# INDUSTRIALIZATION FROM SCRATCH: THE "THIRD FRONT" AND LOCAL ECONOMIC DEVELOPMENT IN CHINA'S HINTERLAND

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December 13, 2017

**Abstract**

Government subsidies to the manufacturing sector are popular in developing countries. This paper studies the long-run effects of a large-scale regional industrialization campaign in China, known as the "Third Front" (TF) construction. Motivated by national defense considerations, the government established large manufacturing plants in China's remote and under-developed hinterland. Using variation from the site-selection criteria for these plants, we find that the TF has positive effects on local economic development. Two decades after the end of the TF, places that received more investment have a larger and more productive private manufacturing sector. Evidence suggests that this result is likely driven by local agglomeration forces. Because the TF reallocated investment across geographic areas, we then investigate its impact on aggregate efficiency. We build a simple model of structural transformation and propose conditions under which the TF improves aggregate efficiency. We show empirically that these conditions are not met.

## 1 Introduction

Governments in developing countries frequently adopt policies directing investment to the manufacturing sector, in the hope that such investment could stimulate industrialization and accelerate economic growth. Such policies could target certain industries or regions of the country. From a neo-classical perspective, such policies make little sense—if specialization in agricultural production is the outcome of an efficient market, then such policies will only introduce distortions and reduce efficiency. However, there are also many accounts of external economies of scale in the

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manufacturing sector.[1] In a scenario in which the economy is inefficiently stuck in agricultural production due to market failure, government policies that encourage manufacturing investment could be beneficial by pushing the economy onto a better equilibrium (Rosenstein-Rodan, 1943; Murphy et al., 1989; Hirschman, 1958).

Given the popularity of such policies, understanding their effectiveness is crucial. Yet convincing empirical evidence is at best limited due to the endogeneity problem—governments take potential growth prospects into account when deciding where to direct investment, rendering it difficult to credibly estimate causal effects.

In this paper we study the long-run impacts of one particular regional industrialization policy, the construction of the "Third Front" (TF) in China, which directed large amounts of manufacturing investment to the country's hinterland, an area known later as the "Third Front Region". Launched in 1964 and lasted for over a decade, the TF was motivated by the threat from potential military confrontations. Its goal was to create self-sustaining industrial clusters in interior China so the country has more "strategic depth" during the war. During the TF, hundreds of large-scale manufacturing plants were built in the remote and mountainous TF region.

The TF provides a unique natural experiment to study policies that direct investment into the manufacturing sector. First and foremost, the site selection process for the TF firms followed a particular set of criteria that prioritized national defense considerations. It provides plausibly exogenous spatial variation in the magnitude of manufacturing investment within the targeted region. In particular, in order to minimize damage from mass bombing while having access to transportation, the TF plants were built in areas with rugged terrain while near existing railways. Second, the subsidies were short-lived and dwindled in the late 1970s. Since the mid-1980s, China embarked on economic reforms and gradually allowed entry of private firms, which became the major contributor of China's post-reform economic growth. This historical setting provides an ideal setting to study the effects of a temporary industrialization policy on long-run economic development through local spillover effects.

Our primary goal is to examine whether the TF investment stimulates the entry and growth of local private manufacturing firms. To identify causal effects we devise two empirical strategies. Our first strategy is to control for the key variables that directly capture the site-selection criteria for the TF plants—ruggedness of the terrain and distance to existing railways—along with a rich set of geographic and pre-TF economic conditions. We show that both variables capturing site-selection criteria are relevant predictors for the distribution of the TF plants, and once conditional on these two variables, the distribution of the TF plants is uncorrelated with initial local economic conditions. Our second strategy uses the timing of railway construction as an instrument for the spatial distribution of the TF investment. Planned and implemented with a great sense of urgency,

[1] The idea of manufacturing spillover effects dates back to as early as Marshall (1920). See Rosenthal and Strange (2004) for a review of potential mechanisms and empirical evidence on local spillovers.

the TF plants were scattered along the *existing* railways for the ease of transportation. Locations that were connected to the railway slightly later did not receive much investment. We show that the timing of railway construction is uncorrelated with economic conditions prior to the TF and thus argue that it is also unlikely to be correlated with unobservable local economic potentials. Both identification strategies produce similar results.

From multiple population censuses, manufacturing surveys, and historic railway maps, we compile a comprehensive dataset of China's local economies spanning over 70 years. We find strong evidence for spillover effects on the local private manufacturing sector two decades after the end of the TF. Based on our preferred two-stage least square estimate, a one percentage point (p.p.) increase in TF plants' share of local employment in 1985 increases the share of local private manufacturing employment in 2004 by 2.1 p.p., or about 80% of its sample mean. This effect is unlikely due to continued state subsidies to the regions or the privatization of state-owned manufacturing plants. We show that the result is robust when we focus on subsamples of private firms that were unlikely to be the results of privatization, or when we directly control for the growth of local state manufacturing sector and the privatization process. Moreover, consistently with the existence of local spillover effects, we also find that the same magnitude of the TF investment increases the average local private firms' productivity by about 10 percent and local average manufacturing wage by about 3 percent.

With variation in investment across different manufacturing industries, we are able to explore the channels of the local spillover effects. Overall, a substantial share of the spillover effects take place within the same 2-digit industry of the original investment. Using various measures of inter-industry linkages, through labor, technology and intermediate goods channels, we find that investment in an industry tends to have a bigger positive impact on the employment and productivity of industries that are economically close. Together, these results are consistent with the patterns of spillovers for firms through local agglomeration economics.

Decision-makers of such policies often need to decide which industries to invest in. Using variation in the industry composition in local TF investment, we further explore what industries generate particularly strong positive externalities. Standard models predict that investment in sectors that suit a country's comparative advantage generates stronger spillover effects (Rodriguez-Clare, 2007). During the sample period, most of China is characteristized with an abundance of labor and has a comparative advantage in labor-intensive industries. We divide manufacturing industries into "heavy" (capital-intensive) and "light" (labor-intensive) and investigate their respective spillover effects. Interestingly, we find that investment in these two broadly-defined industries generates similar spillover effects on the overall local manufacturing sector, but channels differ. Light industries exhibit strong localization economics and disproportionately benefit from spillovers from firms in the same industry. In contrast, heavy industries rely more on positive linkages across different industries.

To understand whether this increase in manufacturing activity benefits local residents, we examine whether increases in local manufacturing employment are due to increased inward migration or from pulling local workers out of agriculture. We find that the TF investment has no impact on inward migration, so the benefits of the TF are captured by local residents. Moreover, we provide direct evidence that the TF investment increases the share of manufacturing workers who were originally form the local rural area.

One major opposition to government interventions in choosing which industries and regions to investment in is that it distorts prices and creates misallocation of resources, which hurts the aggregate economy. In the context of the TF, it is easy to imagine that directing investment from the more productive coastal region to the less-productive and less-developed TF region is likely to result in aggregate efficiency loss. On the other hand, many theories of economic development predict that if an economy is stuck in the "poverty trap," the marginal effect of manufacturing investment could be particularly large (Murphy et al., 1989). If the spillovers are indeed stronger in places with a low initial development level, then even if manufacturing firms to the TF region hurts their productivity, the aggregate output could still increase.

We develop a simple model of structural transformation to analyze TF's impact on the aggregate economy. The model delivers a set of conditions under which the TF could increase the aggregate output. Among these, two empirical conditions are most important: first, whether the TF region is indeed less productive; second, whether the spillover effects are stronger in initially less-developed regions. Using firm- and individual-level data, we show that the TF region is indeed much less productive compared to the rest of the country. Using variation in initial conditions *among* the TF prefectures, we find that the TF investment has almost exactly the same linear spillover effect in places with different levels of initial development. It follows that it is unlikely for the TF investment to have generated much stronger spillovers in the TF regions than had the investment been made to a more developed and productive region. Taken together, our results suggest that the TF likely benefits the residents in the TF prefectures at the expense of aggregate efficiency.

### 1.1 Related Literature

This paper contributes to the empirical studies of place-based policies (Gottlieb and Glaeser, 2008; Neumark and Simpson, 2014; Kline and Moretti, 2014b). While much of the literature is set in the developed countries and focuses on the contemporaneous or short-term effects on wage and employment, we study the long-run effects of a temporary policy on regional economic development.[2] We find that the effects of a favorable place-based policy may persist long after the policy

[2] There is also a small literature that examines economic zones in developing countries and their implications for economic development (Wang, 2012; Alder et al., 2013). Most of their results should be interpreted as contemporaneous effects as these special economic zones are still in place to date. Moreover, because economic zones usually include

has ceased.[3] We show that these positive effects work through local agglomeration economics (Rosenthal and Strange, 2004; Combes and Gobillon, 2015). We join a small group in the literature of agglomeration economics that uses natural experiments to credibly identify agglomeration effects (see, for example, Greenstone et al., 2010). We find the magnitude of the agglomeration economics is largely comparable to the existing estimates and show that inter-industry linkages play an important role in generating local agglomeration economics. The fundamental concern of place-based policies is that spatially targeted policies may simply shift economic activity from one locality to another, with little impact on the aggregate output. Moreover, targeting some particular local economies often results in spatial misallocation and can lead to efficiency loss (Gottlieb and Glaeser, 2008). Consistent with this intuition, we show that by directing investment to a less productive area, the TF likely results in a substantial aggregate loss.

Our study is most closely related to Kline and Moretti (2014a), which examines the impact of the Tennessee Valley Authority (TVA) on the economic development of the U.S. South. By comparing counties inside the TVA region with those just outside the region, the authors find continued manufacturing employment and productivity growth in the TVA counties after subsidies had ceased. The present paper differs from Kline and Moretti (2014a) in several important dimensions. First, the nature the shock is different. Unlike the TVA, which invested in a broad spectrum of infrastructure projects, the TF almost exclusively focused on manufacturing. We are therefore able to test the effect of a development policy that favors the modern sector, which are popular in many developing countries. The industry variation in investment further allows us to study the channels and industry heterogeneity of the spillovers. Second, China's hinterland was much less developed when the TF was initiated.[4] The TF thus provides a unique opportunity to test the effectiveness of an industrial policy on a region with little existing capital or know-how. Last but not the least, thanks to the well-documented investment strategies of the TF, we are able to exploit exogenous variation *within* the targeted region, which adds to the accuracy of measurements and credibility of the identification strategies.

This paper also contributes to the long-standing debate on whether there is a role for government interventions to stimulate industrialization in underdeveloped economies. On the one hand, there may be barriers to industrialization and an economy might be stuck in an inefficiently low level of development. In such a scenario, government investment in the manufacturing sector might generate positive spillovers and pull the economy out of a bad equilibrium (Rosenstein-

packages of policies that differ across prefectures, it is hard to attribute the outcome to any specific policy. In contrast, the setting studied in this paper provides a clear interpretation of the result.

[3]Since this paper focuses on the long-run effect of temporary manufacturing investment, it is also related to the literature investigating whether temporary shocks might have persistent impacts on equilibrium outcomes (see, for example Bleakley and Lin, 2012; Jedwab et al., 2014, among others). In that literature, temporary shocks usually affect long-run outcomes by altering population distribution across prefectures. In the present paper, however, the TF did not significantly affect the population of the treated areas. Despite so, we show that, by changing the industrial composition of local economies, temporary shocks can have persistent impacts.

[4]The average urbanization rate in 1964, the year the TF was initiated, was a mere 7 percent among the TF region.

Rodan, 1943; Hirschman, 1958; Murphy et al., 1989). On the other hand, government interventions might distort prices and lead to resource misallocation (Rostow, 1990; Cheremukhin et al., 2017; Rostow, 1990). We find that the TF investment indeed benefits local economies through agglomeration economics, yet these benefits come at the cost of aggregate efficiency. Importantly, we do not find that the positive externality of manufacturing is particularly large in initially less-developed regions, which suggests that government interventions are not necessary to kick-start industrialization in less developed economies. Empirically, while most existing studies on testing such industrial policies exploit cross-industry or cross-country variations (see, e.g., Beason and Weinstein, 1996), this paper joins a new strand of empirical literature that exploits variation at the subnational national level generated by natural experiments (Criscuolo et al., 2012; Juhász, 2014; Peters, 2017).

Finally, this paper also contributes to the studies on China's transition and economic growth (see Yao, 2014, for a recent review). To our knowledge, we are the first to empirically evaluate the effects of the TF, an important economic event during the era of command economy (between 1949 and 1979), and a prime example of a large-scale location-based industrialization campaign.[5]

The rest of the paper is organized as follows: Section 2 describes the background of the TF. Section 3 introduces the data, sample, and key measures. Section 4 presents the empirical strategies and the baseline results on local spillover effects. Section 5 discusses the implications at the aggregate level. Section 6 concludes.

# 2 Background

## 2.1 Brief History

In the early 1960s, China was a low-income country with a predominantly agrarian economy. The industrial sector,[6] accounting for less than 10 percent of the national employment, was concentrated in a handful of large prefectures in the eastern part of the country. China's vast hinterland was overwhelmingly agrarian and rural, with an industrial sector accounting for less 5 percent of the employment. The economy was recovering from the Great Leap Forward, a failed industrialization campaign, and the subsequent Great Famine between 1959 and 1961. The Five-Year Economic Plan for the period between 1966 and 1970, first drafted in early 1964, stated that the primary goal of economic development was to meet the basic needs of the everyday life.[7]

The focus of economic development changed dramatically in 1964 as the geopolitical situation facing China took a sudden downturn. To the southeast, the Vietnam War escalated in August

[5]Naughton (1988) systematically documents the TF. But his approach was mostly descriptive and did not provide an evaluation of the program in the long-run.

[6]The industrial sector here includes manufacturing, mining and extractions, and utilities (power generation, water treatment, fuel production, etc).

[7]"*jiejue chichuanyong*," which literally means to "solve the problems involving eating, wearing and everyday use."

with the enactment of the Gulf of Tonkin Resolution, followed by mass bombing of the North Vietnam, menacing China's border. To the north, the relationship with the Soviet Union deteriorated when the Soviet troops stationed along the China-Mongolia border, just 500 kilometers across open ground from Beijing. China's leaders worried that the country's existing industrial clusters, being geographically close to the potential war fronts, were vulnerable to military attacks should China find itself at war with the Soviet Union or the United States.

The Third Front construction was launched later that year with a purpose to establish self-sustaining industrial clusters in China's southwest and northwest, an area known later as the "Third Front Region", such that China could still have the industrial capacity to support a war even if it was to lose its factories in the east. In fact, the term "Third Front" was first used as a national defense concept, referring to the vast hinterland that is far away from the potential war fronts. Figure 1 shows China's distinct "three-step-ladder" topography with increasing elevations from the east to the west. The TF region is delineated by the red line. It largely corresponds to the second geographic ladder while avoiding areas with large ethnic-minority populations.[8] It is a vast area that encompasses or intersects with 8 provinces and accounted for about 20 percent of China's population in 1964.[9] Except for a few flat patches, the region is mountainous and its terrain is rugged.

Figure 2 documents the massive scale of the TF. The thick blue line shows capital formation per capita, relative to the national average, in provinces that were included in or intersected with the TF region. The thin red line represents the rest of the country. Capital formation per capita in the TF region was noticeably higher between 1964 and the mid-1970s. During this period, it is estimated that about 40 percent of the nation's industrial investment was dedicated to the TF region (Naughton, 1988; Central Documentary Office, 1992).

Most of the TF investment came in the form of construction of new manufacturing plants and expansion of existing small plants in the region. The investment prioritized in heavy industries that produce basic industrial materials such as steel, as well as sophisticated machinery (including weaponry) and equipment. A small number of light industry plants were established as supporting facilities. Some investment was made to infrastructure such as roads and power generation. Investment to agriculture was minimal.

The TF was planned and carried out in a top-down process, with a central committee in charge of distributing hundreds of projects across the region. Defense from potential attacks, especially mass bombing and nuclear attacks, was the top consideration. In order to reduce damage from such attacks, the site-selection criteria state that the TF plants should be "dispersed, hidden, close to the mountains, and when necessary, in caves" (Central Documentary Office, 1992). Hiding

[8]There is no official geographic definition for the TF Region. We follow the boundaries delineated in Naughton (1988).

[9]These provinces are Sichuan (including Chongqing, which became a provincial-level municipality in 1997), Hubei, Hunan, Guangxi, Yunnan, Guizhou, Guizhou, and Gansu.

plants in the mountains far away from major population centers made transportation a challenge. Therefore, access to the railway was another top consideration.[10]

The shift in the focus of industrial investment is also reflected by the firm-level data. Using a complete list of large and medium manufacturing plants included in the 1985 Industrial Census, Table 1 Panel A reports location characteristics of plants that were established before the TF (before 1964, Column 1) and those during the TF (between 1964 and 1978, Column 2). Only 13% of plants established before the TF were located in the TF region, compared with 32% of those that were established during the TF period. Plants established during the TF period were located in less developed counties, measured by the urban rate and population density in 1964, with more difficult geographic characteristics. They were also farther away from provincial capitals and existing railways. Panel B shows that the plants established during the TF period were more likely in heavy and advanced industries but much less likely in light industries.[11]

Columns 4 to 6 of Table 1 show the same systematic shifts *within* the TF region. Figure 3 plots these manufacturing plants in the TF region. Each dot represents 25 workers and is placed in the county where the plant was located. The red line shows the railways that existed or under construction in 1962. It is obvious from the map that much of the manufacturing employment in the TF region was scattered along the railway and was in rugged areas close to the mountains. It is striking that the Sichuan Basin, being the only large plot of land in the region that is relatively flat, had little manufacturing presence.[12]

Due to the undesirable geographic conditions, the TF was extremely costly, many projects were many times over budget and years behind schedule. With improvement in the geopolitical situations in the 1970s,[13], the TF gradually lost steam and wound down. By the late-1970s, investment was only continued to unfinished projects until they became operational.

