Can Technology Transfers Save Innovation? Evidence from China

Zhangfeng Jin*

Abstract: This paper examines the causal impact of technology transfers on long-term innovation inputs by exploiting variations in the adoption of Soviet-aided industrialization programs across Chinese cities. Focusing on firms located in cities where 156 major industrial projects were aided by the Soviet Union, I find that firms in these adopting localities witness fewer investments in research and development on average after nearly half a century, particularly for non-state-owned firms. This decline in innovation inputs is further supported by a lower probability of patenting in these localities. A likely underlying mechanism is the low adoption of performance-based reward systems, rather than inadequate capital and skilled workers. Despite prior successes during the planned economy era, the adoption of such foreign aid tends to impede innovation as China transitions towards a more market-oriented economy.

Keywords: Foreign Aid; Technology Transfers; Innovation Inputs; Pay for Performance; China

***JEL Code*:** F35; O30; M52

---

* Jin: School of Economics, Zhejiang University of Technology, 288 Liuhe Road, Hangzhou, China, 310000 (Email: zhangfeng1019@gmail.com). A previous version of this manuscript was titled “The Legacies of the Soviet Influence in the 1950s: China’s 156 Major Industrial Projects.” I appreciate valuable comments from Oded Galor, Seema Jayachandran, Raymond Fisman, the participants at the Leibniz Institute for East and Southeast European Studies (IOS) seminar, 27th Annual SIOE Conference and 2024 China India Insights Conference. I am grateful to the World Bank and the Chinese National Bureau of Statistics for providing access to Enterprise Survey Data, and other data sets. I declare that I have no relevant or material financial interests that relate to the research described in this article. Any opinions and conclusions expressed herein are those of the author.

The effectiveness of foreign aid in promoting sustained economic growth remains unclear. Despite the well-known success of the U.S.-aided European Recovery Program in Western Europe (DeLong and Eichengreen 1991; Eichengreen and Uzan 1992; Giorcelli 2019), foreign aid to other countries, particularly in Africa, has been largely unsuccessful (Easterly 2003; 2009). Some scholars argue that past aid failures stem from an overemphasis on financing investments and structural adjustments, and more recently, on improving governance quality, while underestimating the crucial role of technological change in sustained economic growth (UNCATAD 2007; Easterly 2007). However, these is insufficient discussion on the consequences of foreign aid in the form of technology transfers persists (Giorcelli 2019).

This article seeks to address this gap by examining the causal impact of technology transfers on long-term innovation inputs, focusing on China's adoption of 156 major Soviet-aided industrial projects (hereinafter, the "156 Projects") in the 1950s. Specifically, I address two main questions: Has China's adoption of the 156 Projects affected the innovation inputs of firms located in cities where the investments were made after nearly half a century, and, if so, what is the likely underlying mechanism for this effect?

As part of China's First Five-Year Plan (1953–1957) to rebuild its economy, the Soviet-aided 156 Projects represented the most comprehensive technology transfer in modern industrial history (Zhang, Zhang, and Yao 2006). These projects focused on sectors of heavy industry, such as energy, metallurgy, machinery, chemistry, and national defense. The large-scale, capital-intensive 156 Projects totaled more than half of U.S. aid provided to Western Europe under the Marshall Plan (1948–1952).[1] However, the adoption of the 156 Projects was unevenly across Chinese cities (see **Figure A1** in Appendix A1), largely determined by factors such as proximity to resources, potential for economic transformation in underdeveloped areas,

[1] In 2020 Soviet aid to the 156 Projects totaled USD 80 billion (Giorcelli and Li 2021), compared to 142.8 billion in U.S. aid to Western Europe. Conversions into 2020 USD are based on https://www.saving.org/inflation/inflation.php?amount=13.

and military considerations (Bo 1991).[2] These distinctive features of the 156 Projects' adoption provide a unique case for examining the long-run consequences of technology transfers within a developing country.

Innovation is a major force in sustained economic growth. However, precisely measuring innovation activities remains challenging in developing countries like China. First, most firm-level survey data only report research and development (R&D) spending, which at best measures innovation inputs and does not provide information on innovation results. Second, although firm-level census data can be matched with China's State Intellectual Property Office patents to obtain information on the number of patents at the firm level, the extent to which the number of patents captures each firm's innovation results or other unobservable factors (e.g., patent subsidies) remains uncertain. In this article, I define firms' innovation inputs as R&D spending at the extensive margin. Additionally, I use firms' R&D spending at the intensive margin, R&D growth within a given period, and the number of patents for complementary analysis. To some extent, combining these different measures of innovation mitigates concerns about mismeasurement.

To estimate the causal impact of adopting the Soviet-aided 156 Projects on the long-term innovation inputs of firms located in cities where the investments were made, I use an instrumental variable (IV) approach based on plausibly exogenous variations in exposure to risks of armed conflict in the Taiwan Strait in the 1950s across mainland Chinese cities. Specifically, I construct an IV using the geographical distance between each mainland Chinese city and Jinmen, which is two miles from the mainland Chinese city of Xiamen but controlled by Taiwan.[3] The rationale is that mainland Chinese cities closer to Jinmen were exposed to

[2] In 1949, after losing control of mainland China, the Republic of China under the KMT withdrew to Taiwan.

[3] Several recent papers have also employed geographical distance as instruments (Becker and Woessmann 2009; Nunn and Wantchekon 2011; Chen, Kung, and Ma 2020). For example, Becker and Woessmann (2009) use distance to Wittenberg,

higher risks of armed conflict in the Taiwan Strait, due to tensions between mainland China and Taiwan in the early 1950s.[4] Consequently, these cities were less likely to adopt the 156 Projects under the centrally planned economy.

An important assumption for the validity of the IV is that, conditional on observable characteristics (e.g., exposure to foreign trade, exposure to policies enacted by the central government, human capital stocks, etc.), the firm-level outcomes of interest in each locality are independent of the geographical distance between the mainland Chinese cities in which these firms are located and Jinmen. I provide some empirical validation of the IV assumption.

The main findings are as follows. First, I find that China's adoption of the Soviet-aided 156 Projects has significantly reduced the long-run innovation inputs of firms located in cities where the investments were made. The IV estimate shows that a firm's probability of investing in R&D decreases by 0.36 in adopting localities. Second, the decline in innovation inputs is further supported by firms' lower probability of patenting in these localities. Third, a likely underlying mechanism for the decline is the low adoption of performance-based reward systems, rather than a lack of capital and skilled workers. These findings suggest that, despite prior successes during the era of a planned economy, the adoption of such foreign aid tends to impede innovation as China transitions towards a more market-oriented economy.

This article contributes to the literature in three ways. First, it sheds light on the effectiveness of foreign aid in promoting sustained economic growth (Boone 1996; Burnside and Dollar 2000; Easterly, Levine, and Roodman 2004; Rajan and Subramanian 2008; Clemens et al. 2012; Dreher et al. 2021). Most aid focuses on financing investment and structural adjustment, or more recently, on improving the quality of governance in recipient countries.

