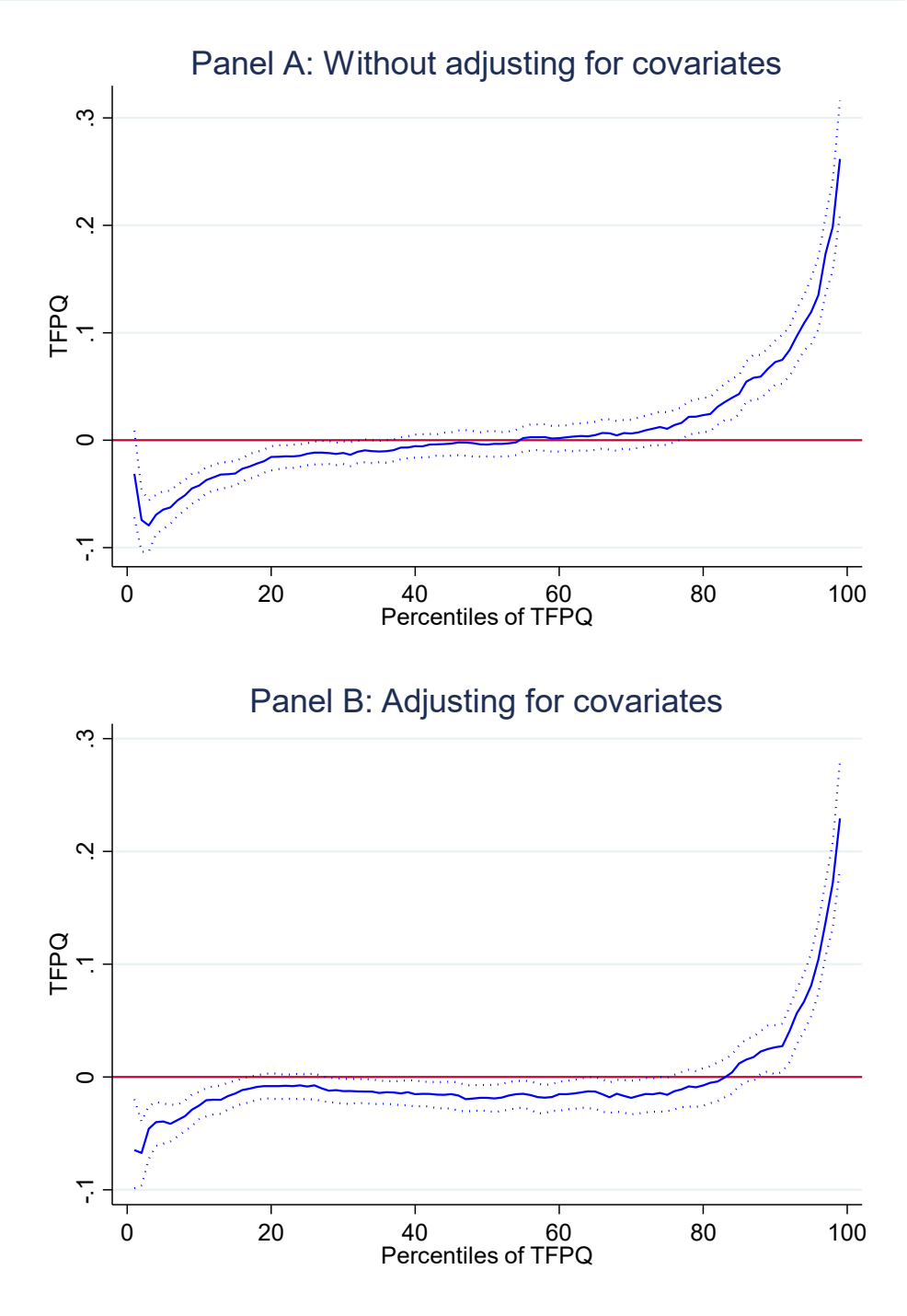
Notes: Horizontal axis shows the variance of TFPR of each four-digit industry in 2000, and the vertical shows the changes in average values before and after 2001.

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



Notes: The control variables include firm's age, export to value-added, and ownership. 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 control variables include firm's age, export to value-added, and ownership. 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.