The TF substantially altered the landscape of China's economic geography. In 1985, the 8 provinces in the TF region accounted for about 37 percent of national industrial output, compared with less than 10 percent in 1960. To date, a large share of the country's sophisticated manufacturing plants and skilled workers are still in the remote, mountainous hinterland. Within the TF region, some locations were chosen to receive large manufacturing plants and had emerged as

[10]The importance of these criteria is evident in the site selection process for the Second Automobile Works (SAW), one of the largest projects during the TF. The site was originally chosen in Xiangxi in western Hunan province for its proximity to mountains and a railway under construction (the Changsha-Guizhou line) (Central Documentary Office, 1992). But as the interpretation of the site-selection criteria was pushed to an extreme, the site-search team worried that the valleys there were not steep enough. The confirmation that another planned railway (the Chengdu-Wuhan line) would pass through the mountainous areas in Hubei province led Shiyan as the final choice for its micro-geography provides a better defense against air attacks.

[11]Because some of the TF investment was spent on expanding existing plants in places that suits the location-choice criteria, the differences shown here are likely to under-estimate the actual shift the government's investment strategy.

[12]Except for Chengdu (on the western end of the basin) and Chongqing (on the eastern end of the basin). Chengdu and Chongqing are provincial capital prefectures and are later excluded from the main sample.

[13]Nixon visited China in 1972. China and the US established the formal diplomatic relationship in 1979.

important industrial centers.[14] At the same time, other locations remained largely agrarian and under-developed.

China's market reform in the industrial sector started in the mid-1980s. With a series of reforms, the TF plants, all of them state-owned, were gradually granted more autonomy but were also weaned from government subsidies. Non-state firms were allowed to enter and grew rapidly. By 2004, they accounted for over 60% of the national manufacturing employment. How did the existence of the TF plants affect the development of the local non-state manufacturing sector? On the one hand, it is possible that the existence of large plants stifled entrepreneurship (Glaeser et al., 2014). Indeed, a popular view is to see the inefficient state-owned sector as a drag on local economic development. On the other hand, equipped with arguably China's most advanced technology and skilled workers of the time, the TF plants could facilitate the entry and growth of local non-state firms by passing on know-how and skills (Glaeser and Kerr, 2009, e.g.,). These local agglomeration effects could be particularly helpful for China's burgeoning non-state sector.

## 2.2 Spatial Distribution of the TF Investment

The peculiar site-selection criteria allow us to isolate exogenous variations in the spatial distribution of the TF investment. We use two variables to represent the site-selection criteria: average slope (as a measure of the ruggedness of the terrain) and the log distance to the 1962 railway (existing or under construction).[15] We first show that these two variables are good predictors for the spatial distribution of the TF investment. We further show that local economic conditions were not an important consideration for site selections once conditional on these two variables.

Panel A of Table 2 reports the results of these tests using a sample of prefectures in the TF region.[16] Magnitude of the TF investment is measured as the number of workers from the list of large and medium manufacturing plants as a percent of prefecture's total employment.[17] Column 1 shows that prefectures that were closer to the 1962 railway received significantly larger TF investment. Ruggedness of the terrain is positively correlated with investment (Column 2), and the correlation is statistically significant once conditional on the log distance to railway (Column 3).[18]

Column 4 shows that prefectures with a higher initial urban population share in 1964 received

[14]These examples include Mianyang (Sichuan) for the semi-conduct industry, Shiyan (Hubei) for the automobile industry, and so on.

[15]Slope is defined as the vertical distance between the highest point and the lowest point in a 1*km*-by-1*km* square, divided by the horizontal distance between the two points. The average slope of a larger area thus describes the overall ruggedness of the terrain for that area. See Dell (2010) and Nunn and Puga (2012) for examples of using ruggedness in economic studies.

[16]A prefecture is a administrative division between a province and a county. In 1982, China was divided into 340 prefectures. See Section 3.2 for details about the sample selection.

[17]Section 3.3 discusses in detail why this is a good measure of the TF investment in the manufacturing sector.

[18]Coefficients in Column 3 shows that a one-standard-deviation (std) reduction in the log distance to railways (1.28) is associated with about 1 ($1.28 \times 0.82$) p.p increase in the share of the TF employment, which is about 88 percent from the mean or 2/3 of a std (1.51). A one-std increase in the prefecture's average slope (2.39) is associated with a 0.3 p.p increase in TF investment.

larger investment. However, once conditional on the site-selection criteria, the correlation becomes much weaker and statistically insignificant (Column 5).[19] Column 6 includes additional proxies for initial economic conditions: log population density in 1964 and the share of industrial employment in 1936. While coefficients associated with site-selection variables remain similar, coefficients associated with initial economic conditions are jointly insignificant. These results suggest that conditional on the site-selection variables, the distribution of the TF investment is uncorrelated with local economic potentials. This observation leads to our baseline identification strategy, which assumes the exogenous distribution of the TF investment conditional on site-selection criteria.

One may be concerned that the initial economic conditions are poorly measured, thus the results found in Panel A is not compelling evidence for the irrelevance of local economic potentials in determining the distribution of the TF investment. To rule out this possibility, Panel B repeats the same regressions but uses a sample of prefectures outside of the TF region.[20] Column 3 shows that being close to the existing railway is still highly correlated with the TF investment, while ruggedness is not.[21] 1964 urban rate is positively and significantly correlated with the TF investment (Column 4) and remains so after conditioning on site-selection criteria (Column 5). The coefficient associated with the 1964 urban rate is three times as large as that in Panel A. Initial economic conditions are also jointly statistically significant after conditioning on the site-selection criteria (Column 6).

# 3 Data, Sample and Measurement

## 3.1 Data Sources

We assemble a database of Chinese prefectures covering a period of more than 70 years from various sources. Some of the data are digitized from historical archives and is, to the best of our knowledge, new to the literature. The data cover a wide range of topics, including local economic conditions as well as demographic and geographic characteristics. Most of these data provide

[19]The coefficient shows that an increase in the 1964 urban rate by one std (2.7) is associated with an increase of only one-tenth of a std of the TF employment share.

[20]The sample excludes autonomous provinces of Inner Mongolia, Xinjiang, Tibet, and Ningxia. It also imposes the same set of restrictions as to the sample in the TF region. The details of the sample restrictions are introduced in Section 3.2. The sample has 146 prefectures, twice as many as those in Panel A. To correct for the fact that null hypotheses are more likely to be rejected simply because of the larger sample size, each observation in regressions in Panel A is frequency weighted by 2. Coefficients associated with log distance to existing railway and average slope would remain statistically significant if weight is not used.

[21]The magnitude of the coefficient is large although it is not statistically significant. The large and imprecise coefficient may be partly due to the fact that outside of the non-TF regions, similar industrialization campaigns were carried out during the period. These campaigns, though at a much smaller scale, followed similar site-selection criteria as the TF. Each coastal province had their own "rear region" where some of their strategic manufacturing firms were moved to. These campaigns are sometimes collectively called the "Small Third Front," in order to distinguish from the "Big Third Front" in the southwest and the northwest.

information at the county or prefecture level, while some are at the individual or firm level. Here we only briefly introduce the main sources of data used in this paper. Details are provided in Appendix A.

Information on manufacturing firms are collected from various manufacturing censuses and large-scale economic surveys. We digitize the 1936 Industrial Survey, which gives the earliest-available nationwide snapshot of the industrial sector in China. We digitize various volumes of publications from the 1985 Industrial Census. In particular, the 1985 Industrial Census provides micro-level data for large- and medium-sized (LMS) manufacturing firms, which allows us to gauge the size and distribution of the TF investment.[22] Firm-level data from the Annual Manufacturing Firm Survey (AMFS) and Economic Census in 2004 allow us to measure the size of the manufacturing sector by ownership and industry in post-reform years. For each firm, we know its location (geocoded at the county level), employment, operational capital, ownership, 4-digit industry, and the year of opening. The AMFS data is unique in including firm's balance sheet, which allows us to calculate firm's total factor productivity (TFP). Population censuses in 1964, 1982, 2000, and mini population census in 2005 are sources for demographic and economic conditions. County-level tabulations are available for the first three censuses while individual-level samples are available for the last three. The 2005 mini-census has individual level information on income and migration. Geographic characteristics are extracted from GIS maps obtained from the China Historical GIS Project. Maps of railway networks in 1962 and 1980 are from Baum-Snow et al. (2012).

### 3.2 Sample

We focus on the TF region and treat each of the 89 prefectures within the region as a local economy.[23] Several restrictions are imposed on the sample. First, we exclude provincial capitals as they enjoy various privileges compared to other prefectures in the province.[24] We further exclude 9 prefectures with higher than 15% urban rate in 1964. The primary reason for this restriction is to focus on prefectures that had little industrial presence initially, such that we can better infer

[22]We digitize the list from the second volume of the *Materials of the 1985 Industrial Census* (*"Dazhongxing gongye qiye minglu"*). For each firm, the list reports its name, detailed address, industry (divided into 39 industries roughly corresponding to 2-digit SIC codes), employment, capital, output, year of first production, and names of its key products. These firms accounted for over 70 percent of total manufacturing employment in the TF region in 1985.

[23]A prefecture is a suitable area for studying the effect of the TF on regional economic development. First, a typical prefecture is large, it covers about 25,000 square kilometers and had about 4 million of population in 2000, and migration across prefecture levels is rare for the most of our sample period. Second, many TF plants moved out of the mountains to nearby cities since the 1980. While sometimes they moved across county borders, they usually remained in the same prefecture. Many variables are available at the county level and the county boundaries have changed over time. We first construct consistently-defined counties and then aggregate them to the prefecture level. Details are provided in the Appendix Appendix A.

[24]They are Chengdu (capital of Sichuan province), Xi'an (Shaanxi), Lanzhou (Gansu), Nanning (Guangxi), Guiyang (Guizhou), Kunming (Yunnan), and Chongqing (which became a province-level municipality in 1997). Our results are essentially unchanged if we include them in the sample and then control for a dummy indicating a provincial capital.

TF investment using data from 1985. The excluded prefectures are either resource-rich or located next to a large provincial capital.[25] The baseline sample has 73 prefectures.

### 3.3 Measurement

The key explanatory variable is the size of the TF investment. It is measured as the employment in the large and medium manufacturing plants from the 1985 industrial census as a share of total prefecture employment.[26] The prefecture's total employment is from the 1982 population census. The sample average of the TF investment is 1.11 and the standard deviation is 1.51.

The prefecture employment share of the LMS manufacturing plants in 1985 is a good measure of the TF investment for several reasons. First of all, the TF plants were ubiquitously large and should be included in the list of the LMS plants. *The Summary Outlines of the Third Five-Year Plan* (Central Documentary Office, 1992) listed major manufacturing projects to be invested in the TF region, and each project on the list can be matched to a corresponding LMS plant in 1985. Second, the timing of the survey serves our purpose well. The 1985 Industrial Census is the first large-scale survey after the initiation of the TF and the only survey that gives a nationwide snapshot of the industrial sector before the market reforms. Although much of the TF investment was made in the late 1960s and early 1970s, it took many TF plants several years before they finally became operational. Moreover, before the market reforms, state-owned firms had little autonomy in hiring and firing decisions, so the employment in 1985 is a good proxy for the size of the investment.[27] We use employment, rather than capital, because prices in a planned economy might be distorted and therefore do not capture true values of investments.

The key outcome variable is the employment in the private manufacturing sector as a share of prefecture aggregate employment in 2004. Employment by sector is available from the 2004 Economic Census, which includes the firm-level data for the universe of all manufacturing firms. We define private firms as those in the non-state sector. We adopt a narrow definition of the non-state sector, which excludes all firms that are solely or partly owned by all levels of the government, and all joint-venture firms with the state sector. Prefecture total employment is taken from the county-level tabulations of the 2000 Population Census. On average, the non-state manufacturing sector accounted for 60% of the total manufacturing employment and 2.7% of all employment in 2004 among the sample prefectures.[28]

[25] The 15% cutoff is arbitrary. The results are quantitatively similar for a wide range of different cutoff values.

[26] We include all LMS plants on the list regardless of their year of opening because some TF investment was to expand existing firms in the region. Results are similar if we only use plants that were established during the TF period.

[27] It is worth noting that these firms, as surveyed in 1985, represented the outcome of the TF investment, not its input. Anecdotal evidence suggests that TF was highly inefficient and wasteful, but without detailed historical data on the cost, a comprehensive cost-and-benefit analysis is beyond the scope of this paper.

[28] Appendix Table B shows the summary statistics of the key variables.

## 4 The Third Front and the Local Manufacturing Sector

### 4.1 Baseline Specification and Results

In this section we estimate the long-run spillover effects of the TF investment on the local non-state manufacturing sector. Our baseline empirical strategy estimates an OLS model controlling for the site-selection criteria and a rich set of initial economic and geographic conditions:

$$y_{i,2004} = s_p + \beta TFInv_{i,85} + \theta_1 \ln DistRail_{i,62} + \theta_2 Slope_i + \mathbf{G}_i \cdot \delta + \mathbf{X}_{i,64} \cdot \gamma + \varepsilon_{it}. \quad (1)$$

In the specification, $y_{i,2004}$ is some measure of the size of the non-state manufacturing sector in prefecture $i$ in year 2004. Because the non-state sector was essentially non-existent when the TF ended, its size in 2004 could also be interpreted as its growth (in levels) since the market reform. $s_p$ is a set of province fixed effects. $TFInv_{i,85}$ is the TF investment in prefecture $i$, measured as the number of employees from the LMS manufacturing plants in 1985 as a percentage of the total prefecture employment. $\beta$ is the key parameter of interest. $\ln DistRail_{i,62}$ is the log distance to the 1962 railway. $Slope_i$ is the average slope of the prefecture's terrain. $\ln DistRail_{i,62}$ and $Slope_i$ capture the key components of the site-selection criteria for the TF plants. $\mathbf{G}_i$ is a vector of additional geographic characteristics including log average elevation, log distance to the provincial capital, and the share of employment in the mining sector (as a measure of natural resources available in the prefecture). $\mathbf{X}_{i,64}$ is a vector of initial economic and demographic conditions prior to the TF, which includes the share of urban population in 1964, log of 1964 population density, and industrial employment share in 1936. $\varepsilon_{it}$ is the error term. Throughout the paper we stick to this linear specification, results are quantitatively similar with more flexible ways of including the covariates.

Table 3 reports the results from Equation 1. Column 1 shows that when the TF employment share increases by 1 percentage point, which is about 90 percent of the sample mean and two-thirds of a standard deviation, the prefecture's share of employment in the non-state manufacturing sector in 2004 increases by 1.6 p.p.[29] The coefficient is statistically significant at the 1% level. This is also a large effect economically, considering that the average employment share of the non-state manufacturing firms is 2.7 percent in the sample (with a standard deviation of 3.1), this effect is about 60 percent of the mean or about half of a standard deviation.

We interpret the result as evidence that the TF plants generate positive spillover effects on local non-state firms. These spillover effects may be driven by local agglomeration economics: the existence of the TF plants makes it easier for new firms to enter and grow by passing on the knowledge about production, market, and management. Indeed, many of China's first-generation entrepreneurs since the market reform spent years in an SOE before starting their own firms.

[29] When the total manufacturing employment share in 2004 (including both state and the non-state sectors) is used as the outcome variable, the coefficient associated with $TFInv_{i,85}$ is 2.035 with a standard deviation of 0.301.

Agglomeration economics also works through sharing of inputs and market: proximity to TF plants can provide new firms access to suppliers and buyers, as well as a pool of workers with relevant skills.

### 4.2 Alternative Explanations

There are several alternative explanations for the estimate in Column 1 other than spillover effects. Since the late 1990s, many state-owned enterprises (SOEs) have been privatized. One important and valid concern is that our estimated effect might simply pick up the changes in ownership. The way we construct non-state employment already provides assurance against this alternative explanation. Specifically, we exclude all firms with any state shares, and all joint ventures between the state sector and the non-state sector. Since the restructuring and privatization usually took the form of creating joint ventures (Naughton, 2007), our measure minimizes the risk of picking up the privatized SOEs.

We provide additional evidence that the result in Column 1 is not due to privatization by estimating alternative versions of Equation 1. In Column 2 we restrict our measure to the non-state firms that were established between 1985 and 1998. By doing this, we include in our measurement only firms that entered after the time the treatment variable is measured but before the large wave of privatization.[30] About a third of the non-state manufacturing employment in 2004 are in these firms. The coefficient associated with the TF investment indicates that if the TF employment share increases by 1 p.p., employment share from non-state manufacturing firms established between 1985 and 1998 increases by 0.51 p.p, which is about 58% of the sample mean. This effect is similar to that from the benchmark specification shown in Column 1, which includes all non-state manufacturing firms.

We also look directly at different part of the firm size distribution. Most state-owned manufacturing firms were large. It is particularly true for the TF plants. The smallest 1% of the TF plants had more than 200 workers in 1985, and the median had over 1,000 workers. We therefore use employment share of small non-state firms (with fewer than 25 workers) as an alternative outcome measure.[31] Column 4 shows that the effect of the TF investment remains economically and statistically significant. The magnitude of the coefficient is about 35% of the average dependent variable. In Column 6, we look at the firm entry margin, and also find significant effect.