---

the hometown of Martin Luther, as an IV for Protestantism. Nunn and Wantchekon (2011) use the historical distance from the nearest coast of an individual's ethnic group location as an instrument for slave exports.

[4] Two separate crises occurred in the Taiwan Straits between 1954 and 1958.

This raises concerns that past aid failures occurred because most aid underestimated the essential role that technological change in sustained economic growth (UNCATAD 2007; Easterly 2007). However, these has been insufficient discussion on the impact of foreign aid in the form of technology transfers. A few studies investigate the impact of foreign aid on existing firms but not on newly-built firms (Giorcelli 2019). This study contributes to closing this gap by examining whether the provision of more technology transfers could be effective in promoting innovation of all firms, including newly-built firms, in recipient countries.

Second, this study closely relates to a broad body of scholarship examining the significance of historical factors in long-term development outcomes (Acemoglu, Johnson, and Robinson 2001; Banerjee and Iyer 2005; Nunn 2009; Jia 2014; Markevich and Zhuravskaya 2018; Lowes and Montero 2021). Specifically, it adds to the emerging literature on the economic impact of adopting the Soviet-aided 156 Projects in China (Heblich et al. 2019; Hu, Li, and Nie 2021; Li and Giorcelli 2022). For example, Li and Giorcelli (2022) compare firms and regions selected to be part of the 156 Projects but received different types of Soviet transfers, demonstrating that the adoption of the 156 Projects positively affects firm performance such as output and productivity.[5] Conversely, Heblich et al. (2019) compare regions where the 156 Projects were located with regions suitable for hosting them but not selected, finding a boom-and-bust pattern in hosting regions due to overspecialization and reduced innovation, leading to long-run decline.

Unlike Heblich et al. (2019) who highlight the negative effect of adopting the 156 Projects due to over-specification, this article explores a largely overlooked mechanism—management practices—through which the adoption of the Soviet-aided 156 Projects can adversely affect

[5] The instrument variable used by Li and Giorcelli (2022) is not applicable in our context given the narrow definition of industry. Moreover, unlike Li and Giorcelli (2022) that investigates the differences within the 156 Projects, our paper compares cities that adopted the 156 Projects with similar cities that did not adopted the 156 Projects. In other words, our instrumental variable provides an alternative approach to examine the consequences of adopting the 156 projects based on a broad category of industries and regions.

long-term innovation outcomes. We distinguish between two mechanisms: we find a positive direct impact of the 156 Projects on long-term innovation but a negative indirect impact through incentive-incompatible management practices. Additionally, unlikely Li and Giorcelli (2022), we concentrate on firms located in cities where the investment was made rather than those directly receiving the know-hows and capital investments. As a result, firm sorting itself becomes a part of the spillover effect examined in this paper.

Third, this article adds to discussions of the causes of differences in the adoption of performance-based reward systems—an important part of management practices—and complements existing studies examining differences in management practices across countries and firms (Bloom and Van Reenen 2010; Bloom et al. 2019; Frederiksen and Manchester 2020; Bloom et al. 2020). In particular, this article examines the long-term consequences of foreign aid on the management practices of firms located in cities where the investments were made in the long term, echoing Giorcelli (2019).

I. The Adoption of the 156 Projects and Its Economic Effects

In 1927, China experienced a civil war between the Kuomintang (KMT)-led government of the Republic of China and the Communist Party of China (CPC). The CPC declared victory and established the PRC on October 1, 1949.[6] The new government aimed to build a modern industrial system, but the country lacked technical knowledge and expertise. On February 14, 1950, China and the Soviet Union signed the Sino-Soviet Treaty of Friendship, Alliance and Mutual Assistance, marking the beginning of large-scale economic and military cooperation between the two nations and the official recognition of the PRC as a strategic partner of the Soviet Union (Zhang, Zhang, and Yao 2006).

[6] Regional armed conflicts between KMT and PRC continued in a number of cities after October 1, 1949.

Between 1950 and 1957, China and the Soviet Union reached various agreements to support large-scale, capital-intensive industrial development, known as the 156 Projects. The total number of projects that received technology transfers from the Soviet Union reached 156.[7] Most of the new projects were in the fields of energy, raw materials, and manufacturing. China received the most advanced technology available in the Soviet Union owing to the adoption of the 156 Projects (Gangchalianke 2002). These programs were unevenly distributed across Chinese cities,[8] generally following three placement considerations: (1) proximity to resources, (2) potential to change economically underdeveloped areas, and (3) military considerations. Yibo Bo, a leader in the Chinese economy, recollected, "National defense and safety was one of the main factors to determine the locations of these Soviet-aided projects" (Bo 1991, p. 210). For more details of the 156 Projects, see Zhang, Zhang, and Yao (2006).

Conceptually, the adoption of the 156 Projects can affect the long-term innovation input of firms located in cities where the investments were made through two opposing forces. On the one hand, the large-scale Soviet-aided technology transfers enhance local industrial firms' capacity to innovate through knowledge spillovers, thereby positively affecting innovation input in the long term (Cohen and Levinthal 1989; Aghion and Jaravel 2015). According to Cohen and Levinthal (1989), R&D not only generates new information but also enhances the firm's capacity to assimilate and exploit existing information. Moreover, several studies have

[7] Only 150 projects were actually constructed. They can be divided into five areas: energy (25 projects in coal, 25 in power), metallurgical and chemical industries (13 in nonferrous metals, 7 in iron and steel, 7 in chemicals, 2 in petroleum), machinery (24 in machine building, 12 in aviation, 10 in electronics), military (16 in weapons, 4 in shipbuilding, 2 in space), and 3 in light industry and pharmacy (Zhang, Zhang, and Yao 2006).

[8] To mitigate the concern that some cities hosted more than one 156 Projects and of different types, I use an alternative measure of the adoption of the156 Projects (i.e., the logarithm of total amounts of investments actually made by the central government for the 156 Projects in each locality) for robustness checks.

shown that access to technology is important for subsequent innovation (Williams 2013; Furman, Nagler, and Watzinger 2021).

On the other hand, the Soviet-aided technology transfers hinder the development of performance-based reward systems as China transitions towards a more market-oriented economy. The prior successes of Soviet-aided industrialization during the era of a planned economy have led to the persistence of collectivism in the economy (Giuliano and Nunn 2021). Specifically, Soviet-aided industrialization contributes to sustaining the centrally planned economy that emphasizes collectivism rather than individualism, and collectivism typically opposes performance-based reward systems (Sutton 1973).[9] Indeed, numerous studies show that foreign aid does not improve and even worsen the quality of governance in recipient countries (Knack 2004; Moss, Pettersson Gelander, and de Walle 2006; Rajan and Subramanian 2007; Djankov, Montalvo, and Reynal-Querol 2008). Considering that a lack of performance-based reward systems disincentivizes local industrial firms from innovating (Lerner and Wulf 2007; Ederer and Manso 2013), firms' innovation input will decline in the long term.

Given the theoretically ambiguous effects of the adoption of the 156 Projects on long-term innovation inputs, seeking empirical evidence is important. This article not only examines the causal impact of the adoption of the 156 Projects on long-term innovation inputs of firms located in cities where the investments were made but also attempts to uncover the likely mechanisms mentioned above.