Our third robustness test is to include in the regression the change in the state manufacturing sector's employment share between 1985 and 2004. If the result is solely driven by privatization, then places with more rapid state-sector growth (indicating less privatization) should see slower non-state employment growth. Column 3 shows that the opposite is true, which suggests a con-

[30] Zhu Rongji became China's premier in 1998 and carried out substantial reforms on state-owned enterprises.

[31] The 25-worker cutoff is of course arbitrary, the results are robust to alternative cutoffs.

temporaneous positive spillover effects of the state sector on the non-state sector.[32] Conditional on contemporaneous state-sector employment growth, the effect of the TF investment remains similar to, if anything, larger than what we find in the baseline. This suggests that the contemporaneous spillover also does not drive our result.

Finally, we exploit cross-industry variation in the state-sector reforms. Over the past decades, some industries gradually opened up to private entrants, while others, especially those related to infrastructure, natural resources and national defense, are still under strict state control and private entry is limited. If privatization is important for our result, we should expect that prefectures receiving more investment in the industries under firm state control to have a smaller private sector. We construct a "state-share index" for each TF prefecture to implement this test. We first calculate the *national* share of employment in the state sector for each 2-digit manufacturing industry $j$, denoted $\tau_j$, using the 2004 economic census. We then calculate the share of industry $j$ in the TF investment in prefecture $i$ as $s_{ij} = TFInv_{ij}/TFInv_i$, where $TFInv_i$ is the total TF investment in prefecture $i$. The "state-share index" is then calculated as $S_i = \sum_j(\tau_j - \bar{\tau})s_{ij}/\sigma_\tau$, where $\bar{\tau}$ is the average share of state-sector employment across all industries and $\sigma_\tau$ is the standard deviation of $\tau_j$'s. $S_i$ is zero if the TF investment in prefecture $i$ is evenly distributed across all industries. We include $S_i$ and its interactive term with $TFInv_i$ in the regression. If privatization plays an important role in driving our result, the coefficient associated with the interactive term would be negative and the magnitude of the coefficient on $TFInv_i$ would become much smaller. Column 5 shows that this hypothesis is not supported by the data. The interactive term has a positive sign and is not statistically different from zero; the coefficient associated with $TFInv_i$ is quantitatively similar to that in Column 1.

Results in Columns 4 and 5 also allow us to rule out the continued government subsidies as the main driver of our results. If continued government subsidies matter, we should expect that once we control for the state-sector employment growth, the magnitude of the effect of the TF investment as measured in 1985 would be substantially diminished. But Column 4 suggests otherwise. In addition, we should expect continued government subsidies to be larger in industries that are still under the state control, and controlling for the "state-share index" would substantially reduce the coefficient associated with $TFInv_i$ if those subsidies are driving our results. Results in Column 5 also reject this hypothesis. Taken together, these robustness tests suggest that privatization and continued government subsidies are unlikely to drive our results.

Finally, the TF investment also has a positive effect on the number of non-state firms. Column 6 shows that as the TF employment share increases by 1 p.p., there is one additional non-state manufacturing firm per 10,000 workers in 2004. This is roughly a 30% increase from the sample

[32]One may also be concerned that this additional control variable is endogenous: places more suitable for the development of the manufacturing sector would have a faster-growing manufacturing sector. If it is true, then controlling for the growth in the state-sector employment, which implicitly (and partly) controls for the unobserved locational characteristics, should reduce the coefficient associated with the TF investment. This is not what we find.

mean. Recall that Column 1 shows that the same increase in the TF investment has an effect on non-state manufacturing employment by about 60% of the sample mean, we conclude that the overall effect on employment can be roughly equally accounted for by more firm entries and a larger average firm size.

### 4.3 Discussion of the Identification Assumption

The consistent estimation of $\beta$ using Equation 1 requires the usual conditional independence assumption:

$$E[TFInv_{i,85} \cdot \varepsilon_{it} | \mathbf{Z}_i, s_p] = 0, \tag{2}$$

where $\mathbf{Z}_i = \{\ln DistRail_{i,62}, Slope_i, \mathbf{X}_{i,64}, \mathbf{G}_i\}$. The assumption posits that conditional on the variables already controlled in the regression, the explanatory variable of interest is not correlated with the error term.

In most cases this assumption is likely violated: where a firm chooses to locate usually depends on various existing conditions and economic potentials of that location, many of which unobservable to the econometrician. The TF is unique in that we have a good understanding of what factors go into the decision making process and can control directly for them. Indeed, Table 2 shows that distance to the existing railway and ruggedness of the terrain are strong predictors of the TF investment, and once controlling for these two variables, initial economic conditions prior to the TF do not predict the size of the TF investment. In this subsection we provide two additional tests of this key identification assumption.

#### 4.3.1 Coefficient Stability

The historical background of the TF and the results in Table 2 suggest that an even stronger conditional independence assumption should hold:

$$E[ManuEmp_{i,85} \cdot \varepsilon_{it} | \ln DistRail_{i,62}, Slope_i, s_p] = 0.$$

In other words, if we have correctly characterized the site-selection criteria and successfully isolated the exogenous spatial variation in the TF investment, controlling for additional geographic and initial economic conditions would not matter for the consistency of the estimate. To the extent that these additional covariates are predictors of the outcome variable, if the key variable of interest is endogenous, its coefficient will change when the additional covariates are taken out of the regression (Altonji et al., 2005).

In Table 4 we start with the baseline specification and gradually drop geographic and initial economic conditions. Columns 2 to 4 show that the coefficient associated with the TF investment remains similar. For each column, the Hausman test cannot reject the null hypothesis that the coefficient associated with $TFInv_i$ is statistically the same as that in Column 1. Excluding these additional covariates reduces the $R-$squared by about 0.18, so variables are relevant (Oster, forthcoming). Column 5 includes the quadratic terms of all the covariates, the $R-$squared increased moderately by 0.06, the coefficient associated with $TFInv_i$ remains essentially unchanged.

The stability of the key coefficient with respect to additional covariates reassures that the endogeneity problem is likely limited. Admittedly, this is not a direct test of the role of the unobserved factors. After all, the exogenous (or predetermined) covariates we can observe and control for are fairly limited. In the next subsection we propose a direct test on the role of the unobserved factor based on a case study. In Section 4.4 we propose an instrumental variable for the TF investment.

#### 4.3.2 The Case Study of the SAW as a Specification Test

The process of selecting the site for a TF plant resembles a tournament: decision-makers weigh the pros and cons among potential locations with different characteristics and pick one that they believe is the most suitable. With a large number of similar locations to choose from, the final decision is likely to be made between a pair of locations that are fairly close in overall suitability, and the winner and the runner-up would be decided in by a slim margin, resembling a coin-toss. We can estimate the causal effect of the TF plants by simply comparing the outcomes of the winner locations and the runners-up.[33]

Unfortunately, for only one case we know the detailed site-selection process. As documented in Footnote 10 in Section 2, the site for the Second Auto Works was originally chosen in Xiangxi while Shiyan edged out in the end for its micro geographic features (deeper valleys). Clearly one single case does not give us a statistical estimate of the treatment effect. However, under the additional assumption that the winners and the runners-up have similar economic potentials, we are able to directly test the conditional independence assumption.

To see how, first notice that we can construct a statistical comparison for the treated unit (Shiyan) based on observable characteristics, $\mathbf{Z}_i$, and compare its outcomes to those of the runner-up (Xiangxi). If the runner-up and the statistical comparison have similar results, then we can conclude that, in deciding where to place the industrial project, the decision-maker does not use additional information that matters for the outcomes of interest besides those we are able to control for. In other words, and there is no omitted variables problem.

Formally, denote the treated prefecture as $i$, the runner-up as $j$, and the statistical comparison

[33] This is the intuition of the identification strategy in an influential work by Greenstone et al. (2010).

for the treated prefecture as $j'$. The data generating processes for outcomes $y$'s are:

$$y_i = \mathbf{Z}_i \cdot \beta + \gamma + v_i + \xi_i \tag{3}$$

$$y_j = \mathbf{Z}_j \cdot \beta + v_j + \xi_j \tag{4}$$

$$y_{j'} = \mathbf{Z}_{j'} \cdot \beta + \xi_{j'}, \tag{5}$$

where $\mathbf{Z}_i$ is a set of determinants observable to the econometrician. $\gamma$ is the treatment effect. $v$ is the omitted variable and is unobservable to the econometrician. We assume the decision-maker observes both $\mathbf{Z}_i$ and $v$. The validity of the baseline specification requires that $E[v_i] = 0$. $v_{j'}$ is 0 by construction. $\xi$ is the *i.i.d* shock with $E[\xi] = 0$.

For the simple comparison between $y_i$ and $y_j$ to be a valid estimation of the treatment effect, it requires that the winner and the runner-up have the same characteristics relevant for the outcomes and are decided by a coin-toss, that is

$$\mathbf{Z}_i \cdot \beta + v_i = \mathbf{Z}_j \cdot \beta + v_j. \tag{6}$$

The statistical comparison $j'$ is constructed such that it shares the same characteristics with the treated unit $i$ in terms of the observables to the econometrician, i.e., $\mathbf{Z}_{j'} = \mathbf{Z}_i$. The expected difference between $j$ and $j'$ is

$$\begin{aligned} E[y_j - y_{j'}] &= E[(\mathbf{Z}_j - \mathbf{Z}_{j'}) \cdot \beta + v_j] \\ &= E[(\mathbf{Z}_j - \mathbf{Z}_i) \cdot \beta + v_j] \\ &= e[v_i], \end{aligned}$$

where the second equation uses Equation 6. Therefore, a test for the difference between the runner-up and the statistical comparison is equivalent to a test for the omitted variable bias. The advantage of this specification test is that it is a direct test on the unobserved error term. As a trade-off, we need to make an additional assumption that Equation 6 holds.

We use the synthetic control method to construct the statistical comparison for Shiyan and conduct statistical inference (Abadie et al., 2010).[34] The difference between $y_j and y_{j'}$ (as well as

[34]Synthetic Shiyan ($j'$) is constructed as the weighted average of potential comparison prefectures ($k$'s) such that the distance of the vector of observed characteristics ($\mathbf{Z}$) between the treated unit and its synthetic control is minimized. The weights are restricted to be bounded between 0 and 1 and sum up to 1. Formally, we find the set of weights that solve the following minimization problem:

$$\begin{aligned} \omega_k \quad &= \quad \underset{\omega_k}{argmin} ||\mathbf{Z}_i - \sum_{k \in K} \omega_k \mathbf{Z}_k||, \\ s.t., \quad & \omega_k \in [0, 1], \ \forall k \\ & \sum_k \omega_k = 1. \end{aligned} \tag{7}$$

between $y_i and y_{j'}$) can be statistically tested using permutation tests.[35]

Table 5 Panel A compares the geographic and initial economic conditions (**Z**) of Shiyan, Xiangxi, and synthetic Shiyan. Shiyan and Xiangxi had very similar values in these conditions. If anything, Shiyan had a lower urban rate in 1964 and a more rugged terrain, although it is impossible to evaluate the statistical significance of these differences. By construction, Shiyan and its synthetic control have very similar initial conditions. The differences between the two are not statistically significant (Column 4). The differences in between Xiangxi and synthetic Shiyan are also small and statistically insignificant, except that Xiangxi had a significantly higher initial urban rate (Column 5).

Panel B shows that Shiyan received large investment during the TF while Xiangxi and synthetic Shiyan did not. Panel C shows the measures of the non-state manufacturing sector in 2004. Shiyan had 5.6% of its workers employed in the non-state manufacturing sector, compared with 2% in Xiangxi and 1.4% in synthetic Shiyan. The difference between Shiyan and synthetic Shiyan is statistically significant. The difference between Xiangxi and synthetic Shiyan is small and not statistically significant, suggesting that the omitted variable, if any, is not important. Other measures of the non-state manufacturing sector point to the same conclusion.

### 4.4 Instrumental Variable Estimation

In this subsection we propose an alternative identification strategy based on an instrumental variable estimation. We use the log distance to the 1962 railway as an instrument for TF investment. Table 2 shows, as one of the key criteria for investment allocation, log distance to the 1962 railway is highly correlated with TF investment. The relevance of the proposed instrument is also salient from Figure 3, which shows strong spatial correlation between the 1962 railway and the TF plants.

One obvious concern for the validity of this instrument is that access to railway may have a direct effect on economic development. To address this concern, we control for the log distance to the 1980 railway. Because we focus on local economic development after 1985, log distance to the 1980 railway is a predetermined variable for these outcomes. Because the railway network is additive, the 1980 railway includes the segments built (or under construction) in 1962. If there is any direct effect of access to railway, it is captured by the log distance to the 1980 railway. Conditional on log distance to railway in 1980, log distance to railway in 1962 captures the effect when a location is connected to the railway *earlier*. Therefore, the instrumental variable exploits

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The donor pool of potential comparison units, $K$, includes all prefectures in the TF region that did not receive large industrial investment during the TF. There are 40 prefectures in the comparison group. We drop Xiangxi from the donor pool.

[35]The details of the permutation tests are as follows: A placebo treatment is assigned to each potential comparison prefecture. The synthetic control is constructed from the remaining comparison prefectures in the same way that we construct synthetic Shiyan. Denote the synthetic control for each unit $b$ from the donor pool as $y_i^b$, we calculate differences parallel to $d$ and $d_0$ as $d^b = y_i - y_i^b$ and $d_0^b = y_s - y_i^b$. We rank all the $d^b$'s ($d_0^b$'s) along with the original estimate, $d$ ($d_0$), and use the percentile of $d$ ($d_0$) in the distribution as the $p-$value of the relevant test.

the *timing* of the railway construction. The identification assumption is that the sequence of the railway construction is uncorrelated with the error term.

Formally, we estimate the following equation using the Two-Stage Least Squares (2SLS) estimation:

$$y_{it} = s_p + \beta TFInv_{i,85} + \theta_1 \ln DistRail_{i,80} + \theta_2 Slope_i + \mathbf{G}_i \cdot \delta + \mathbf{X}_{i,64} \cdot \gamma + \varepsilon_{it}, \tag{8}$$

where $TFInv_{i,85}$ is instrumented using $\ln DistRail_{i,62}$.

Conditional on $\ln DistRail_{i,80}$, $\ln DistRail_{i,62}$ still has a strong predictive power on the distribution of the TF investment. This can be seen clearly in Figure 3: places near the 1980 railway (blue lines) but not the 1962 railway (red lines) had few TF plants. Figure 4 shows a scatter plot for the first stage regression, where both the endogenous variable and the instrumental variable are first regressed on the full set of controls and residuals are plotted. The linear fit exhibits a clear and strong negative correlation (the slope is -0.85 and the standard error is 0.23).

Two facts contribute to the strong first stage. First, there was considerable amount of railway construction in or near the TF region between 1962 and 1980, which gives us sufficient variation to separately identify two distance-to-railway variables. Second, the reason that the TF plants only concentrated along earlier segments of the railway is that the TF was prepared and carried out in a short period of time. To secure access to transportation, the decision makers had to spread the TF plants along the existing railway lines. By the time new railway lines were constructed, the TF had already lost much of its momentum. Therefore, areas near these new lines did not receive much investment.

### 4.4.1 IV Validity

We discuss and rule out several concerns about the validity of the instrument. First, the route and timing of the railway could be endogenous: locations may be chosen to be connected by railway based on their economic development prospects and favorable locations might be connected earlier.

We argue these concerns are unlikely to matter for several reasons. First, because we control for access to the 1980 railway, the endogenous route choice does not compromise the validity of the IV as long as the route choice for the earlier segments of the railway is the same as the later segments.[36] Second, railways were constructed to connect major economic hubs, primarily provincial capitals (Banerjee et al., 2012; Baum-Snow et al., 2012). We have excluded provincial capitals and most urbanized prefectures from the sample. Third, for the prefectures in the sample, the variation in access to railway is likely from whether they happen to fall on the line connecting

[36] Of course, when the route is endogenously chosen, the coefficient associated with $\ln DistRail_{i,80}$ will be biased. But it is not a parameter of interest.

between two provincial capitals, or whether the engineering technology was there to build the railway over certain types of terrain. Due to its rugged terrain, it was very difficult to build railways in the TF region. Sometimes engineering difficulties in a small segment could drastically delay the completion of the whole railway line.[37]

One may also be concerned that the new and old railways may have different impacts on subsequent economic development. It is unlikely. Most of the 1962 railways were built only in the 1950s (with many segment still under construction in 1962), so the railway technology should not be dramatically different to the railways constructed in the 1960's and 1970's.[38]

We provide additional statistical evidence about the validity of the instrumental variable. Although we cannot directly test the correlation between the route and timing of the railway construction and unobservable heterogeneity of local economic potentials, we can test their correlations with the pre-TF economic conditions, which likely correlate with the local economic potential. We test these correlations by regressing initial economic conditions on log distance to the 1962 railway, controlling for a set of province fixed effects and other geographic characteristics, and with and without controlling for log distance to the 1980 railway.

Column 1 in Table 6 shows that the correlation between the 1964 urban rate and log distance to 1962 railway is negative but is small in magnitude and not statistically significant at any conventional level. The coefficient suggests that a prefecture that is 1 log point closer to the 1962 railway (roughly reducing distance by 70%) is associated with 0.5 p.p higher in the 1964 urban rate, or less than 7% of the sample mean. This suggests that the route is not endogenously chosen to connect better-performing locations. Column 2 adds log distance to the 1980 railway and tests the potential endogeneity of the timing of railway construction. The coefficient associated with log distance to the 1962 railway decreases further by 40%. Railway lines that were constructed earlier did not pass by more prosperous prefectures. Coefficient associated with the log distance to the 1980 railway is also small and not statistically significant, confirming that overall the route of the railways is not endogenously chosen.

Columns 3 and 4 report results using log population density in 1964 as the outcome variable. The coefficients associated with log distance to the 1962 railway are all small, statistically insignificant, and in Columns 4 even has the "wrong" sign. Columns 5 and 6 show that the same conclusion holds for the 1936 industrial employment share.[39]

One remaining concern with including log distance to the 1980 railway as a control is that part

[37]For example, a railway line that would connect the Sichuan Basin to eastern China (the *chuan-han* railway) was planned and partially constructed since the 1910s. Due to a small segment near the border between Sichuan and Hubei which is extremely difficult to construct, the line was not completed until 2009, almost a hundred years behind schedule.

[38]Much of the technology improvement in railway transportation during that period was in locomotives, which are easily deployed on all segments of the railway. The electrification of the railways, which involves upgrading the tracks, started in China in the 1990s.

[39]The vast majority of the prefectures in our sample had no industrial presence in 1936. The relatively large and imprecise estimate in Column 6 may reflect the limited variation in the outcome variable.

of the 1980 railway was constructed after the initiation of the TF. So it could be an outcome of the TF. To the extent that log distance to 1980 railway affects the outcome, including it as a control introduces bias (Rosenbaum, 1984; Deuchert and Huber, 2017). In the Appendix we test directly whether the TF investment causes subsequent railway constructions and find it does not.

### 4.4.2 IV Results

Table 7 reports the results from 2SLS estimations of Equation 8. The Kleibergen-Paap F-statistic of the first stage regression is 14, which passes the rule-of-thumb threshold for strong first stage and is close to the Stock-Yogo critical value for 10% of maximal IV bias (16.4).[40] The coefficients associated with the TF investment are between 30-50% larger in 2SLS estimates than those in OLS estimates reported in Table 3. The It suggests that, if anything, the remaining omitted variables in the OLS biases the results downward. The differences are not statistically significant though, with the 90% confidence intervals of the two estimates overlapping substantially with each other. We perform additional robustness tests of IV regressions in Appendix Table D and find results insensitive to what control variables to include.[41] Based on the results in Tables 3 and 7, we conclude that both identification strategies are likely valid.

## 4.5 Firm Efficiency and Worker Wages

We estimate the effects of the TF investment on manufacturing firms' TFP and workers' wages. We estimate firm-level TFP using the 2004 Annual Manufacturing Firm Survey (AMFS), which covers all state-owned firms and non-state firms with annual sale above 5 million *yuan*, and accounts for over 80% of the total industrial output.[42] We run the following regression:

$$TFP_{fji} = s_p + \lambda_j + \beta TFInv_{i,85} + \mathbf{Z}_i \cdot \gamma + \varepsilon_{fji}, \tag{9}$$

where $TFP_{fji}$ is log TFP for firm $f$ in industry $j$ in prefecture $i$; $\lambda_j$ is a set of industry dummies. Each firm is weighted by its employment share of all firms in the prefecture that are included in the sample, so all prefectures have the same weight in the regression. $\beta$ can be interpreted as

[40] The only exception is Column 5, where we instrument for both TF investment and its intreaction with the state-share index (using both log distance to the 1962 railway and its interaction with the state-share index as instruments). The coefficients are less precisely estimated and the magnitudes are larger, although the results are still qualitatively similar.

[41] In Appendix Table D, Column 1 replicates the results in Table 7 Column 1, Column 2 takes out the site-selection criteria. Column 3 takes out the log distance to the 1980 railway, and Column 4 includes only province fixed effects as controls. The estimated coefficients are all similar.

[42] The TFP measure here is the Solow residual from regressing log value added on labor and capital inputs. Given the large differences in production technologies across industries, we focus on a relative measure of TFP within industries. We do this by separately calculating the Solow residuals of firms within the same 2-digit industry and calculating a relative measure within each industry. Appendix A describes the procedure in detail.

the effect of the TF investment on the weighted average efficiency of firms in the prefecture. The standard errors are clustered at the prefecture level.

Table 8 Column 1 reports the effect on the prefecture-average TFP of all manufacturing firms. The coefficient implies that a 1 p.p. increase in the TF investment increases local manufacturing firms' TFP by about 11 log points. Column 2 shows that the same treatment increases the average non-state firm's TFP by 10 log points. These findings are consistent with the existence of local agglomeration economics.

The next two columns investigate the effects on wages. The wage data is individual worker's monthly income reported in the 2005 Mini Population Census. Each workers is weighted by the inverse of the number of sample workers in the prefecture to ensure that each prefecture is equally weighted. Column 3 shows that a 1 p.p. increase in the TF employment share increases the average manufacturing wage by about 3 log points. The large effect on manufacturing employment and firm efficiency combined with the small effect on manufacturing wages suggests that the labor supply in the manufacturing sector is relatively elastic, a phenomenon common at the early stages of structural transformation (Lewis, 1954).

Given that agricultural land is fixed, pulling more agricultural workers into the manufacturing sector would also increase wage in the agricultural sector. Column 4 shows suggestive evidence of this. TF investment had an indirect effect on the agricultural wages, although the estimate effect is not statistically significant.

## 4.6 Inter-Industry Linkages and Heterogeneous Effects

### 4.6.1 Inter-Industry Linkages

With industry-level variation in TF investment across regions, we are able to further explore the channels of the spillover effects, and whether they differ by different industries the TF plants. Understanding these channels is practically relevant because often development policies focuses on fostering specific industries. We estimate different versions of the following specification:

$$y_{ij} = s_p + \lambda_j + \rho \sum_k IndLink_{jk} \cdot TFInv_{ik} + \mathbf{Z}_i \cdot \gamma + \varepsilon_{ij}, \tag{10}$$

$y_{ij}$ is the outcome of firms in industry $j$ in prefecture $i$. There are 19 2-digit manufacturing industries. $IndLink_{jk}$ is some measure of the relation between industry $j$ and $k$. $TFInv_{ik}$ is the TF investment in industry $k$ in prefecture $i$. Other variables are defined in the same way as before. Because our instrumental variable only exploits variation across prefectures, we estimate Equation 10 using OLS. Coefficient $\rho$ tells us how TF investment affect industry-specific outcomes via inter-industry linkages.

Recent studies in urban economics identify a few channels for positive spillovers among local firms, which include knowledge spillovers, labor sharing and input sharing (Rosenthal and Strange, 2004). All these channels are likely stronger for firms within the same industry. On the other hand, too many firms in the same industry may intensify competition for specialized labor and material inputs. We first investigate the spillover effects within the same 2-digit industry. Column 1 in Table 9 Panel A shows that when the TF investment in an industry increases by 1 p.p., the non-state manufacturing employment share in the same 2-digit industry increases by 0.3 p.p. This number is around 20% of the baseline OLS estimate reported in the first column of Table 3. Recall that there are a total of 19 2-digit industries, so the within-industry spillover accounts for a disproportionately large share of the overall spillover effect, and dominates any negative effect from market competition.

More generally, following the literature in urban economics, we use three broad sets of measures that capture the different channels of the local spillover effects and agglomeration economics: labor market pooling, technological spillover, and intermediate input linkages. To avoid endogeneity issue, we use the data from the U.S., which captures the "fundamental" aspects of industry relations that are exogenous to the Chinese economy. We use the data from Greenstone et al. (2010), in which labor market pooling is measured as worker flows between industries (CPS worker transitions), technological spillovers are measured using patent citation patterns and the input-output table for R&D expenditures (technology input/output), and intermediate input linkages are captured using the input-output table.[43] All these measures are standardized across industries such that the coefficients associated with different measures are largely comparable. The data indicate that all inter-industrial linkages play a role. Columns 2 to 7 show that all these measures of industrial linkages are positively correlated with employment size and most of them are statistically significant.

Spillover effects via inter-industry linkages also matter for firm efficiency. Panel B shows that investment in an industry has an economically large impact on the average TFP of non-state firms in the same industry, although the coefficient is not precisely estimated. The TF investment also improves the efficiency of the non-state firms when those firms are in industries more closely related to the industry of investment.

#### 4.6.2 Heterogeneous Effects by Industry

Many developing countries adopt policies that subsidize modern and sophisticated industries in the hope that these industries can generate strong positive externalities to the economy. Standard trade models, on the other hand, predict that investment in industries that suit the country's comparative advantage is more sensible (Rodriguez-Clare, 2007). For developing countries, these industries usually include those require less sophisticated technologies and are labor intensive.

[43]Detailed definitions of these measures are listed in Appendix Table E

With variation in the industry of TF investment, we explore whether investment in modern industries or more traditional industries have a bigger impact on the local economy. We split the industries into two categories: heavy (or capital-intensive) and light (labor intensive). Light industries basically include textile and apparel, food and drink, and heavy industries include those produce machinery, metal and chemical products, electric and electronic equipments. Till now, China has a comparative advantage in labor-intensive light industries.

We examine whether investment in the two types of industries generate different spillover effects. Somewhat to our surprise, Panel A of Table 10 shows that light and heavy industries have similar spillover effects on the overall manufacturing employment. Thus it does not seem that investing in sectors with comparative advantage generates larger returns.

The seemingly homogeneous spillover effects from heavy and light industries may mask important differences in the channel of these spillovers. Heavy industries may generate strong agglomeration economics in the sense that they generate strong knowledge spillovers and create input-output linkages that benefit local firms in other industries. In contrast, light industries may exhibit strong localization economics, where the spillover effects are concentrated within the same industry.

Panels B and C test these potential differences by estimating the relative strength of within-industry and cross-industry spillovers separately for light and heavy industries. Column 1 of Panel B shows that as the TF investment in the prefecture increases by 1 p.p., and the TF investment in all 19 industries increase by 0.053 p.p., the 2004 non-state employment share from a typical light industry increases by 0.03 p.p. (relative to the sample average of 0.156). Column 2 shows that as the TF investment in the same 2-digit industry increases by 0.053 p.p., the 2004 non-state employment share from that industry increases by 0.03 p.p.. In other words, almost the entirety of the effect of the TF investment can be accounted for by within-industry spillovers. In Contrast, Panel C shows that within-industry spillover only accounts for less than 40% of the overall effect. Columns 3 to 8 investigate the effects of inter-industry spillovers separately for light and heavy industries, there we see larger effects for heavy industries.

### 4.7 Inter-prefecture Migration

We have shown that the TF investment increased the local manufacturing activity, but it does not automatically prove that it benefited the local residents. In particular, the increased manufacturing opportunities in the prefecture may attract more inward migration, squeezing out potential benefits to local residents. Recent studies in urban economics show that inter-regional mobility indeed play an important role in the effectiveness of location-based policies (Kline and Moretti, 2014a; Gottlieb and Glaeser, 2008). Using individual-level data from the 2005 Mini Population Census, we directly test whether the TF investment results in a larger inward migration.

We define migration based on where one's *hukou* is registered. China maintains a strict *hukou* system, which by-and-large ties each person to his birthplace. We determine a worker as an inward migrant if he works in the current prefecture but his *hukou* is registered in another prefecture. In 2005, the average prefecture in the sample had about 1.1% of its workers whose *hukou* was registered in another prefecture. Column 1 in Table 11 shows that the TF investment has essentially no effect on the share of workers who are inward migrants.

If the increase in manufacturing workers are not due to increased inward migration, then it must represent the structural transformation of the local economy: local agricultural workers are transformed into manufacturing workers. Thanks to the special features of the *hukou* system, we can direct test this hypothesis. There are two types of *hukou*: rural and urban. A rural *hukou* usually indicates that the person was born in a rural community and is historically tied to agriculture. When the local economy industrializes, some were able to change their rural *hukou* into urban ones if they find a job in the urban sector. However, some work in the manufacturing sector yet remain a rural *hukou*. Many of these workers are employed in non-state firms and township and village enterprises (TVEs) which do not sponsor urban *hukou*. We focus on workers who retained a rural *hukou* in 2005 and investigate whether the TF investment increases the fraction of manufacturing workers among those people. Column 2 shows that increasing the TF employment share by 1 p.p. increases the manufacturing share by 0.23 p.p.. The effect is significant at the10% level; and with about 2% of those with rural *hukou* work in the manufacturing sector in the average sample prefecture, the coefficient is also economically meaningful.[44]

### 4.8 Discussion of the Empirical Findings

To summarize our empirical results, we find that the TF investment, two decades after its cessation, increases the size and productivity of the local non-state manufacturing sector, and leads more local workers from the agricultural sector to reallocate to the manufacturing sector. These results suggest that, in the early stage of the structural transformation, agglomeration forces in the manufacturing sector is an important force for the long-run development of the local economy. Although within-industry spillover accounts for a substantial share of the overall effect, we show that cross-industry spillovers through various economic linkages play an important role. These inter-industry linkages play a different role for different industries: while labor-intensive light industries benefit mostly from the localization of single-industry economic clusters, capital and knowledge intensive industries benefit from the agglomeration of firms in many related industries.

It is instructive to compare our results to the large body of literature that empirically estimates the magnitude of agglomeration economics. In a meta-analysis, Melo et al. (2009) find that the

[44]Note that this estimate is likely to be a drastic under-estimate for the overall agriculture-to-manufacturing transformation among local residents because many who were born rural obtained an urban *hukou* later in life.

elasticity of average wage relative to employment density is between 0.04 and 0.07. Our estimate in Table 8 Column 3 translates into a wage elasticity with respect to the share of manufacturing employment of about 0.04, which is on the lower end of existing estimates.[45]

Our contribution to this literature is two folds. First, while most existing studies focus on the contemporaneous relationship between employment density and wage, this paper investigates the impacts over a period of two decades. Second, we exploit exogenous variation from the TF in estimating the spillovers, which is related to a small group of papers in using natural experiment to estimate agglomeration (see, for example, Greenstone et al., 2010).

## 5 Aggregate Implications of the TF Investment

Having found that the TF investment has positive effects on the local manufacturing sector by stimulating local structural transformation, we proceed to discuss its implication for aggregate efficiency.

Because the manufacturing sector has a higher labor productivity than the agricultural sector, by reallocating workers from agriculture to manufacturing, the TF investment increased the output of the local economy. However, this does not necessarily imply that the TF is efficiency-improving. The TF was effectively a regional transfer program, which diverted investment to the TF region at the cost of the rest of the country. Indeed, any local gains might be offset by the counterfactual losses of output in other regions.[46] In this section, we discuss the aggregate effect of the TF. A direct evaluation of the TF on aggregate efficiency involves in comparing the causal effect of the TF investment and the counterfactual causal effect if the investment is made in other parts of the country. Our identification strategy and empirical setting does not allow us to estimate the latter. Instead, we build a simple model to identify the empirically-testable necessary conditions for the TF to be efficiency-improving in the aggregate. To preview the results, we find that such conditions are not met, hence we conclude the TF reduces aggregate efficiency.

[45] The sample average of TF investment is about 1.14 percent of total employment. A 1 p.p. increase in that share translates into 88 percent increase from the mean (1/1.14) and is associated with 3.4 percent increase in average manufacturing wage, which corresponds to an elasticity between 0.039 (3.4/88).

[46] This is related to the point about the aggregate effect of place-based policies in the context with free mobility (Kline and Moretti, 2013; Gottlieb and Glaeser, 2008). The main message in that context is that agglomeration effect in one region from a place-based policy comes at the expense of reduced agglomeration in other regions because of the reallocation of manufacturing activities across space. In our context, because of migration frictions, the reallocation should be best thought of as between agricultural and manufacturing sectors *within* the local region. Yet the same logic applies: absent of the TF, the investment could have gone to other potentially more productive regions, so to investigate the aggregate effect of the TF investment, we need to take into account this "opportunity cost".

### 5.1 The Model

#### 5.1.1 Environment

Our model is at the prefecture level. Each prefecture is a small open economy that takes world prices as given. The representative consumer in a prefecture enjoys agricultural and manufacturing outputs according to the following utility function:

$$U = C_A^{\beta} C_M^{1-\beta},$$

where $C_A$ is the agricultural output and $C_M$ is the composite manufacturing output.

Each prefecture is endowed with a number of workers, denoted $L$. To capture the constraint in worker mobility in China, we assume workers are immobile across prefecture. In order to speak to the gains from structural transformation, we assume that all workers originally work in the agricultural (rural) sector, and each needs to pay a $\frac{\tau-1}{\tau}$ ($\tau > 1$) fraction of urban income to switch to the manufacturing (urban) sector.[47] In the context of China, due to the *hukou* restrictions, many rural migrants have no access to local public goods, such as education, social insurance, and medical care. This migration cost captures that rural migrants have to pay a higher price to access to these goods. Under this assumption, there will be a wage gap between the manufacturing and the agricultural sector:

$$\tau w^A = w^M. \tag{11}$$

#### 5.1.2 Production and Technological Spillovers

The agricultural output is produced with labor (denoted $L_A$) and a constant supply of land, normalized to 1:

$$Y_A = L_A^{\alpha}.$$

$\alpha$ is the labor share in agricultural production and is assumed to be a constant throughout our analysis. The composite manufacturing output is produced using intermediate manufacturing varieties, denoted $y(i)$:

$$Y_M = [\int_0^N y(i)^{\frac{\sigma-1}{\sigma}} di]^{\frac{\sigma}{\sigma-1}},$$

where $N$ is the number of varieties produced by firms in the prefecture, who compete monopolistically against one another. To produce $y$ units of variety $i$, $\frac{y(i)}{T}$ units of labor is needed, that is:

$$y(i) = Tl(i),$$

[47] See Fan (2015) for an estimate of this cost in a structural model.

in which $l(i)$ is labor input, and $T$ is the manufacturing productivity in the prefecture. The agricultural and composite manufacturing output are freely tradable, with their prices given by the world prices, $P_A^*$ and $P_M^*$, respectively. The intermediate manufacturing goods are non-tradable. Although somewhat nonstandard, this assumption simplifies the analysis and highlights the key channel.