II. Data Sources and Variables

To measure each city's adoption of the 156 Projects, I manually sort a dataset containing information on each industrial project (e.g., name, industry, geographic location, and total

[9] According to Sutton (1973), after 1917 Soviet scientists made great contributions to scientific theory but few fundamental industrial innovations. One of the most important reasons lay in the Soviet's centrally planned economy, in which enterprises were not the principal elements, thereby creating a lack of the motivation for innovation.

investments) from the literature (Dong and Wu 2004; Chen 2020).[10] I then match this information with firm-level data in each city. I construct a dummy variable to indicate whether a city adopted any of the 156 Projects from 1953 to 1957.[11] For a robustness check, I use the total amount of investments toward that project in each locality as an alternative measure, which further accounts for the heterogeneous adoption of the 156 Projects across adopting localities (e.g., some cities hosted more than one 156 Projects and of different types).

The firm-level dataset comes from an Enterprise Survey for firm managers conducted by the World Bank in 2005. The survey covers 12,400 Chinese manufacturing firms in 120 cities across all provinces, autonomous regions, and directly administrated cities, with the exception of Tibet.[12] The survey includes a broad range of firm-level information, such as firm age, employee wage components, labor conditions, and financial statements. I focus on two variables of interest: pay for performance and innovation inputs.

To measure each firm's adoption of performance-based reward systems, I focus on a single dimension: the extent to which each firm adopts bonuses and piece-rate wages. Using the wage components of all employees for each firm, I calculate the percentage of bonuses and piece-rate wages in total compensation among permanent workers. Firms with a higher percentage of bonuses and piece-rate wages in total compensation among permanent workers are identified as having higher intensity of pay for performance. Conceptually, the minimum intensity of pay

[10] China's constitution provides three de jure levels of government. However, five practical (de facto) levels of local government currently exist as follows: provincial (including province, autonomous region, municipality, and special administrative region), prefecture, county, township, and village. For simplicity, we treat "prefecture-level city" and "city" as interchangeable in this article.

[11] This approach does not distinguish between cities that adopted different industrial projects, projects that were built as planned with Soviet machinery and technical assistance, or other projects realized by China only (Giorcelli and Li 2021).

[12] More information on the survey methodology can be found at http://www.enterprisesurveys.org/methodology.

for performance is 0 (%), and the maximum is 100 (%). I also use alternative measures of pay for performance for robustness checks.

To measure each firm's innovation inputs, I construct a dummy variable indicating whether a firm has positive research and development (R&D) expenditure (i.e., innovation inputs at the extensive margin) based on annual total R&D expenditure. For robustness, I also use three alternative measures: the percentage of R&D expenditure in total sales (i.e., innovation inputs at the intensive margin), a dummy variable indicating positive R&D growth from 2002 to 2004, and a dummy variable indicating positive R&D by aggregating R&D across multiple years (2002-2004) for each firm.

To further measure each firm's innovation results, I complement the main dataset with the Chinese Annual Survey of Industrial Firms (1998–2015), created by the National Bureau of Statistics of China. This survey includes all industrial firms owned by the state or with sales above 5 million RMB. It covers all industrial sectors, including the mining sector, and accounts for roughly 88 percent of the national industrial output. The survey contains extensive information about firm production, including total output, employment, wages, assets, total sales, exports, and more, but it does not contain information on pay for performance.[13] Importantly, the additional firm-level dataset can be matched to China's State Intellectual Property Office patents.[14] The matched firm-level dataset contains variables on innovation results, such as the total number of patents and the number of patents by category (invention, utility model, design).

[13] Several studies, including Bloom et al. (2018) and Hau et al. (2020), have tried to match other survey data about management practices in 564 Chinese firms sampled in 2006, 2007, 2008, and 2010 by Bloom and Van Reenen (2010). The sample size of this dataset, however, is too small to conduct my analysis.

[14] He et al. (2018) provide details on the matching process.

Finally, I construct several other important variables as follows. (1) I use hand-collected archival data on the date of KMT's defeat by the CPC in each Chinese mainland city during the civil war to construct a dummy variable indicating whether the armed conflict of civil war ended before October 1, 1949 in each city.[15] (2) I use hand-collected archival data on the number of universities and colleges in each mainland city in 1949 to proxy for human capital stocks accumulated prior to the establishment of the PRC. (3) I consult the China City Statistical Yearbook (1987), provided by the National Bureau of Statistics of China, to construct cultivated land per capita across cities.[16] (4) I construct measures of the severity of the Great Famine of 1959-1961, the severity of Cultural Revolution, and collectivism culture at the county level, following the literature (Meng, Qian, and Yared 2015; Walder and Lu 2017; Zhu, Ang, and Fredriksson 2019; Chen et al. 2020). (5) I use geographic coordinates (i.e., latitude and longitude) of each location to generate geographical distance variables such as distance to Jinmen, distance to coastline, distance to Beijing, and the shortest distance to a port. **Appendix A1 (Table A1)** reports summary statistics for the main variables.

III. Model Specification and Identification Strategy

To examine the causal impact of China's adoption of the 156 Projects on the long-run innovation inputs of firms located in cities where the investments were made, I use the following two-stage least squares (2SLS) model:[17]

$$T_c = \beta_T^Z \cdot Z_c + \beta_T^K \mathrm{K_{ic}} + \varepsilon_{ic} \quad (1)$$

---

[15] According to the matched firm-level data, about 23 percent firms were located in cities that ended the armed conflict after October 1, 1949, when Chairman Mao Zedong announced the establishment of the PRC.

[16] The cultivated land per capita in 1986 is the earliest data available to us.

[17] Considering that the main variable of interest is a dummy variable, we also resort to Poisson Pseudo-Maximum Likelihood (PPML) to check the robustness of estimation results (details can be found in **Table A5**). Unsurprisingly, our main results still hold, enhancing the credibility of the findings.

$$Y_{ic} = \beta_Y^T \cdot T_c + \beta_Y^K \mathrm{K_{ic}} + \eta_{ic} \quad (2)$$

where Y_{ic} is a dummy variable indicating positive investments in R&D (or positive growth in R&D investments) for each firm i in city c.[18] T_c is a dummy variable indicating THE adoption of a project in city c. Z_c is the instrument, defined as the geographical distance between the centroid of each mainland Chinese city c and the centroid of Jinmen. K_{ic} refers to firm characteristics such as the age, ownership dummies, 2-digit industry dummies for firm i in city c, logarithm of the geographical distance between county c in which firm i is located and the coastline, and the logarithm of the geographical distance between county c in which firm i is located and the capital of the PRC.[19] ε_{ic} and η_{ic} are error terms. β_Y^T is the parameter of interest. Standard errors are clustered at the city level.[20]

Estimating the causal impact of the 156 Projects on the long-run innovation inputs of firms located in cities where the investments were made presents some empirical challenges. For example, innovative firms may self-select into localities that are closer to the technology frontier, resulting in reverse causality issues that render the ordinary least squares (OLS) estimate biased and inconsistent. Additionally, firms may differ in production technology. If

---

[18] Although the firm-level dataset primarily covers only one year for most variable, it includes R&D information spanning three consecutive years from 2002 to 2004. In our benchmark model, we concentrate on a dummy variable indicating whether firms made positive R&D investments in the survey year. Additionally, we utilize the available data from 2002 to 2004 to explore R&D growth in the survey year as a robustness check. Moreover, given that a firm might incur significant R&D spending in one year and none in the following year, we aggregate R&D across multiple years (2002-2004) for each firm to ensure that the results are not unduly influenced by specific events affecting regional R&D variation in a certain year. Unsurprisingly, we find consistent results across these approaches (details can be found in **Table A4**).