There are two types of intermediate good producers in the manufacturing sector. The first type is local private firms started by local workers. Entrants need to pay a fixed setup cost, $f$, in labor, before they can start producing. The second type is the state-sponsored firms. The government has a fixed number of firms and decides where to allocate them. The state firms exist prior to all the private firms. Their fixed setup cost has already been paid, otherwise they behave exactly as private firms in production and pricing.

The state firms generate spillovers to local private firms. We capture the spillover effect by allowing the local efficiency of production, $T$, to be increasing in the number of state firms assigned to the local economy:

$$\log(T) = \log(T_0) + f(T_0, N^{ini}), \tag{12}$$

where $N^{ini}$ is the number of state firms in a prefecture, $T_0$ is the prefecture's innate productivity. The TF can be thought of as reallocating some $N^{ini}$ from places with higher $T_0$ and $N^{ini}$ to the TF region which had a low innate productivity (due to difficult geography) and little initial government investment. $f$ captures agglomeration economics, $\partial f/\partial N^{ini} > 0$. The TF could be efficiency improving in the aggregate if $\partial^2 f/\partial T_0 \partial N^{ini} < 0$ or $\partial^2 f/\partial {T_0}^2 < 0$, in other words, if the spillover effect is stronger in less productive locations or in places with less initial investment.

#### 5.1.3 Equilibrium

We consider an equilibrium without perfect specialization, so both manufacturing and agricultural sector are present. We further assume the equilibrium number of firms active in a prefecture is larger than $N^{ini}$, so there will be private entrants.

Cost minimization of the agricultural producer implies that:

$$w^A = \alpha P_A L_A^{\alpha-1}, \tag{13}$$

which is also the labor demand curve in the agricultural sector. The cost minimization problem of the final manufacturing good producer gives the familiar constant-elasticity demand for intermediate varieties:

$$y(i) = \left(\frac{p(i)}{P_M^*}\right)^{-\sigma} Y_M,$$

where $p(i)$ is the price for individual variety $i$. The monopolistic competition assumption implies a fixed markup:

$$p(i) = \frac{\sigma}{\sigma - 1}\frac{w^M}{T}.$$

The cost for the composite manufacturing good is given by:

$$P_M = [\int_0^N p(i)^{1-\sigma} di]^{\frac{1}{1-\sigma}} = \frac{\sigma}{\sigma - 1} N^{\frac{1}{1-\sigma}} \frac{w^M}{T}$$

In equilibrium $P_M = P_M^*$. This implies the following relationship between the wage and the number of manufacturing varieties:

$$w^M = \frac{\sigma - 1}{\sigma} T \frac{P_M^*}{N^{\frac{1}{1-\sigma}}}. \tag{14}$$

Since intermediate input producers charge a fixed markup, their profits are a fixed fraction of their total variable labor cost. Letting $q(i)$ be the number of varieties produced by firm $i$, $q(i)w^M$ is then the total variable labor cost. The zero profit condition for private entrants is:

$$\frac{q(i)w^M}{\sigma - 1} = f w^M,$$

which implies that $q(i) = (\sigma - 1)f$. The total demand for workers in the manufacturing sector consists of two parts: the workers hired by state and private firms for production, and the workers hired by private firms to pay for the entry cost. The labor market clearing condition is:

$$\underbrace{f(\sigma - 1) * N}_{\text{Production Cost}} + \underbrace{(N - N^{ini})f}_{\text{Fixed Entry Cost}} = L_M = L - L_A,$$

where $L_M$ is the total employment in manufacturing. Solving for the equilibrium number of firms, and combine it with Equations 11 and 14, we obtain the following equation:

$$\alpha \tau P_A L_A^{\alpha - 1} = \frac{\sigma - 1}{\sigma} T(N^{ini}) P_M^* (\frac{L_M + N^{ini} f}{f\sigma})^{\frac{1}{\sigma - 1}}, \tag{15}$$

in which $T$ is written as a function of $N^{ini}$ to highlight the spillover effect.

Equations 15 determines the equilibrium wage and sectoral composition of the local economy. Figure 7 can be used to analyze how the economy changes with exogenous parameters. The solid curve in the figure depicts the left hand side of the equation. The fixed land supply implies that, as agricultural employment approaches zero, the marginal product of labor approaches infinity. The dotted line is the right hand side of the equation, which indicates that the manufacturing wage increases with $L_M$. This reflects the increasing return to scale in the manufacturing sector. It is straightforward to verify that when $\sigma > 2$,[48] The solid curve is convex while the dotted curve is concave, so the two curves have at most two intersections. One of these two is unstable, hence there will be a unique stable equilibrium.

The model suggests that the state firms affect local economies through two channels. First, they directly contribute to the structural transformation by recruiting people from the agricultural sector. Second, it increases local manufacturing productivity via agglomeration economics, which further encourages private entry. In Figure 7, An increase in $N^{ini}$ leads to an upward shift of the dotted line, resulting in increases in wage and manufacturing employment share. Both predictions are consistent with our empirical findings.

## 5.2 Aggregate Efficiency of the TF

To shed light on the aggregate effect of the TF, consider two prefectures, one inside the TF region (denoted as TF) and the other outside (denoted as NTF). Due to its access to the market and better geography, NTF has a higher innate productivity, $T_{TF,0} < T_{NTF,0}$. Consistent with the historical background, we assume that all state firms are in NTF, that is,, $N^{ini}_{TF} < N^{ini}_{NTF}$. We view the TF as reallocating a small number of plants, $\delta$, from NTF to TF.

Based on the model, we can write the per-capita output in prefecture $i, i \in \{TF, NTF\}$ as

$$y_i = \underbrace{\frac{w_i^A l_i^A}{\alpha}}_{\text{Agricultural income}} + \underbrace{w_i^M l_i^M}_{\text{Non-agricultural labor income}} + \underbrace{\frac{w_i^M N^{ini} f}{L_i}}_{\text{TF firm profits}}, \tag{16}$$

where $l_i^s$, $s \in \{A, M\}$ is the employment *share* in sector $s$. Equation 16 simply states that the average income is the weighted sum of agricultural and manufacturing wages, plus the per-capita profit from the state firms.[49]

Given Equation 16, the effect of a marginal increase of the investment, $\delta$, on per-capita income can be decomposed into three channels—wage, reallocation, and profit—as follows:

$$\begin{aligned}\frac{\partial \log(y_i)}{\partial \delta} &= \underbrace{l_i^A \frac{w_i^A}{\alpha y_i} \frac{\partial \log(w_i^A)}{\partial \delta} + l_i^N \frac{w_i^N}{y_i} \frac{\partial \log(w_i^N)}{\partial \delta} + \frac{f w_i^M}{L_i y_i} N_i^{ini} \frac{\partial log(w_i^M)}{\partial \delta}}_{\text{wage channel}} \\ &+ \underbrace{\frac{(w_i^M - \frac{w_i^A}{\alpha})}{y_i} \frac{\partial l_i^N}{\partial \delta}}_{\text{reallocation channel}} + \underbrace{\frac{f w_i^M}{L_i y_i}}_{\text{profit channel}}\end{aligned} \tag{17}$$

The wage channel consists of three components. The first two components capture the effect of the

[48]Empirical studies tend to find $\sigma$ in the range of 5-10.

[49]The free entry condition implies that the private firms make zero profit. The migration cost the rural workers have to pay can be seen as a transfer to the local government, so it does not show up in the welfare accounting.

investment through raising agricultural and manufacturing wages directly. The third component captures the indirect effect on the state firms' profit through wage—because profit is proportional to the manufacturing wage, when local manufacturing wage increases, the state firms also make more profit. The reallocation channel captures the effect on income by reallocating workers from agriculture to manufacturing. The strength of this component depends on two factors: the productivity gap between the two sectors, which is equal to $w_i^M(1-\frac{1}{\tau\alpha})$, and the effect of the investment on reallocation, $\frac{\partial l_i^M}{\partial \delta}$. Finally, the profit channel simply captures the profit from the marginal firm being reallocated. This channel is more important when manufacturing wage is higher relative to the average income.

From Equation 17, the aggregate effect of reallocating one marginal plant from NTF to TF is given by:

$$\begin{aligned}
\frac{\partial y_{total}}{\partial \delta} &= y_{TF}\frac{\partial \log(y_{TF})}{\partial \delta} - y_{NTF}\frac{\partial \log(y_{NTF})}{\partial \delta} \\
&= \underbrace{[\frac{f w_{TF}^M}{L_{TF}} - \frac{f w_{NTF}^M}{L_{NTF}}]}_{\text{Profit shifting}} + \underbrace{[(1-\frac{1}{\alpha\tau})w_{TF}^N\frac{\partial l_{TF}^M}{\partial \delta} - (1-\frac{1}{\alpha\tau})w_{NTF}^N\frac{\partial l_{NTF}^M}{\partial \delta}]}_{\text{Net reallocation effect}} \\
&\quad + \underbrace{[w_{TF}^M(l_{TF}^M + \frac{l_{TF}^A}{\tau\alpha} + \frac{f N_{TF}^{ini}}{L_{TF}})\frac{\partial \log(w_{TF}^M)}{\partial \delta} - w_{NTF}^M(l_{NTF}^M + \frac{l_{NTF}^A}{\tau\alpha} + \frac{f N_{NTF}^{ini}}{L_{NTF}})\frac{\partial \log(w_{NTF}^M)}{\partial \delta}]}_{\text{Wage effect}}.
\end{aligned} \tag{18}$$

The second equality in the expression follows from migration decision condition: $w_i^A = \frac{w_i^M}{\tau}$. We assume $L_{TF} = L_{NTF}$. As Equation 18 makes it clear, whether the TF leads to aggregate efficiency gains boils down to whether the sum of the three terms are positive. In the following, we empirically determine the signs of each of these three terms.

#### 5.2.1 The Profit-Shifting Channel

The profit-shifting effect depends only on which prefecture has a higher wage. Intuitively, the profit of a plant depends on local productivity. Plants in regions with higher a labor productivity (hence a higher wage) will make more profit. As shown in Table 12, manufacturing productivity and wages are both higher outside of the TF region. The difference in average efficiency range between 15% to 30%. So by investing in a less productive region, the TF reduces profits to the state firms and generates a first order welfare loss.

#### 5.2.2 The Reallocation Channel

We now turn to the reallocation channel. According to Equation 18, two terms are important for its sign and magnitude. First, the agricultural-manufacturing wage gap, $w_i^M(1-\frac{1}{\tau\alpha})$. This term captures the increase in average income by transforming an additional worker from the agricultural sector to the manufacturing sector. Table 12 shows that the relative sectoral wage gap is similar in both TF and NTF (2.9 and 2.7), while NTF overall has higher wages, reallocating one worker from agriculture to manufacturing generates a larger gain in the non-TF region (563 v.s. 453).

The second term important for the reallocation effect is the marginal effect of investment on reallocation of workers across sectors, $\frac{\partial l_i^M}{\partial \delta}$. One rationale for transferring resources to less developed regions is that there might be some sort of poverty trap at an early stage of development. For example, at the subsistence level, workers may lack the necessary saving to invest in the manufacturing sector. They may also be constrained in skills and knowledge required to run a manufacturing firm. Temporary help in the manufacturing sector may help overcome these constraints and jump start a virtuous cycle of sustained industrialization. In such scenarios, marginal investment in an initially less-developed region could lead to a larger sectoral reallocation of workers.

We test this hypothesis by exploiting variation in levels of initial economic development *within* the TF region. We divide our sample into halves according to the prefecture's 1964 urban rate.[50] Figure 5 shows the relationship between the TF investment and 2004 non-state manufacturing employment share (both are residuals from first regressing on a set of covariates as in Equation 1) for both groups. The blue dots represent sample prefectures with a 1964 urban rate below the median while the red crosses represent those above. First notice that dots and crosses are similarly distributed along the horizontal axis: TF investment is overall uncorrelated with initial economic development. The two groups exhibit almost identical marginal effect of TF investment on non-state manufacturing employment.[51]

One may suspect that due to the existence of frictions in initializing industrialization, the effect of investment could be non-linear: only large-enough investment could pull the economy out of the poverty trap. In Figure 5 we fit a flexible local weighted smoothing for both groups and find no evidence, at least within the range of the TF investment, that the marginal effect is particularly big for large investment. Taken together, the evidence suggests that the spillover effect is not stronger in initially poorer regions, that is, $\frac{\partial l_{TF}^M}{\partial \delta} = \frac{\partial l_{NTF}^M}{\partial \delta}$.[52]

[50]The median 1964 urban rate among sample prefectures is 6.5%. The average urban rate for prefectures above that median is 9.1%, while that for prefectures below that median is 5.1%.

[51]The slope for the linear fit for prefectures above the median is 1.68 (0.27), for those below the median is 1.58 (0.42). Estimating the effects using the 2SLS specification as in Equation 8, the slopes are 1.76 (0.41) and 1.63 (0.63), respectively.

[52]Of course, there might be a concern whether extrapolating from heterogenous results within the TF region to a comparison between TF and non-TF regions is valid. For example, it is possible that the average non-TF prefecture is already so large that the congestion effect from additional investment dominates agglomeration effect, then reallocating resources to the less productive TF region could still improve the aggregate efficiency. In the Appendix we explain this possibility in more detail, and present evidence that this situation is not supported by the data.

### 5.2.3 The Wage Effect

Finally, the wage effect captures a general equilibrium response: by increasing the manufacturing labor demand, the government's investment in the local manufacturing sector increases local wages. Empirically, estimates reported in Table 8 suggest that a 1 p.p. increase in the TF employment share raises the local manufacturing wage by about 3%.

But in order to determined whether the TF improves the aggregate efficiency via the wage channel, we need to compare $\frac{\partial \log w_{TF}^M}{\partial \delta}$ and $\frac{\partial \log w_{NTF}^M}{\partial \delta}$. We do not have a causal estimate of the wage effect outside of the TF region, and therefore look within the TF region to see if the wage effect differs by prefectures with different levels of initial development.

Similar to our approach in the previous subsection, we split the TF prefectures by the the 1964 urban rate and separately estimate the effects of the TF investment on local manufacturing wages in both groups. Figure 6 shows that the two fitted lines almost perfectly overlap with each other, indicating no evidence of larger wage effect in initially less developed regions.[53]

We now turn to the term $(l_i^M + \frac{l_i^A}{\tau\alpha} + \frac{fN_i^{ini}}{L_i})$. Since the TF region had no manufacturing plants in the beginning, and still had fewer plants than the non-TF region by the end of the TF, $\frac{fN_{NTF}^{ini}}{L_{NTF}} > \frac{fN_{TF}^{ini}}{L_{TF}} \approx 0$. Moreover, since the non-TF region were more industrialized, as long as $\tau > \frac{1}{\alpha}$,[54] $l_{TF}^M + \frac{l_{TF}^A}{\alpha\tau} < l_{NTF}^M + \frac{l_{NTF}^A}{\alpha\tau}$. Therefore, $(l_i^M + \frac{l_i^A}{\tau\alpha} + \frac{fN_i^{ini}}{L_i})$ is also larger in the non-TF region. This, together with the results that $w_{TF}^M < w_{NTF}^M$, and $\frac{\log(w)_{TF}^M}{\partial \delta} = \frac{\log(w)_{NTF}^M}{\partial \delta}$, implies that the wage effect is negative.

## 5.3 Discussion

To summarize, this section develops a simple model and uses it to evaluate the aggregate welfare effects of the TF. By reallocating plants to an under-developed region, the TF benefits local workers in that area, but these benefits are likely smaller than the losses in the rest of the country. An important finding underlying this aggregate efficiency loss is the lack of heterogeneous spillover effect, either by the initial development level of the local economy or by the size of the investment—The TF investment is not particularly more effective in less developed prefectures or only when the magnitude of the investment is sufficiently large.

This result is related to a large literature testing the existence of poverty traps. Most of those

[53]One might be concerned that the lack of accuracy in the wage effect estimation might be the reason that we do not find larger effect in poorer regions. An alternative way of getting at the wage effect is to rely on the structural of the model and exploit the relationship between the wage effect and the employment effect. Notice $log(w_i^A) = log(w_i^M) - log(\tau)$, and $\frac{\partial \log w_i^A}{\partial \delta} = \frac{\partial \log w_i^A}{\partial \log L_i^A}\frac{\partial \log L_i^A}{\partial \delta} = (\alpha - 1)\frac{\partial l_i^A}{\partial \delta}\frac{1}{l_i^A}$, in which the second equality follows from Equation 13. Our employment effect estimate suggests $\frac{\partial l_{TF}^A}{\delta} = \frac{\partial l_{TF}^A}{\delta}$. Therefore if any, the wage effect should be stronger in prefectures with a lower share of employment in agriculture, $l_i^A$, namely the non-TF region.

[54]In the data, from the rural-urban wage gap, $\tau \approx 3$. From input-output table, labor compensations account for 81% of agricultural labor value added, so $\alpha = 0.81$.

studies use country-level data (see Easterly, 2006 for a recent example). Exploiting spatial variation within a country, we do not find evidence for some of the key mechanisms underlying the existence of poverty traps. Our finding is consistent with Kline and Moretti (2014a). Our findings generalize their results in a setting in which regions are at a much earlier stage of economic development, with presumably larger distortions in the capital and labor markets.

# 6 Conclusions

The Third Front provides a unique setting for estimating the long-run effects of government investment in the manufacturing sector in a largely agrarian economy. Focusing on regional economies, our results show that such policies are effective in stimulating structural transformation and benefit local economies. We show that local agglomeration economics plays an important role. By exploiting inter-industry relations, the government investment may be able to focus on specific industries in order to maximize positive externality. We interpret our finding as a cautious addition to the debate on the effectiveness of industrial policies.

Despite its substantial positive impact on the local economy, by reallocating scarce resources to less productive regions, the TF likely results in a substantial efficiency loss at the aggregate level. This is consistent with volumes of studies evaluating location-based policies. Aiming at helping less-developed regions, such policies often results in aggregate efficient loss. Of course, the TF is effective in reducing regional inequality. China's restrictive cross-region migration helps ensure that local residents benefit from improved regional economic development.

This paper contributes to the discussion about the importance of local agglomeration and fundamental geographical characteristics in economic development (Gallup et al., 1999; Bleakley and Lin, 2012). Our findings show that, despite manufacturing agglomeration, geography and geography-related factors, such as transportation, market access, etc., remain important for economic performance.

The unusual historical background and peculiar policies adopted in the construction of the Third Front generate arguably exogenous variation, which gives us a rare opportunity to answer an important research question, yet they also raise the valid concern whether our results are relevant for similar policies in normal circumstances. Indeed, one would suspect that a regional development policy of such kind could be much less wasteful and more effective than the TF. With this caveat in mind, we would like to point out that the empirical evidence for the aggregate efficiency exploits variation within the specific region. In addition, many regional development policies also target under-developed regions with innate low productivity.

## Appendix A Data Sources and Variables

*List of Large and Medium Manufacturing Plants in the 1985 Industrial Census*. It provides basic information for 6,878 key manufacturing plants. For each firm, the list reports its name, detailed address, industry (divided into 39 industries roughly corresponding to 2-digit SIC codes.), sizes of employment, capital and output, year of first production, and the names of its key products. The list also includes 710 plants in the mining, power generating and transmission, and water production sectors. The list does not include weaponry plants directly controlled by the military. The total 7,588 plants accounted for over 70% of the nationwide industrial output in 1985.

*County-level tabulations of population censuses in 1964, 1982, and 2000* provides county-level demographic and economic characteristics. Information included in differ by census. The 1964 Census provides a snapshot of initial economic conditions before the TF. We construct the share of urban population (by *hukou*) in 1964 as the key measure for initial economic conditions. County boundaries in China have been constantly changing. It does not impose much problem for us because in most cases the boundaries for prefectures have not changed. We nevertheless create variables for counties with consistent boundaries. GIS maps of county boundaries are available for each census year. We overlap these maps and construct variables for consistent counties using the 1982 boundaries. The consistent counties are constructed using areas of intersected segments as weights. For a variable $x$ that is "share" in nature (such as share of urban population, share of employment in manufacturing, etc), for a county in 1982, if $\alpha$ share of it belonged to county $A$ in 1964 while $1-\alpha$ share of it belonged to county $B$, the county's $x$ in 1964 would be $\alpha \cdot x_{A,1964} + (1-\alpha) \cdot x_{B,1964}$, where $x_{A,1964}$ is the value of variable $x$ in county $A$ in 1964. For a variable $y$ that is "count" in nature (such as the number of manufacturing workers), for a county in 1982, if its area is composed of $\beta_A$ share of the 1964 county $A$ and $\beta_B$ share of the 1964 county $B$, then the county's value in variable $y$ in 1964 is $\beta_A \cdot y_{A,1964} + \beta_B \cdot y_{B,1964}$. This procedure assumes that population and economic activity are evenly distributed geographically within a county.

*The individual-level sample of the 2005 Mini Population Census* is a 1-in-5 sample of the 1% national survey of individuals. It provides detailed information on individual's demographic and economic conditions. We extract migration and wage information from this data. We call a worker is a migrant if her *hukou* is registered in a different prefecture. The sample reports monthly income from the previous month. For rural households whose main income is from agriculture, the monthly income is calculated as last year's income divided by 12 months and the number of laborers in the household. The data also report worker's occupation and industry, although we do not know whether the worker works in the state sector or the non-state sector.

*The 1936 Industrial Survey* is, to the best of our knowledge, the first nationwide survey of the industrial sector. We digitize the firm-level information and calculate each prefecture's 1936 industrial employment as a share of 1964 total employment. It provides a measure of industrial sector development prior to the TF.

*2004 Economic Census* provides basic firm-level information. We have the universe of all manufacturing firms. For each firm, we know it address (then geocoded to the county level), year of opening, 4-digit industry, ownership type, employment, and registered asset. The dataset allows us to construct various measures of the size of the manufacturing sector by ownership, size, and year of opening.

*2004 Annual Manufacturing Firm Survey (AMFS)* is a firm-level dataset that includes all state-sector firms and other firms with annual sales more than 5 million *yuan*. These firms account for about 80% of the total manufacturing output. The dataset reports a firm's detailed balance sheet. Most importantly, it reports the firm's value added, which allows us to calculate firm's TFP. Assuming a Cobb-Douglas production function, we first regress log value added on log capital input and log employment. In light of different production technologies in different industries, we also include a full set of 2-digit industry dummies. Firm's TFP is the residual from this equation.

*GIS maps with geographic characteristics* are obtained from the China Historical GIS project.[55] Major geographic characteristics, such as elevation and ruggedness, are derived from the digital elevation model (DEM) map of China.

*GIS maps of railway networks in 1962 and 1980* are from Baum-Snow et. al (2016), which we obtain via the University of Toronto library.

## Appendix B Additional Robustness

One remaining concern with including log distance to the 1980 railway as a control is that part of the 1980 railway was constructed after the initiation of the TF and could be an endogenous outcome. We test this concern specifically.

Table C shows that prefectures that received larger amounts of TF investment were indeed better connected to the railway in 1980. However, once conditioning on the log distance to the 1962 railway, the correlation becomes much smaller in magnitude and statistically insignificant.[56] Column 2 does not address the concern that TF investment could be endogenous (although the endogeneity is likely to bias the coefficient associated with the TF investment downward). Column 3 adds geographic and initial economic conditions as controls. The coefficient associated with the TF investment increases slightly but remains statistically insignificant and economically unimportant.

[55] Url: https://www.fas.harvard.edu/~chgis/data/chgis/v5/

[56] The sample mean of the log distance to the 1980 railways is 3.2 and its stand deviation is 1.4.

## Appendix C Additional Welfare Discussion

We evaluate the reallocation effect using variation *within* the TF region. As discussed at the end of Section 5.2.2, the extrapolation might not be valid. In particular, if the non-TF prefectures are already over-sized in the sense that adding more plants would generate larger congestion costs than welfare gains, then moving some plants to the the less crowded TF region could be welfare improving, even though the TF region is less productive.

To explain this possibility in more detail, consider two counteracting forces. Agglomeration effect makes denser economic activity more attractive while congestion effect makes it less so. When economic density is low, agglomeration effect dominates, adding an additional firm increases the average efficiency; when economic density is too high, congestion effect dominates, adding an additional firm reduces the average efficiency. So economic efficiency as a function of economic density may follow an inverted-U shape.

Panel A of Figure A shows a scenario in which directing resources from a more productive location to a less productive location improves the aggregate efficiency. Suppose there are two regions $A$ and $B$. Firms in $B$ have a higher average efficiency than those in $A$. $A$ is in the upward-sloping portion of the efficiency-density curve while $B$ is in the downward-sloping portion. Moving some firms from $B$ to $A$ would raise efficiency in both places. It is worth noting that a profit-maximizing firm would choose to locate in $B$ because the firm will have a higher efficiency level there. But by doing that, it hurts efficiency of all other firms in $B$. Due to this negative externality, government intervention could be efficiency-improving.

We test whether this scenario reflects reality by drawing the efficiency-density curve of prefectures inside and outside of the TF region. Economic density is measured as the log manufacturing employment density (number of manufacturing workers per square kilometers) in 2004.[57] The average efficiency of the prefecture is measured as the log weighted average of the TFP from manufacturing firms in the prefecture. In Panel B, each red dot represents a prefecture in the sample, each blue cross represents a prefecture outside of the TF region. First notice that despite the investment from the TF, the red dots are clustered on the left part of the graph: the sample prefectures overall were still much less industrialized than the rest of the country by 2004. Overall, there is a weak upward-sloping relationship between manufacturing density and average firm efficiency. The grey line shows the local weighted scatterplot smoothing for prefectures outside of the TF region. The average productivity seems to increase with log manufacturing density when the log manufacturing density is between 2 and 4 (between 7 and 55 manufacturing workers per square kilometer) The efficiency-density line seems to be flat outside of this range. Importantly, there is not a downward-sloping trend among prefectures with the highest manufacturing employment density, which suggests that the congestion effect is not too strong to offset the produc-

[57] Here we use geographic density. Results are similar if we use manufacturing employment share instead.

tivity spillover. This result is also consistent with the finding from Au and Henderson (2006), who suggest that overall Chinese prefectures are too small.

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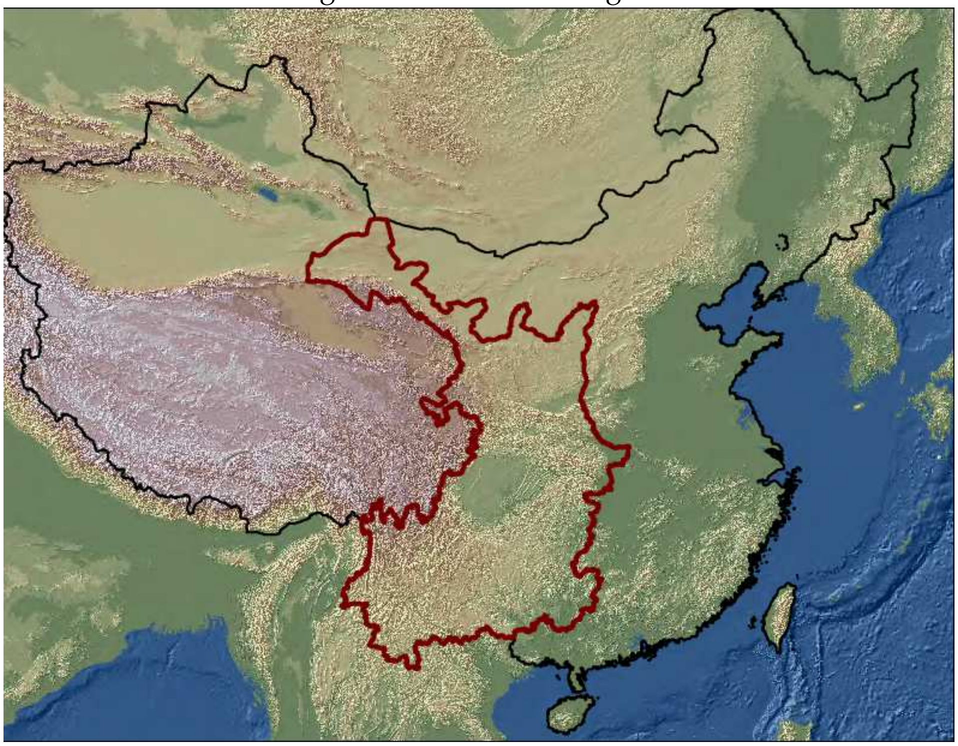
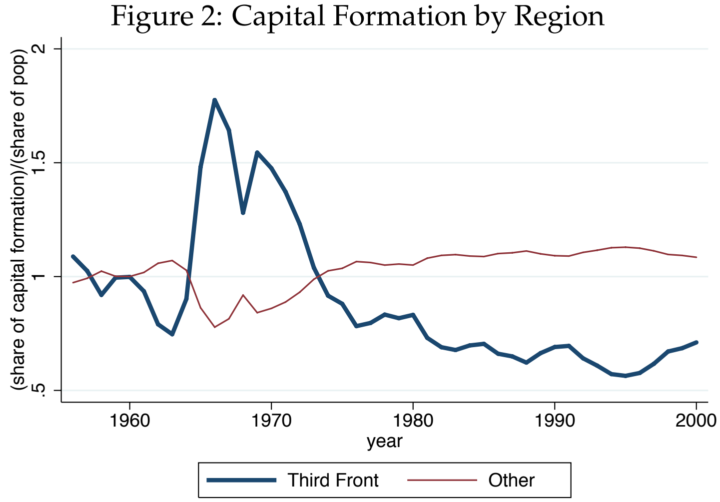
## Figures and Tables

Figure 1: Third Front Region



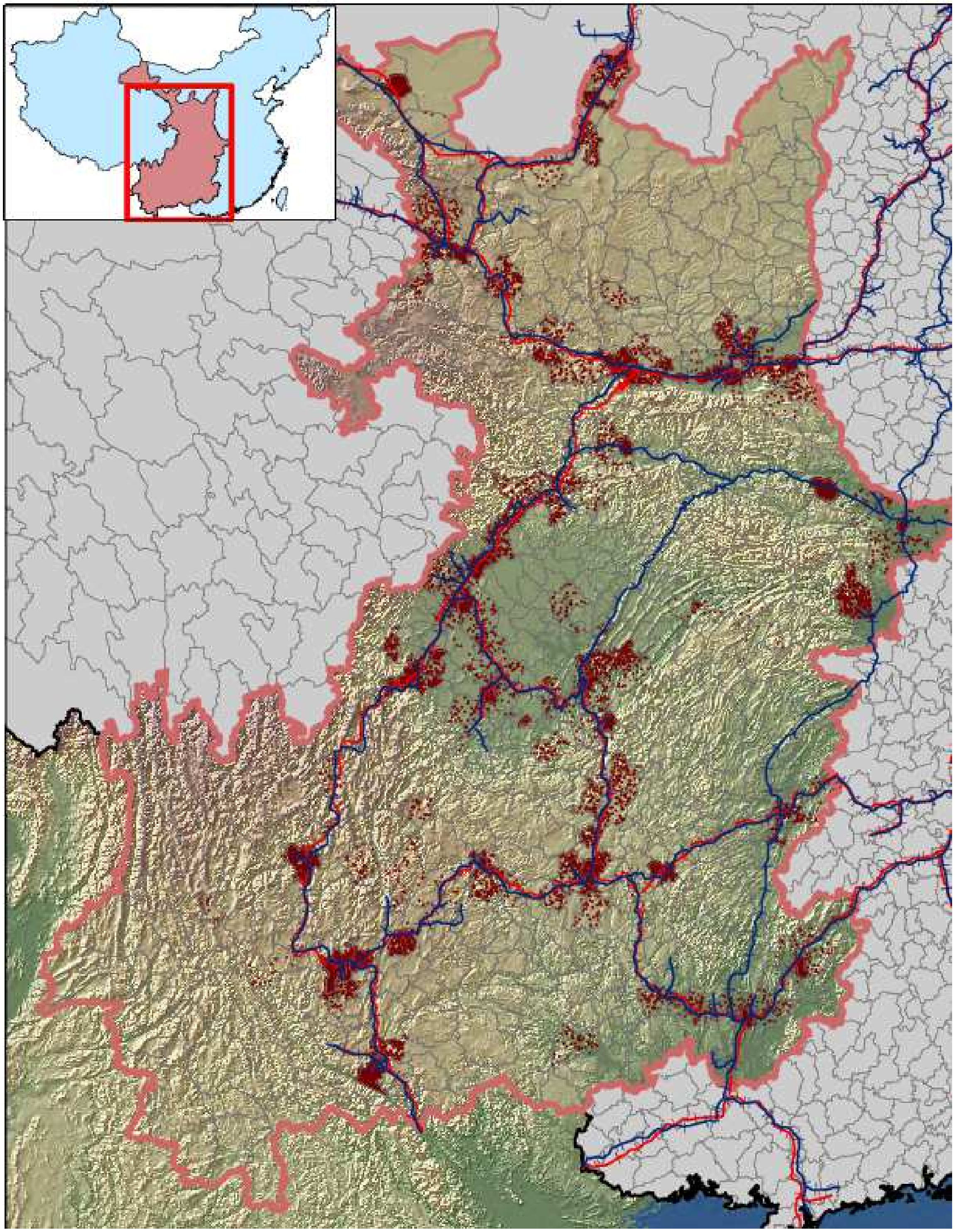
Note: Red line delineates the boundary of the Third Front region.