[19] Our main results are robust when controlling for distance to coastline and distance to the capital of PRC in levels rather than in logarithms.

[20] To test whether our results are robust to alternative standard errors, we apply Conley standard errors to account for spatial autocorrelation (Conley 1999; Conley 2008). We find that the coefficient of interest remains significant. Conley standard errors were estimated using the *spatial_hac_iv* command for Stata (Foreman 2020).

firms' access to production technology is relevant to the adoption of the 156 Projects in a locality, omitting this variable also biases and makes the OLS estimate inconsistent.

To address these endogeneity concerns, I use an instrumental variable (IV) approach. This approach leverages plausible exogenous variations in the exposure to risks of armed conflict in the Taiwan Strait in the 1950s across mainland Chinese cities. Specifically, I use the geographical distance between the centroid of each mainland Chinese city and the centroid of Jinmen to capture the city-level exposure to risks of armed conflict between mainland China and Taiwan in the Taiwan Strait in the 1950s. The rationale is that mainland Chinese cities closer to Jinmen were exposed to higher risks of armed conflict and were thus less likely to adopt the 156 Projects.

The validity of the IV depends on two important assumptions. First, the geographical distance between mainland Chinese cities and Jinmen is positively associated with the probability of adopting the 156 Projects. Second, conditional on observable characteristics (e.g., exposure to foreign trade, exposure to policies enacted by the central government, human capital stocks, etc.), the geographical distance between mainland Chinese cities and Jinmen affects long-run innovation inputs only through the adoption of the 156 Projects. The first assumption can be tested empirically, but the second assumption is more challenging. Although it is empirically impossible to rule out all other factors that vary with distance to Jinmen and could be correlated (even incidentally) with long-term innovation inputs, I provide some empirical validation of the IV exclusion restriction assumption by testing some of the most likely channels through which the IV may affect long-run innovation inputs:

(1) Exposure to foreign trade. Distance to Jinmen (IV) may be correlated with other geographical characteristics such as distance to coastline and thus exposure to foreign trade. In addition to controlling for local firms' geographical distance to the coastline, as in the benchmark model, I further control for local firms' shortest geographical distance to a port.

(2) Exposure to policies enacted by the central government. Distance to Jinmen may be correlated with other geographical characteristics such as distance to the capital of the PRC and thus exposure to policies enacted by the central government. In addition to controlling for distance to Beijing, as in the benchmark model, I further control for a dummy variable indicating whether the armed conflict of civil war ended before October 1, 1949 in each mainland city. Intuitively, the central government is more likely to favor cities where the armed conflict ended earlier.

(3) Human capital stocks. Distance to Jinmen may be correlated with other city-level characteristics such as the access to universities and colleges and thus exposure to human capital stocks. Therefore, I further control for the number of universities and colleges in each mainland city in 1949 accumulated prior to the establishment of the PRC.

(4) Adverse circumstance. Distance to Jinmen may be correlated with other historical events such as the Cultural Revolution and the Great Famine of 1959-1961 and thus exposure to adverse circumstance. Therefore, I further control for the local severity of the Cultural Revolution and the local severity of the Great Famine following the literature (Meng, Qian, and Yared 2015; Walder and Lu 2017; Chen et al. 2020).

(5) Social norms. Distance to Jinmen may be correlated with farming practices (e.g., rice-farming versus wheat-farming) and thus exposure to individualistic/collectivistic culture (Ang 2019; Talhelm and English 2020; Fiszbein, Jung, and Vollrath 2022). Therefore, I further control for a measure of collectivism culture based on the natural suitability of rice-farming relative to wheat-farming. If including all these control variables does not significantly affect our parameter of interest, it is safer to argue that the IV exclusion restriction assumption is not violated in our context.

To further test the instrument validity, I propose a new IV based on geographical variations in the cultivated land per capita across Chinese mainland cities. Unlike the main IV (i.e., distance to Jinmen), the new IV leverages plausible exogenous variations in the land resources endowment across regions (**Figure A2**). Regions endowed with more land resources are more likely to adopt the 156 Projects, which are capital intensive, given that these regions have relatively higher food production capacity to finance such industrialization due to China's unique food procurement policy under the centrally planned economy (Meng, Qian, and Yared 2015). The additional IV thus allows me to estimate and compare the parameters of interest using different IVs and to test the validity of instruments through the Hansen overidentification test.

IV. Empirical Results

IV.A. Impact of the 156 Projects on Long-run Innovation Inputs

Table 1 reports the main results. Columns 1 and 2 present the OLS estimate of the impact of the adoption of the 156 Projects on R&D investments at the extensive margin for firms located in cities where the investments were made in the long run. Without controlling for additional variables, the coefficient of interest is −0.04, which is not statistically significant at the conventional level. After controlling for other firm-level characteristics, the coefficient decreases to −0.06. Both findings suggest a negative relationship between China's adoption of the 156 Projects and the long-run innovation inputs of firms located in the cities where the investments were made.

As previously discussed, the OLS estimate may be biased by endogeneity problems. Column 3 shows the IV estimate. The coefficient of interest decreases substantially to −0.36, suggesting that the 156 Projects reduced the average firm's probability of investing in R&D by 0.36. The OLS estimate is biased upward for at least two reasons. First, innovative firms are more likely to relocate to areas where the 156 Projects have been adopted to improve their access to the technology frontier, resulting in reverse causality. Second, firms differ in their access to production technology, and when the access to production technology is positively associated with the adoption of the 156 Projects, omitting this variable causes the OLS estimate to be biased upward.

The first-stage results reported in Column 4 show that a one-standard-deviation increase in the geographical distance between each mainland Chinese city and Jinmen leads to a 0.17 higher probability of adopting the 156 Projects on average. The bottom rows of **Table 1** report the results of the weak identification test and the endogeneity test. The Kleibergen-Paap rk Wald F statistic is 14.5, which rejects the null hypothesis that the IV suffers from weak identification problems.[21] Moreover, the p-values from the endogeneity test of endogenous regressors leads to rejecting the null hypothesis that the OLS estimator is consistent and efficient at the 5 percent level. Finally, the reduced-reform results reported in Column 5 show that a one-standard-deviation increase in the geographical distance between each mainland Chinese city and Jinmen reduces the average firm's probability of investing in R&D by 0.06. Collectively, this evidence support the validity of my IV approach.

To rule out the possibility that the IV may not be plausible beyond or below a limited number of kilometers from Jinmen, I further explore the first stage and reduced form results in more detail to confirm that the effects identified occur over a plausible distance (and over the same distances). First, I focus on cities that are at least 300, 500, and 800 km from Jinmen, respectively (Columns 1–6 of **Table 2**). Second, I focus on cities that are at most 3,500, 3,000, and 2,500 km from Jinmen, respectively (Columns 7–12 of **Table 2**). Third, I focus on cities that are between 800 and 2,500 km from Jinmen (Columns 13 and 14 of **Table 2**). All these findings confirm that the first stage and reduced form effects occur over a plausible distance (and over the same distances).

[21] We find robust results when using a Montiel-Olea-Pflueger effective F statistic that does no rely on an assumption of homoskedasticity (Olea and Pflueger 2013).

To mitigate concerns that the IV exclusion restriction assumption is violated, I control for and investigate some of the most likely channels (e.g., exposure to foreign trade, exposure to policies enacted by the central government, human capital stocks, adverse circumstance, social norms) through which the distance to Jinmen may affect long-run innovation inputs. After controlling for all these observable channels, I find that the coefficient of interest changes slightly to −0.37 (Columns 1 to 6 of **Table 3**), suggesting that controlling for these channels does not seriously threaten the main findings. Additionally, I find that the coefficient is significantly positive for two variables: past human capital stocks and the timing of ending the armed conflict of the civil war.

As an additional test, I regress the measure of past human capital stocks and the timing of ending the armed conflict of the civil war on the IV with the included controls, respectively. I find that the distance to Jinmen had no obvious impact on both outcomes (Columns 7 and 8 of **Table 3**), further mitigating concerns that the IV assumption is violated.

Finally, I propose a new IV by leveraging plausible exogenous variations in arable land resources across mainland cities. Specifically, I construct a measure of cultivated land per capita and use it as an instrument for the adoption of the 156 Projects. The coefficient of interest is −0.33 (Column 9 of **Table 3**). The first-stage and reduce-reform results confirm that cities endowed with more land resources were more likely to adopt the 156 Projects and firms located in cities with more arable land resources were less likely to invest in R&D in the long term, respectively (Columns 10 and 11 of **Table 3**). Additionally, I exploit both instruments to test the validity of IVs. The coefficient of interest is −0.33 (Column 12 of **Table 3**). The bottom row of **Table 3** reports results of the Hansen overidentification test (p-value is 0.9266), which fails to reject the null hypothesis that the instruments are valid.

Overall, this evidence suggests that the adoption of the 156 Projects adversely affects the long-run innovation inputs of firms located in cities where the investments were made. To some extent, this finding echoes a recent study by Heblich et al. (2019), who showed that places that adopted the 156 Projects were far less innovative regarding patenting activities than other places in the absence of the 156 Projects.

[Place Tables 1, 2 and 3 about here]

IV.B. How Do the 156 Projects Impede Innovation Inputs?

Various reasons may explain the decline in long-term innovation inputs in adopting localities. One possibility is that Soviet-aided industrialization helped sustain the centrally planned economy that emphasized collectivism rather than individualism (Sutton 1973). The resulting persistence of collectivism in the economy hindered the adoption of performance-based reward systems (Giuliano and Nunn 2021). Studies have shown that pay for performance affects worker productivity (Lazear 2000; Shearer 2004) and innovation results (Lerner and Wulf 2007; Ederer and Manso 2013). Unlike Heblich et al. (2019), who focused on the mechanism of overspecialization for the decline in innovation activities, this article explores whether the low adoption of pay for performance in firms located in cities where the investments were made is a likely underlying mechanism through which adopting the 156 Projects reduces innovation inputs.

I estimate the causal impact of the 156 Projects on the long-term adoption of pay for performance by firms located in cities where the investments were made as follows:

$$M_{ic} = \beta_M^T \cdot T_c + \beta_M^K \mathrm{K}_{ic} + \epsilon_{ic} \quad (3)$$

This approach is identical to equation (2), except M_{ic} replaces Y_{ic}. The first-stage equation (1) remains the same. M_{ic} is the use of pay for performance adopted by firm i in county c, defined as the percentage of bonuses and piece-rate wages in total compensation among permanent workers. β_M^T is the parameter of interest. I cluster standard errors at the city level.

Table 4 reports the main results. Columns 1 and 2 present the OLS estimate of the impact of the 156 Projects on the adoption of pay for performance by firms located in cities where the investments were made. Without any control variables, the coefficient of interest is −8.20. After controlling for other firm-level characteristics, the coefficient of interest is −9.24. As previously discussed, the OLS estimates are likely to be biased due to endogeneity problems.

Using the same IV approach, the coefficient of interest decreases substantially to −32.01, suggesting that the 156 Projects led to a 32-unit decrease in the intensity of pay for performance on average. This evidence demonstrates a negative impact of the 156 Projects on the long-term adoption of pay for performance, supporting the notion that the prior successes of Soviet-aided industrialization during the era of a planned economy led to the persistence of collectivism in the economy. To some extent, these findings echo those of recent studies by Giorcelli (2019) and Bloom et al. (2020), who found that the impact of management interventions can persist over time. Further details on the first-stage results, reduced-from results, and relevant tests for the IV are presented in **Table 4**.

[Place Table 4 about here]

The extent to which the 156 Projects have affected China's long-run innovation inputs via the use of pay for performance remains unclear. Thus, a mediation analysis can be useful. A mediation model consists of a treatment variable T, a final outcome Y, and a mediating variable M, which represents a mechanism through which T affects Y. Essentially, mediation models decompose the "total effect" of T on Y into an "direct effect" and an "indirect effect" running through M. Traditional approaches to mediation analysis assume that both T and M are exogenous (Baron and Kenny 1986; MacKinnon 2008). However, such approaches cannot deal with setups in which T, M, or both T and M are endogenous.

I therefore employ an identification framework for a causal mediation analysis in IV settings, as developed by Dippel et al. (2019, 2020). This framework enables the use of the same instrument Z to assess the causal effect of the intermediate outcome M on the final outcome Y. I further estimate the following two-stage model:

$$M_{ic} = \gamma_M^Z \cdot Z_c + \gamma_M^T \cdot T_c + \gamma_M^K \mathrm{K_{ic}} + \epsilon_{ic} \quad (4)$$

$$Y_{ic} = \beta_Y^M \cdot M_{ic} + \beta_Y^T \cdot T_c + \beta_Y^K \mathrm{K_{ic}} + \eta_{ic} \quad (5)$$

The estimation procedure associated with equations (1) and (2) follows the standard IV approach. By contrast, the estimation procedure associated with equations (4) and (5) is novel to the framework of Dippel et al. (2019), where Z_c is the IV used to identify the causal effect of M_{ic} on Y_{ic} when conditioned on T_c. All variables are the same as before. β_Y^M and β_Y^T are the coefficients of interest. I cluster standard errors at the city level.