Figure 2: Capital Formation by Region



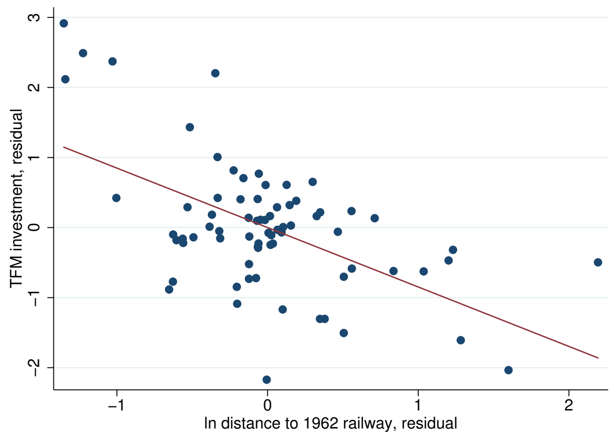

Note: Relative investment intensity is measured as the region's share of national investment divided by its share of national population. Source: 60-year Statistical Summary constructed by the National Bureau of Statistics of China.

Figure 3: Spatial Distribution of TF Employment



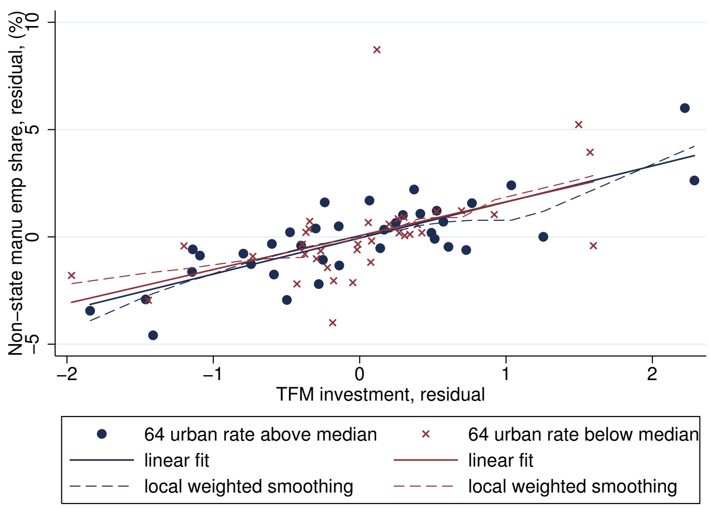
Note: Each red dot indicates 25 workers from large and medium manufacturing firms in 1985. Red lines show existing or planned railways in 1962. Blue lines show railways in 1980.

Figure 4: First Stage



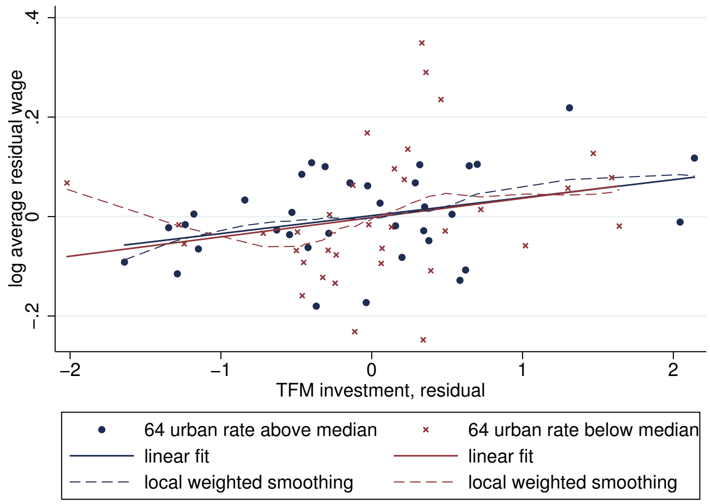

Note: Residuals are taken from OLS regressions on with the full set of controls as in Table 7.

Figure 5: Employment Effect by Urban Rate in 1964




Note: The sample prefectures are divided into two equal sized groups based on whether the prefecture's urban rate in 1964 was above or below the sample median. For each group, TF investment and non-state manufacturing employment share are first regressed on a set of covariates and province fixed effects as in Column 1 of Table 3. Solid lines are linear fits. Dashed lines are local weighted scatterplot smoothing.

Figure 6: Wage Effect by Urban Rate in 1964




Note: The sample prefectures are divided into two equal sized groups based on whether the prefecture's urban rate in 1964 was above or below the sample median. For each group, TF investment and average manufacturing wage are first regressed on a set of covariates and province fixed effects as in Column 1 of 3. Solid lines are linear fits. Dashed lines are local weighted scatterplot smoothing.

Figure 7: Equilibrium in the Model

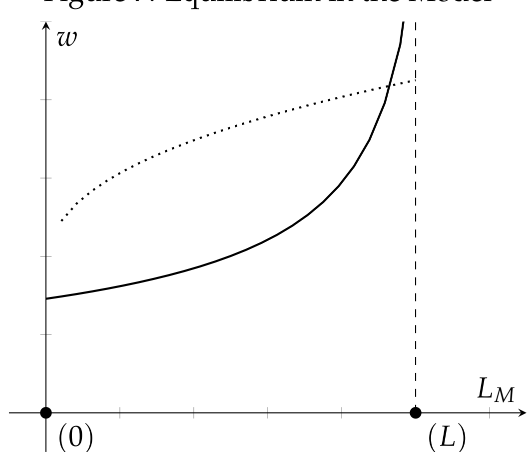


Table 1: Firm Characteristics by Time of Opening

| time of opening | Nationwide before TF (1) | Nationwide during TF (2) | (2)-(1) (3) | TF Region before TF (4) | TF Region during TF (5) | (5)-(4) (6) |
|---|---|---|---|---|---|---|
| **Panel A: County characteristics** | | | | | | |
| = 1 if in TF region | 0.13 | 0.32 | 0.19 | - | - | - |
| | (0.33) | (0.47) | (0.01) | - | - | - |
| in provincial capital prefecture | 0.44 | 0.21 | -0.23 | 0.39 | 0.17 | -0.22 |
| | (0.5) | (0.41) | (0.01) | (0.49) | (0.37) | (0.02) |
| average slope | 1.23 | 1.92 | 0.69 | 2.58 | 3.1 | 0.52 |
| | (1.42) | (1.76) | (0.04) | (2.06) | (2.04) | (0.11) |
| log mean elevation | 4.29 | 5.27 | 0.97 | 6.56 | 6.7 | 0.13 |
| | (1.88) | (1.72) | (0.05) | (0.74) | (0.71) | (0.04) |
| log distance to provincial capital | 2.71 | 3.93 | 1.22 | 3.16 | 4.22 | 1.06 |
| | (2.49) | (2.11) | (0.06) | (2.56) | (1.99) | (0.13) |
| log distance to 1962 railway | 0.6 | 1.24 | 0.64 | 0.88 | 1.33 | 0.46 |
| | (1.28) | (1.84) | (0.04) | (1.51) | (1.95) | (0.1) |
| urban rate in 1964 | 60.1 | 35.52 | -24.58 | 36.82 | 22.28 | -14.54 |
| | (80.81) | (55.51) | (1.68) | (21.78) | (21.13) | (1.2) |
| log 1964 population density | 6.68 | 5.76 | -0.92 | 6.05 | 5.37 | -0.68 |
| | (1.49) | (1.35) | (0.04) | (1.12) | (1.01) | (0.06) |
| 1936 industrial employment share | 54.55 | 18.52 | -36.03 | 13.00 | 3.81 | -9.19 |
| | (105.77) | (59.01) | (1.99) | (23.66) | (13.92) | (1.09) |
| **Panel B: Sector** | | | | | | |
| mining | 0.06 | 0.04 | -0.02 | 0.08 | 0.04 | -0.04 |
| | (0.23) | (0.2) | (0.01) | (0.26) | (0.18) | (0.01) |
| light industries | 0.3 | 0.22 | -0.08 | 0.28 | 0.19 | -0.09 |
| | (0.46) | (0.42) | (0.01) | (0.45) | (0.39) | (0.02) |
| power/water | 0.07 | 0.06 | -0.01 | 0.09 | 0.05 | -0.03 |
| | (0.25) | (0.24) | (0.01) | (0.28) | (0.22) | (0.01) |
| chemical | 0.14 | 0.15 | 0.02 | 0.11 | 0.1 | -0.01 |
| | (0.35) | (0.36) | (0.01) | (0.31) | (0.3) | (0.02) |
| ferrous and non-ferrous metal | 0.1 | 0.06 | -0.03 | 0.1 | 0.07 | -0.03 |
| | (0.3) | (0.24) | (0.01) | (0.3) | (0.26) | (0.02) |
| machinery | 0.25 | 0.29 | 0.04 | 0.25 | 0.35 | 0.1 |
| | (0.43) | (0.46) | (0.01) | (0.44) | (0.48) | (0.03) |
| electric and electronic | 0.09 | 0.16 | 0.08 | 0.1 | 0.2 | 0.1 |
| | (0.28) | (0.37) | (0.01) | (0.3) | (0.4) | (0.02) |
| # of plants | 4927 | 2049 | - | 634 | 657 | - |

Note: Data on firms are from the list of large and medium manufacturing firms in 1985. Time is divided into two periods: "before TF" indicates years before 1964, "during TF" indicates years between 1964 and 1978. Standard deviations (Columns 1, 2, 4, and 5) or standard errors (Columns 3 and 6) are in parentheses. County characteristics are from various population censuses, manufacturing censuses, and GIS maps.

Table 2: Determinants of TF Investment

| dep var: share of employment from TF plants | | | | | | |
|---|---|---|---|---|---|---|
| **Panel A: Third Front Region** | (1) | (2) | (3) | (4) | (5) | (6) |
| log distance to 1962 railway | -0.784*** | | -0.823*** | | -0.781*** | -0.734*** |
| | (0.139) | | (0.135) | | (0.156) | (0.195) |
| average slope | | 0.054 | 0.130** | | 0.112* | 0.167*** |
| | | (0.074) | (0.057) | | (0.066) | (0.049) |
| urban rate in 1964 | | | | 0.165*** | 0.063 | 0.084 |
| | | | | (0.044) | (0.043) | (0.058) |
| log population density in 1964 | | | | | | 0.286 |
| | | | | | | (0.206) |
| industrial emp share in 1936 | | | | | | 0.002 |
| | | | | | | (0.025) |
| province FE | X | X | X | X | X | X |
| N | 73 | 73 | 73 | 73 | 73 | 73 |
| $R^2$ | 0.484 | 0.139 | 0.513 | 0.215 | 0.524 | 0.537 |
| joint test for initial conditions ($p-$val) | | | | | | 0.276 |
| **Panel B: Non-Third Front Region** | (1) | (2) | (3) | (4) | (5) | (6) |
| log distance to 1962 railway | -0.544*** | | -0.586*** | | -0.440*** | -0.430*** |
| | (0.142) | | (0.146) | | (0.157) | (0.159) |
| average slope | | -0.050 | 0.144 | | 0.096 | 0.238* |
| | | (0.114) | (0.102) | | (0.082) | (0.126) |
| urban rate in 1964 | | | | 0.249*** | 0.199*** | 0.163*** |
| | | | | (0.043) | (0.046) | (0.049) |
| log population density in 1964 | | | | | | 0.421 |
| | | | | | | (0.262) |
| industrial emp share in 1936 | | | | | | 0.034* |
| | | | | | | (0.018) |
| province FE | X | X | X | X | X | X |
| N | 146 | 146 | 146 | 146 | 146 | 146 |
| $R^2$ | 0.257 | 0.107 | 0.266 | 0.293 | 0.376 | 0.411 |
| joint test for initial conditions ($p-$val) | | | | | | 0.000 |

Note: The dependent variable is the share of 1985 employment from large- and medium-sized manufacturing firms. Panel A includes sample prefectures. Panel B includes prefectures outside of the TF region (also excluding Tibet, Inner Mongolia, and Xinjiang) with the same restrictions (excluding provincial capitals and prefectures with 1964 urban rate higher than 15%). Regressions in Panel A are estimated using a frequency weight of 2 to match the number of observations in Panel B. Robust standard errors are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. $p-$value is for a joint test for initial conditions: urbanization rate in 1964, log population density in 1964, and industrial employment share in 1936.

Table 3: Effects on the Local Non-state Manufacturing Sector in 2004 (OLS Estimates)

| | emp share | | | | | # firms per |
|---|---|---|---|---|---|---|
| | all | estab. '85-'98 | emp $\leq 25$ | all | all | 100 workers |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| TF investment | 1.643*** | 0.511*** | 0.010*** | 2.075*** | 1.543*** | 0.011*** |
| | (0.260) | (0.115) | (0.002) | (0.420) | (0.275) | (0.003) |
| '85-'04 change in state manu emp share | | | | 0.585 | | |
| | | | | (0.413) | | |
| TF inv$\times$ state-share index | | | | | 1.315 | |
| | | | | | (2.080) | |
| state-share index | | | | | -0.030 | |
| | | | | | (1.123) | |
| geo and initial conditions | X | X | X | X | X | X |
| province FE | X | X | X | X | X | X |
| mean dep var | 2.690 | 0.875 | 0.029 | 2.690 | 2.690 | 0.038 |
| N | 73 | 73 | 73 | 73 | 73 | 73 |

Note: The table focuses on the non-state manufacturing sector in 2004. Data are from 2004 Economic Census. Controls include a full set of province fixed effects, criteria for site selection: log distance to 1962 railway and average slope; other geographic characteristics: log average elevation, log distance to provincial capital, and employment share in the mining sector (as a proxy for natural resources); initial economic conditions: 1964 urban rate, log population density in 1964, and industrial employment share in 1936. All models are estimated by OLS. Robust standard errors are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: OLS Robustness: Coefficient Stability

| dep var: non-state manu emp share | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| TF investment | 1.643*** | 1.586*** | 1.580*** | 1.445*** | 1.688*** |
| | (0.260) | (0.340) | (0.330) | (0.260) | (0.288) |
| initial economic conditions | X | | | | X |
| distance variables | X | | X | | X |
| geographic variables | X | | | X | X |
| site-selection criteria | X | X | X | X | X |
| province FE | X | X | X | X | X |
| quadratic terms of covariates | | | | | X |
| N | 73 | 73 | 73 | 73 | 73 |
| $R^2$ | 0.73 | 0.55 | 0.55 | 0.56 | 0.79 |
| $H_0$ : same as coeff in Col 1 $p-$value | | 0.25 | 0.25 | 0.30 | 0.74 |

Note: The dependent variable is the share of employment in 2004 that came from non-state sector manufacturing firms. All models are estimated using OLS. Control variables are the same as in Table 3. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Case Study of the SAW

| | (1) Shiyan (treated) | (2) Xiangxi (comparison) | (3) synthetic Shiyan | (4) (1)-(3) $p-$value | (5) (2)-(3) $p-$value |
|---|---|---|---|---|---|
| **Panel A: matching quality** | | | | | |
| 1964 urban rate | 5.26 | 7.93 | 5.21 | 0.24 | 0.02 |
| log distance to 1962 railway | 5.23 | 4.30 | 4.94 | 0.28 | 0.76 |
| average slope | 4.67 | 3.22 | 4.67 | 0.43 | 0.96 |
| log distance to provincial capital | 5.56 | 5.78 | 5.64 | 0.74 | 0.13 |
| log average elevation | 6.60 | 6.30 | 6.56 | 0.67 | 0.91 |
| log 1964 population density | 4.48 | 4.50 | 4.49 | 0.72 | 0.26 |
| 1936 industrial emp share | 0.00 | 0.00 | 0.22 | 0.89 | 0.89 |
| **Panel B: treatment** | | | | | |
| TF investment | 5.07 | 0.11 | 0.25 | 0.00 | 0.67 |
| **Panel C: non-state manufacturing sector in 2004** | | | | | |
| emp share | 5.60 | 2.03 | 1.41 | 0.02 | 0.22 |
| emp share from firms estab. '85-'98 | 1.44 | 0.79 | 0.47 | 0.02 | 0.11 |
| emp share from firms with emp$\leq$ 25 | 0.09 | 0.01 | 0.02 | 0.00 | 0.65 |
| # of firms per 100 workers | 0.05 | 0.02 | 0.03 | 0.09 | 0.52 |

Note: Conditions for Shiyan are reported in Column 1. Conditions for the natural comparison, Xiangxi, are reported in Column 2. Conditions for synthetic Shiyan are reported in Column 3. Column 4 reports the $p-$values for the differences between Shiyan and synthetic Shiyan. Column 5 reports the $p-$values of the differences between Xiangxi and synthetic Shiyan. The $p-$values are obtained using the permutation-like method.