According to Dippel et al. (2019), identifying β_Y^M and β_Y^T using a single instrument variable Z_c requires an additional partial confounding assumption. This assumption posits that unobserved confounding variables that jointly lead to the treatment and intermediate outcomes (first causal relation) are independent of the confounders that cause the intermediate and final outcomes (second causal relation). In my context, confounders in the first causal relation capture unobserved workers' values and beliefs (e.g., collectivism versus individualism) in a locality that adopted the 156 Projects. The greater adoption of pay for performance could be due to workers' values and beliefs or to the adoption of the 156 Projects in that locality. In contrast, the confounders in the second causal relation represent firms' production technology that supports both the adoption of pay for performance and innovation inputs. If workers' values and beliefs are uncorrelated with firms' production technology, then the partial confounding assumption is likely to hold.

Table 5 reports the main results. Panel A presents the results of the second-stage equation (5). Column 1 assesses the mediating effect changes in the use of pay for performance. The point estimate $\hat{\beta}_Y^M$ in column 1 indicates that a 10-percentage-point increase in the intensity of pay for performance raises the average probability of firms' investing in R&D by 0.13. This represents the overall effect of the use of pay for performance on firms' probability of investing in R&D, whether caused by the adoption of the 156 Projects or not.

The real importance of the point estimates $\hat{\beta}_Y^M$ lies in generating the indirect effect $IE = \hat{\beta}_Y^M \times \hat{\beta}_M^T$, as reported in Panel B of **Table 5**, along with other relevant parameters of the mediation model. The $\hat{\beta}_M^T$ of the 156 Projects on the intensity of pay for performance is estimated at -32. The indirect effect IE is the effect of changing the intensity of pay for performance, as caused by the adoption of the 156 Projects, on long-run innovation inputs. An adopting locality that decreases the pay for performance subsequently reduces firms' probability of investing in R&D by 0.41 on average.

Relating this outcome to the total effect of adoption on long-run innovation inputs estimated in **Table 5**, the use of pay for performance can, as mediator *M*, explain around 117 percent of the overall effect of adoption on long-run innovation inputs of firms located in cities where the investments were made. β_Y^T and $\beta_M^T \cdot \beta_Y^M$ add up to the effect estimated in **Table 5** (i.e., DE+IE=TE).

[Place Table 5 about here]

The indirect effect of the adoption of the 156 Projects is larger than the total effect, implying a moderating direct effect whereby adoption raises the probability of firms investing in R&D through channels unrelated to the use of pay for performance (e.g., access to production technology). This finding suggests that adoption would have a stronger negative effect on long-run innovation inputs if it only affected the use of pay for performance. However, the effect would be different: the adoption of the 156 Projects would not negatively affect, or might even positively affect, long-run innovation inputs if the impact of adoption on pay for performance could be mitigated (e.g., through the development of incentive-compatible management practices across firms).

IV.C. Impact of the 156 Projects on Innovation Results

To address concerns that R&D spending may not fully capture innovation activities, I use an additional dataset that links China's State Intellectual Property Office patents to firms in

China's annual survey of industrial enterprises (1998–2015) for a complementary analysis. This dataset contains rich information on innovation results at the firm level, such as the total number of patents and number of patents by category (i.e., invention, utility model, and design).

Using the same IV approach, I find that the adoption of the 156 Projects reduces the average probability of patenting for firms located in cities where the investments were made by 0.04 (Column 3 of **Table 6**). Further analysis of the heterogeneous effects by patent category shows that the impact is more pronounced for design patents (−0.08, Column 8 of **Table 6**), followed by utility model patents (−0.06, Column 7 of **Table 6**). In contrast, the impact on invention patents is smaller (−0.01, Column 6 of **Table 6**) and not statistically significant at the conventional levels. These findings indicate that adoption disproportionately affects different types of innovation outcomes, possibly because increasing the adoption of pay-for-performance alone is inadequate to induce breakthrough innovation (Ederer and Manso 2013). By further analyzing the heterogeneous effects over time, I find that the impact is significant for all periods but decreases over time (Columns 9 to 11 of **Table 6**). All of this evidence further supports the argument that adopting the 156 Projects impedes innovation in firms located in cities where the investments were made. Further details for the estimation can be found in **Table 6**.

[Place Table 6 about here]

IV.D Competing Mechanisms

As mentioned before, various factors may explain the decline in innovation inputs in adopting localities. To address concerns that the negative impact of adoption on long-run innovation inputs of firms located in cities where the investments were made is driven by other competing channels (e.g., overspecialization), I further compare the impact of the 156 Projects between state-owned and non-state-owned firms. Given that state-owned firms have less flexibility in technological choices than their non-state-owned counterparts in China due to fewer autonomies, the long-run innovation inputs of state-owned firms should be less responsive to the adoption if the pay for performance mechanism dominates the negative impact. Otherwise, there are other mechanisms at play. Specifically, if the overspecialization mechanism dominates, state-owned firms are more likely to get locked into specialized structures and face little incentives to innovate compared to non-state-owned firms. Consequently, state-owned firms would suffer more from the increasingly specialized structure in adopting localities.

The main findings are presented in **Table A6**. The results indicate that the negative impact of the adoption on the long-run innovation inputs of firms located in cities where the investments were made is more pronounced for non-state-owned firms than state-owned firms. Additionally, non-state-owned firms' adoption of pay for performance is more responsive to the 156 Projects than their state-owned firms, supporting the notion that state-owned firms are less flexible in technological choices compared to their non-state-owned counterparts.

As an additional check, I further analyze the effects of the adoption of the 156 Projects on several firm-level outcomes such as employment, capital, capital-labor ratio, exports, skill composition of employees, and technological adoption in terms of computer use. Using the same IV approach, I find no evidence that adoption affects local firms' employment size, assets, capital-labor ratio, percentage of exports, percentage of employees who received formal training, or percentage of employees who regularly use computers. However, I find that adoption significantly and positively affects the percentage of employees with high school education or above, as well as the percentage of employees with college education or above. These findings mitigate concerns that the decline in innovation inputs in adopting localities is caused by a lack of capital and skilled workers, and further support that a lack of pay-for-performance systems is a likely underlying mechanism through which adoption negatively affects R&D. Further details on the estimation results can be found in **Appendix A3** (**Table A7**).

IV.E. Robustness Checks

I conduct several robustness checks to validate the main findings. First, to account for the heterogeneous adoption of the 156 Projects across localities, I use an alternative measure: the logarithm of total investment amounts actually made by the central government for the 156 Projects in each locality. Second, I use alternative measures of pay for performance, including: (1) the percentage of bonuses in total compensation (excluding piece-rate wages) among permanent workers; (2) the percentage of piece-rate wages in total compensation (excluding bonuses) among permanent workers; (3) the percentage of bonuses and piece-rate wages in total compensation among all workers (including temporary workers); and (4) a dummy variable indicating whether the general manager's annual income is directly related to the company's performance. Third, I use three alternative measures of innovation inputs: (1) the percentage of R&D expenditure in total sales; (2) a dummy variable indicating positive R&D growth from 2002 to 2004; and (3) a dummy variable indicating positive R&D by aggregating R&D across multiple years (2002-2004) for each firm. I find no evidence that contradicts the main findings. Further details on these robustness checks can be found in **Appendix A2** (**Tables A2–A4**).

V. Conclusion

To the best of my knowledge, this is one of the first studies to investigate the causal impact of technology transfers on long-run innovation inputs of firms located in cities where the investments were made within a developing country. The most important lesson of this study is that the Soviet-aided technology transfers substantially reduce the long-term innovation inputs of firms in these cities. Another key finding is that low adoption of performance-based reward systems, rather than a lack of capital and skilled workers, is a likely underlying mechanism. These findings suggest that, despite prior successes achieved during the era of a planned economy, the adoption of such Soviet aid impedes long-run innovation, possibly due to the persistence of collectivism in the economy, which hinders the development of performance-based reward systems.

This is not to suggest that other developing countries should not resort to foreign aid to develop their economy. But authorities should understand the long-term challenges that foreign aid poses and take necessary measures to navigate these challenges. For China, this article suggests that developing incentive-compatible management practices could help manage the unintended effects of Soveit-aided industrialization programs on innovation and economic development, even after nearly half a century.

Table 1 Impact of the adoption of the 156 Projects on firms' innovation inputs

Variables	(1) OLS	(2) OLS	(3) IV	(4) First Stage	(5) Reduced
Access to 156 Projects	-0.0430	-0.0636***	-0.3585***		
	(0.0266)	(0.0228)	(0.1103)		
IV: Distance to Jinmen (km)				0.0003***	-0.0001***
				(0.0001)	(0.0000)
Observations	11200	11195	11195	11195	11195
R-squared	0.0013	0.0645	0.0099	0.2380	0.0718
F-stat	2.6132	24.8511	13.8141	2.8600	25.7824
Weak IV test (F statistic)			14.4622		
Endogeneity test (p-value)			0.0001		
Control variables	NO	YES	YES	YES	YES

Notes: This table reports the impact of the adoption of the 156 Projects on firms' innovation inputs. Columns 1 and 2 report the OLS results, with and without control variables, respectively. Columns 3 and 4 report the IV estimates and first-stage results. Column 5 reports the reduced reform results. Control variables consist of firm-level variables such as age, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the county in which firms are located and the coastline, and the logarithm of the distance between the county in which firms are located and Beijing. The 156 Projects variable is constructed based on a city's access to the 156 Projects in the 1950s. Firm-level variables come from World Bank's Enterprise Survey in 2005. Standard errors are clustered at the city level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2 First-stage and reduced form in more detail

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	⩾800 km		⩾500 km		⩾300 km		⩽3,500 km	
	First Stage	Reduced Form	First Stage	Reduced Form	First Stage	Reduced Form	First Stage	Reduced Form
IV: Distance to Jinmen	0.0004***	-0.0001***	0.0003***	-0.0001***	0.0003***	-0.0001***	0.0003***	-0.0001***
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Observations	7896	7896	10095	10095	10595	10595	11095	11095
R-squared	0.3161	0.0699	0.2617	0.0768	0.2359	0.0747	0.2148	0.0718
F-stat	4.2475	46.4564	3.2592	47.4065	3.1081	44.1689	2.3964	26.5831

Variables	(9)	(10)	(11)	(12)	(13)	(14)
	⩽3,000 km		⩽2,500 km		800–2,500 km	
	First Stage	Reduced Form	First Stage	Reduced Form	First Stage	Reduced Form
IV: Distance to Jinmen	0.0003***	-0.0001***	0.0002**	-0.0001***	0.0004***	-0.0002***
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Observations	11095	11095	10895	10895	7596	7596
R-squared	0.2148	0.0718	0.1792	0.0725	0.2499	0.0722
F-stat	2.3964	26.5831	1.8911	26.9248	2.8483	49.0381

Notes: This table reports first stage and reduced form results in more detail. Columns 1 and 2 report first stage and reduced form results by focusing on cities that are at least 800 km from Jinmen. Columns 3 and 4 report first stage and reduced form results by focusing on cities that are at least 500 km from Jinmen. Columns 5 and 6 report first stage and reduced form results by focusing on cities that are at least 300 km from Jinmen. Columns 7 and 8 report first stage and reduced form results by focusing on cities that are at most 3,500 km from Jinmen. Columns 9 and 10 report first stage and reduced form results by focusing on cities that are at most 3,000 km from Jinmen. Columns 11 and 12 report first stage and reduced form results by focusing on cities that are at most 2,500 km from Jinmen. Columns 13 and 14 report first stage and reduced form results by focusing on cities that are between 800 and 2,500 km from Jinmen. Standard errors are clustered at the county level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3 Test the validity of the IV exclusion restriction assumption

Variables	(1)	(2)	(3)	(4)	(5)	(6)
			IV: Control for other channels			
	Distance to port	Armed conflict	Human capital	Historical events	Cultural difference	All channels
Access to 156 Projects	-0.3793***	-0.3447***	-0.3494***	-0.3553***	-0.3696***	-0.3705***
	(0.1286)	(0.0973)	(0.0994)	(0.1151)	(0.1187)	(0.1211)
Observations	11195	11195	11195	10795	11195	10795
R-squared	0.0023	0.0209	0.0193	0.0096	0.0057	0.0200
F-stat	13.0274	14.9187	14.9816	12.2951	13.3857	14.8208
Weak IV test (F statistic)	10.8308	16.5283	16.3850	13.2126	14.1302	11.2886
Endogeneity test (p-value)	0.0001	0.0003	0.0001	0.0001	0.0002	0.0005
Control variables	YES	YES	YES	YES	YES	YES

Variables	(7)	(8)	(9)	(10)	(11)	(12)
	Regress Armed conflict on IV	Regress human capital on IV	IV	New IV First Stage	Reduced	Both IVs
Access to 156 Projects			-0.3296***			-0.3333***
			(0.1031)			(0.0943)
IV: Distance to Jinmen (km)	-0.0002	-0.0000				
	(0.0004)	(0.0001)				
IV: Cultivated land per capita				0.1552***	-0.0511***	
				(0.0360)	(0.0110)	
Observations	11195	11195	10995	10995	10995	10995
R-squared	0.0840	0.3656	0.0198	0.2425	0.0693	0.0185
F-stat	1.5683	3.4343	14.5740	3.5309	23.1596	14.4961
Weak IV test (F statistic)			18.5418			10.6713
Endogeneity test (p-value)			0.0003			0.0001
Hansen test (p-value)						0.9266
Control variables	YES	YES	YES	YES	YES	YES

Notes: This table tests the validity of the IV exclusion restriction assumption. Columns 1 to 6 shows the IV estimate by controlling several likely channels (i.e., exposure to foreign trade, exposure to policies enacted by the central government, human capital stocks, historical events, and cultural differences) through which the IV may affect the local firms' innovation inputs. Column 7 regresses the timing of ending the armed conflict of civil war on the IV with included controls. Column 8 regresses past human capital stocks in 1949, accumulated prior to the establishment of the People's Republic of China, on the IV with included controls. Columns 9 to 11 show the IV estimate, first-stage estimate, and reduced form estimate using a new IV i.e. cultivated land per capita. Column 12 shows the IV estimate by using two IVs together. The main IV refers to the geographical distance between each mainland Chinese city and Jinmen. Firm-level variables come from World Bank's Enterprise Survey in 2005. Standard errors are clustered at the city level. Standard errors are in parentheses. *** p < .01, ** p < .05, * p < .1.