Table 6: Route and Timing of Railway Construction and Initial Economic Conditions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 1964 urban rate | | log 1964 pop density | | 1936 ind emp share | |
| log dist to 1962 railway | -0.490 | -0.290 | -0.042 | 0.059 | -0.012 | -0.172 |
| | (0.412) | (0.527) | (0.066) | (0.085) | (0.115) | (0.208) |
| log dist to 1980 railway | | -0.237 | | -0.120 | | 0.189 |
| | | (0.361) | | (0.062) | | (0.174) |
| geographic chars | X | X | X | X | X | X |
| province FE | X | X | X | X | X | X |
| $N$ | 73 | 73 | 73 | 73 | 73 | 73 |
| mean dep var | 7.136 | 7.136 | 4.418 | 4.418 | 0.336 | 0.336 |

Note: Geographic characteristics include log average elevation, log distance to provincial capital, and employment share in the mining sector. Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effects on and the Local Non-state Manufacturing Sector in 2004 (2SLS Estimates)

| | all | estab. '85-'98 | emp share emp $\leq 25$ | all | all | # firms per 100 emp |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| TF investment | 2.124*** | 0.727*** | 0.018*** | 2.691*** | 2.749*** | 0.016*** |
| | (0.348) | (0.145) | (0.003) | (0.490) | (0.739) | (0.003) |
| '85-'04 change in state manu emp share | | | | 0.890*** | | |
| | | | | (0.269) | | |
| TF inv× state-share index | | | | | -6.178 | |
| | | | | | (5.684) | |
| state-share index | | | | | 4.947 | |
| | | | | | (3.408) | |
| geo and initial conditions | X | X | X | X | X | X |
| province FE | X | X | X | X | X | X |
| mean dep var | 2.690 | 0.875 | 0.029 | 2.690 | 2.690 | 0.038 |
| first-stage F-statistic | 14.056 | 14.056 | 14.056 | 14.354 | 1.307 | 14.056 |
| N | 73 | 73 | 73 | 73 | 73 | 73 |

Note: The table focuses on the non-state manufacturing sector in 2004. Data are from 2004 Economic Census. All models are estimated by 2SLS. Log distance to the 1962 railway is used as the instrument for TF investment. Controls include a full set of province fixed effects, average slope; log distance to the 1980 railway; other geographic characteristics: log average elevation, log distance to provincial capital, and employment share in the mining sector (as a proxy for natural resources); initial economic conditions: 1964 urban rate, log population density in 1964, and industrial employment share in 1936. Robust standard errors are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Firm Efficiency and Worker Wages

| | log TFP | | log wage | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | all | non-state | manufacturing | agricultural |
| TF investment | 0.106** | 0.096* | 0.034* | 0.053 |
| | (0.035) | (0.055) | (0.019) | (0.038) |
| geo and initial conditions | X | X | X | X |
| prov FE | X | X | X | X |
| N | 11078 | 4738 | 9526 | 216501 |
| First stage -F | 18.579 | 18.931 | 18.787 | 18.823 |

Note: All models are estimated using the 2SLS estimator. Data for Columns 1 and 2 are from the 2004 AMFS, each observation is a firm, and each firm is weighted by its share of employment in the same category of firms in the prefecture. Data for Columns 3 to 6 are from the sample of 2005 Mini Census, each observation is a worker in the corresponding sector, and each worker is weighted by the inverse of the number of workers in the corresponding sector in the prefecture. Standard errors are clustered at the prefecture level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Inter-Industry Linkages and Employment

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | | CPS worker transitions | citation pattern | technology input | technology output | manufacturing input | manufacturing output |
| **Panel A** | | dep var: share of 2004 employment from non-state manufacturing firms | | | | | |
| TF investment in same industry | 0.304** | | | | | | |
| | (0.126) | | | | | | |
| linkages | | 0.004** | 0.018 | 0.018*** | 0.043** | 0.012 | 0.020 |
| | | (0.002) | (0.012) | (0.008) | (0.018) | (0.008) | (0.014) |
| N | 1387 | 1387 | 1387 | 1387 | 1387 | 1387 | 1387 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Panel B** | | | | dep var: firm TFP | | | |
| TF investment in same industry | 0.103 | | | | | | |
| | (0.085) | | | | | | |
| linkages | | 0.007*** | 0.061* | 0.071*** | 0.058** | 0.058*** | 0.057*** |
| | | (0.002) | (0.033) | (0.022) | (0.023) | (0.022) | (0.019) |
| geography and initial conditions | X | X | X | X | X | X | X |
| province FE | X | X | X | X | X | X | X |
| industry FE | X | X | X | X | X | X | X |
| N | 4631 | 4631 | 4631 | 4631 | 4631 | 4631 | 4631 |

Note: This table focuses on the non-state sector manufacturing firms. In Columns 2 to 7, each linkage is indicated in the header. Each observation is a prefecture-2 digit industry in Panel A. Each observation is a firm in Panel B. The standard errors are clustered by prefecture, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Inter-Industry Linkages and Employment

| **Panel A** | dep var: share of 2004 employment from non-state manufacturing firms | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | | | | | | | |
| TF inv in light industry | 1.546** | | | | | | | |
| | (0.585) | | | | | | | |
| TF inv in heavy industry | 1.521*** | | | | | | | |
| | (0.222) | | | | | | | |
| mean dep var | 2.69 | | | | | | | |
| N of prefecture obs | 73 | | | | | | | |
| **Panel B** | dep var: share of 2004 employment from non-state manufacturing firms (prefecture-industry cells, light industries) | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| TF inv in all industries | 0.030*** | | | | | | | |
| | (0.011) | | | | | | | |
| TF inv in the same industry | | 0.573*** | | | | | | |
| | | (0.119) | | | | | | |
| linkages | | | 0.002*** | 0.011** | 0.010*** | 0.026*** | 0.005** | 0.005** |
| | | | (0.001) | (0.004) | (0.003) | (0.009) | (0.002) | (0.002) |
| linkage description | | | CPS worker transitions | citation pattern | technology input | technology output | manufacturing input | manufacturing output |
| mean dep var | 0.156 | 0.156 | 0.156 | 0.156 | 0.156 | 0.156 | 0.156 | 0.156 |
| N of prefecture-industry obs | 803 | 803 | 803 | 803 | 803 | 803 | 803 | 803 |
| **Panel C** | dep var: share of 2004 employment from non-state manufacturing firms (prefecture-industry cells, heavy industries) | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| TF inv in all industries | 0.039*** | | | | | | | |
| | (0.020) | | | | | | | |
| TF inv in the same industry | | 0.286** | | | | | | |
| | | (0.132) | | | | | | |
| linkages | | | 0.009* | 0.044 | 0.049** | 0.069* | 0.027 | 0.130* |
| | | | (0.005) | (0.038) | (0.029) | (0.040) | (0.028) | (0.068) |
| linkage description | | | CPS worker transitions | citation pattern | technology input | technology output | manufacturing input | manufacturing output |
| mean dep var | 0.121 | 0.121 | 0.121 | 0.121 | 0.121 | 0.121 | 0.121 | 0.121 |
| N of prefecture-industry obs | 584 | 584 | 584 | 584 | 584 | 584 | 584 | 584 |

Note: All regressions include province fixed effects, industry fixed effects, and the full set of geographic and initial economic conditions. Robust standard errors for Panel A, and clustered standard errors (at prefecture level) for panels B and C, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Inter-prefecture Migration and Local Structural Transformation

| | inward migration rate | share of rural *hukou* in manu sector |
|---|---|---|
| | (1) | (2) |
| TF investment | -0.082 | 0.225* |
| | (0.090) | (0.118) |
| geo and initial conditions | X | X |
| province FE | X | X |
| N | 70 | 70 |
| First stage F-stat | 14.184 | 14.184 |
| mean dep var | 1.114 | 1.964 |

Note: Data are from individual-level sample of 2005 Mini Population Census. Both columns are estimated using the IV specification. The dependent variable in Column 1 is the percent of workers in a prefecture with *hukou* from another prefecture. The dependent variable in Column 2 is the percent of manufacturing workers among workers with a rural*hukou* in registered in the prefecture. Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Parameters for TF Region and NTF Region

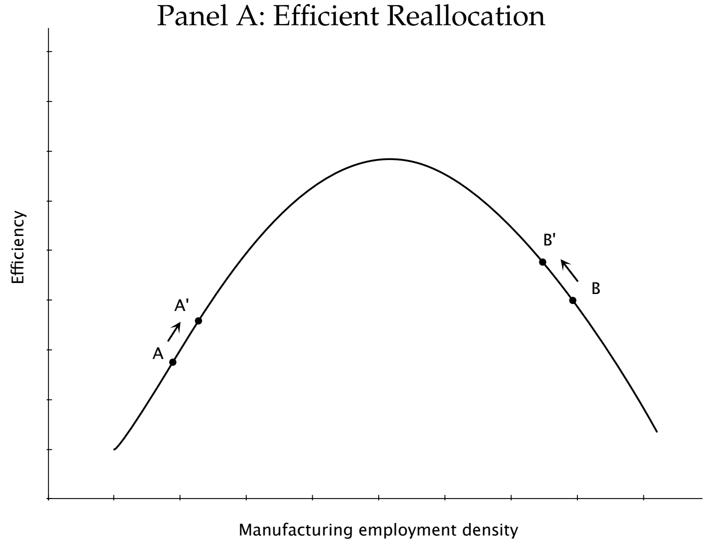
| parameter | variable | TF Region | Non-TF Region |
|---|---|---|---|
| $W^M$ | average manufacturing wage | 687 | 900 |
| $W^A$ | average agricultural wage | 234 | 337 |
| $W^M - W^A$ | manu-ag wage gap (absolute value) | 453 | 563 |
| $W^M/W^A$ | manu-ag wage gap ($\tau$) | 2.9 | 2.7 |
| $l^A$ | agriculture employment share | 0.80 | 0.47 |
| $TFP^s$ | average log TF of state firms | -0.25 | -0.04 |
| $TFP^{ns}$ | average log TF of non-state firms | -0.10 | 0.04 |

Note: Wage data are from 2005 Mini Population Census. Wages reported here are monthly income. TFP is calculated from 2004 AMFS.

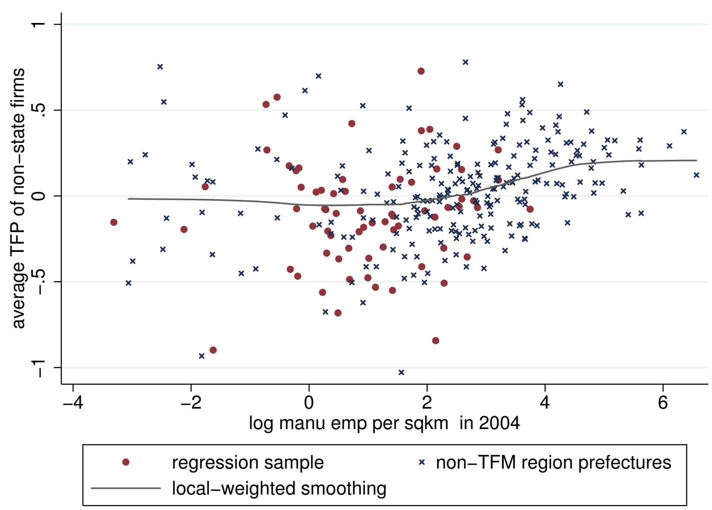
# Appendix Figures and Tables

Figure A: Congestion and Efficient Reallocation

Panel A: Efficient Reallocation




Panel B: Manufacturing Employment Density and Firm Efficiency




Note: The top graph illustrates a case in which reallocating resources from the high-productivity region to the low-productivity region improves aggregate efficiency. In the bottom graph, each red dot represents a prefecture in the baseline sample. Each blue cross represents a prefecture not in the baseline sample. The grey line is the local weighted scatterplot smoothing of non-TF-region prefectures. The median log manufacturing employment density (workers per squared kilometer) in 2004 for the non-TF prefectures is about 2.4.

Table A: Definitions of Key Variables

| variable | definition | unit | source |
|---|---|---|---|
| TF investment | manufacturing employment from large- and medium-sized manufacturing firms reported in the 1985 industrial census. Total employment from 1982 population census. | pp | pc82, ic85 |
| distance to 1962 railway | first calculate the distance to existing or planned railways in 1962 at the county level, then average at the prefecture level using 1982 county population as weight | km | pc82, rr |
| average slope | Slope is calculated as the slope between the highest point and the lowest point in a $1km \times 1km$ square. Then take average among all the squares the prefecture covers | - | dem |
| 1964 population density | # of residents in 1964 per sqkm. Prefecture areas calculated from GIS boundary data | $\#/km^2$ | pc64 , bd |
| 1936 industrial employment share | # of industrial employment in 1936 divided by population in 1964, then multiply by 10,000 | 1/10000 | pc64, mc36 |
| distance to provincial capital | first calculate each county's distance to provincial capital (centroid-to-centroid), then average at the prefecture level using 1982 county population as weight | km | bd |
| mean elevation | elevation from the DEM data, then average within the boundary | m | dem, bd |
| distance to 1980 railway | distance to existing railways in 1980 | km | rr |
| urban rate | share of population with urban *hukou* | pp | pc64-pc00 |
| industrial employment share | share of employment in the industrial sector (including manufacturing) | pp | pc64-pc00 |
| non-agricultural employment share | share of employment in the non-agricultural sector (including manufacturing) | pp | pc64-pc00 |
| 2004 manufacturing employment share by sector | number employment in the manufacturing sector in 2004 divided by total employment from 2000 census. | pp | ec04, pc00 |
| rural in-/out-migration rate | in-/out-migration rate among workers with rural *hukou* | pp | pc05 |
| rural manufacturing/non-agricultural employment share | share of workers with rural *hukou* in the manufacturing/non-agricultural sector | pp | pc05 |

Note: Abbreviation for units: pp - percentage points. Abbreviation for data sources: bd - GIS maps for county boundaries, dem - GIS digital elevation model data with pixels of elevation data, ec04 - 2004 economic census, ic85 - 1985 industrial census, ms04 - 2004 survey of manufacturing firms, pc - population census, rr - digitized railway maps from Baum-Snow et al. (2017),

Table B: Summary Statistics of the Regression Sample

| | mean | s.d. | p10 | p50 | p90 |
|---|---|---|---|---|---|
| *treatment* | | | | | |
| TF investment | 1.11 | 1.51 | 0.00 | 0.54 | 2.88 |
| *site-selection criteria* | | | | | |
| log distance to 1962 railway | 3.68 | 1.28 | 2.33 | 3.76 | 5.30 |
| average slope | 4.47 | 2.39 | 1.76 | 4.37 | 7.25 |
| *initial conditions* | | | | | |
| 1964 urban rate | 7.14 | 2.70 | 4.07 | 6.53 | 11.68 |
| log 1964 population density | 4.42 | 0.94 | 3.32 | 4.50 | 5.56 |
| 1936 industrial employment share | 0.34 | 1.85 | 0.00 | 0.00 | 0.00 |
| log distance to provincial capital | 5.35 | 0.45 | 4.66 | 5.38 | 5.89 |
| log mean elevation | 7.05 | 0.58 | 6.28 | 7.09 | 7.73 |
| log distance to 1980 railway | 3.16 | 1.39 | 1.35 | 3.09 | 5.00 |
| *2004 manufacturing employment* | | | | | |
| share of total employment | 4.29 | 4.05 | 1.26 | 2.99 | 9.43 |
| non-state | 2.69 | 3.12 | 0.65 | 1.69 | 4.93 |
| non-state and opened after 1985 | 1.57 | 2.02 | 0.37 | 0.95 | 3.09 |
| *migration flows in 2005* | | | | | |
| in-migration rate | 0.96 | 1.01 | 0.13 | 0.76 | 1.94 |
| out-migration rate | 8.67 | 8.69 | 0.74 | 5.74 | 23.35 |
| *workers with rural hukou* | | | | | |
| manufacturing employment share | 1.96 | 1.12 | 0.81 | 1.77 | 3.16 |
| non-agricultural employment share | 7.91 | 3.53 | 4.49 | 7.37 | 12.49 |
| *structural transformation* | | | | | |
| 1982 industrial employment share | 4.06 | 3.14 | 1.49 | 3.21 | 6.40 |
| 1990 industrial employment share | 5.52 | 3.43 | 2.14 | 4.81 | 9.08 |
| 2000 industrial employment share | 6.42 | 3.05 | 3.33 | 5.83 | 11.34 |

Note: There are 73 prefectures in the regression sample.

Table C: Endogeneity of Subsequent Railway Construction

| | (1) | (2) | (3) |
|---|---|---|---|
| | log distance to 1980 railway | | |
| TF investment | -0.397*** | 0.051 | 0.084 |
| | (0.098) | (0.068) | (0.075) |
| log distance to 1962 railway | | 0.911*** | 0.949*** |
| | | (0.105) | (0.113) |
| geo and initial conditions | | | X |
| province FE | X | X | X |
| N | 73 | 73 | 73 |

Note: Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D: Effects on the Non-state Manufacturing Employment: 2SLS Robustness

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| TF investment | 2.124*** | 2.160*** | 2.328*** | 1.872*** |
| | (0.348) | (0.342) | (0.487) | (0.260) |
| site-selection criteria | X | | X | |
| log distance to 1980 railway | X | X | | |
| other initial economic and geo controls | X | X | X | |
| province FE | X | X | X | X |
| *First Stage* | | | | |
| log distance to 1962 railway | -0.848*** | -0.819*** | -0.530*** | -0.804*** |
| | (0.226) | (0.224) | (0.172) | (0.362) |
| First stage F-statistic | 14.056 | 13.416 | 9.507 | 17.058 |
| N | 73 | 73 | 73 | 73 |

Note: The dependent variable is the non-state manufacturing employment share in 2004. All models are estimated using 2SLS. TF investment is instrumented by log distance to the 1962 railway. Site-selection criteria include average ruggedness. Other initial economic and geographic controls are the same as in Table 3. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E: Measures of Industry Linkages

| **measure of industry linkage** | **description** |
|---|---|
| *labor market pooling* | |
| CPS worker transitions | proportion of workers leaving a job in this industry that move to TF firm industry. |
| *intellectual or technology spillovers* | |
| patent citation pattern | percentage of manufacturing industry patents that cite patent manufactured in TF firm industry. |
| technology input | R&D flows from TF industry, as a percentage of all technological expenditure in this industry. |
| technology output | R&D flows to TF industry, as a percentage of all technological expenditure in this industry. |
| *proximity to customer and suppliers* | |
| manufacturing input | industry inputs from TF industry, as a percentage of manufacturing inputs of this industry. |
| manufacturing output | industry inputs used by TF industry, as a percentage of manufacturing inputs of this industry. |

Note: Measures of industry linkages are taken from the US data and follow Greenstone et al. (2010).