Table 4 Impact of the 156 Projects on the use of performance-based reward systems

Variables	(1) OLS	(2) OLS	(3) IV	(4) First Stage	(5) Reduced
Access to 156 Projects	-8.1950*** (1.6699)	-9.2425*** (1.6714)	-32.0128*** (9.4444)		
IV: Distance to Jinmen (km)				0.0003*** (0.0001)	-0.0088*** (0.0012)
Observations	10942	10938	10938	10938	10938
R-squared	0.0103	0.0825	0.0135	0.2354	0.0873
F-stat	24.0822	15.7280	14.1982	2.8460	18.1517
Weak IV test (F statistic)			13.9820		
Endogeneity test (p-value)			0.0003		
Control variables	NO	YES	YES	YES	YES
Variables	(6) Control likely channels	(7) New IV	(8) First Stage	(9) Reduced	(10) Two IVs
Access to 156 Projects	-33.7427*** (11.5572)	-29.7504*** (10.2515)			-30.4072*** (9.0120)
IV: Cultivated land per capita			0.1552*** (0.0360)	-4.5993*** (1.3273)	
Observations	10545	10742	10995	10742	10742
R-squared	0.0095	0.0297	0.2425	0.0881	0.0261
F-stat	12.2082	14.6509	3.5309	15.4625	14.6764
Weak IV test (F statistic)	10.9694	18.5252			10.5621
Endogeneity test (p-value)	0.0016	0.0019			0.0004
Hansen test (p-value)					0.8442
Control variables	YES	YES	YES	YES	YES

Notes: This table reports the impact of the adoption of 156 Projects on the use of performance-based reward systems. Columns 1 and 2 report the OLS results, with and without control variables, respectively. Columns 3 to 5 report the IV, first-stage, and reduced form estimates. Column 6 shows the IV estimate by controlling for several likely channels (i.e., exposure to foreign trade, exposure to policies enacted by the central government, human capital stocks, historical events, and cultural differences) through which the IV may affect the use of performance-based reward systems. Columns 7 and 9 show the IV, first-stage, and reduced form estimate using a new IV i.e. cultivated land per capita. Column 10 shows the IV estimate by using two IVs together. Control variables consist of firm-level variables such as age, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the county in which firms are located and the coastline, and the logarithm of the distance between the county in which firms are located and Beijing. Firm-level variables come from World Bank's Enterprise Survey in 2005. Standard errors are clustered at the city level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5 Estimates of the mediation model

Mediating Variables	(1)
Panel A: Second Stage (Equation 5)	
β_Y^M	0.0130***
	(0.0028)
DE: β_Y^T	0.0614
	(0.0358)
F-Stat Instruments	25.016
Panel B: Model Parameters	
β_M^T	-31.9968
IE: $\beta_M^T \cdot \beta_Y^M$	-0.4161
TE	-0.3552
IE+DE	-0.3552
S=IE/TE	1.17
S=IE/(IE+DE)	1.17
Panel C: First-Stage Equation (Equation 4)	
γ_M^Z	-0.0071***
	(0.0014)
γ_M^T	-6.1697***
	(1.5929)
Observations	10938
R-Squared	0.0918

Notes: This table reports estimates of the mediation model. Panel A reports the second-stage results, based on equation (5). Panel C reports the first-stage results based on equation (4). Panel B reports main parameters of the mediation model. I use the STATA code *ivmediate* to estimate the main results above (Dippel, Ferrara, and Heblich 2020). Firm-level variables come from World Bank's Enterprise Survey in 2005. Standard errors are clustered at the city level. Standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 6 Impact of the adoption of the 156 Projects on firm patenting

Variables	(1)	(2)	(3) All patenting	(4)	(5)	(6) Invention only
	OLS	OLS	IV	First Stage	Reduced	IV
Access to 156 Projects	-0.0082	-0.0157**	-0.0479***			-0.0080
	(0.0087)	(0.0068)	(0.0171)			(0.0329)
Distance to Jinmen (IV)				0.0004***	-0.0000***	
				(0.0001)	(0.0000)	
Observations	298741	238918	238918	238918	238918	238918
R-squared	0.0210	0.0299	0.0294	0.3516	0.0300	0.0765
F-stat	91.5269	437.8270	384.2544	5.5965	440.5144	813.6184
Weak IV test (F statistic)			15.6100			15.6100
Control variables	NO	YES	YES	YES	YES	YES

Variables	(7) Utility only	(8) Design only	(9) Period (2001-2005)	(10) Period (2006-2010)	(11) Period (2011-2015)
	IV	IV	IV	IV	IV
Access to 156 Projects	-0.0679***	-0.0824***	-0.1538***	-0.1104***	-0.0567*
	(0.0248)	(0.0284)	(0.0466)	(0.0265)	(0.0321)
Observations	238918	238918	25181	49702	160928
R-squared	0.1134	0.0551	0.0542	0.0445	0.0541
F-stat	996.8022	478.6567	324.8081	409.3025	399.9549
Weak IV test (F statistic)	15.6100	15.6100	11.3295	17.3773	15.6064
Control variables	YES	YES	YES	YES	YES

Notes: This table reports the impact of the adoption of the 156 Projects on firms' propensity to patenting. Columns 1 and 2 report the OLS results, with and without control variables, respectively. Columns 3 to 5 report the IV, first-stage, and reduced form estimates. Columns 6 to 8 further report IV estimates by the category of patenting, namely invention patenting (Column 6), utility patenting (Column 7), and design patenting (Column 8). Columns 9 to 11 further report IV estimates by using different periods for estimation, namely period from 2001 to 2005 (Column 9), period from 2006 to 2010 (Column 10), and period from 2011 to 2015 (Column 11). Control variables consist of firm-level variables such as age, 3-digit ownership dummies, 2-digit industry dummies, the logarithm of the distance between the county in which firms are located and the coastline, the logarithm of the distance between the county in which firms are located and Beijing. The 156 Projects variable is constructed based on a city's access to the 156 Projects in the 1950s. Firm-level date come from Chinese Annual Survey of Industrial Firms (1998–2015), matched with China's State Intellectual Property Office patents. Standard errors are clustered at the city level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

References

Acemoglu, Daron, Simon Johnson, and James A Robinson. 2001. "The Colonial Origins of Comparative Development: An Empirical Investigation." *American Economic Review* 91 (5): 1369–1401.

Aghion, Philippe, and Xavier Jaravel. 2015. "Knowledge Spillovers, Innovation and Growth." *The Economic Journal* 125 (583): 533–73.

Ang, James B. 2019. "Agricultural Legacy and Individualistic Culture." *Journal of Economic Growth* 24 (4): 397–425.

Banerjee, Abhijit, and Lakshmi Iyer. 2005. "History, Institutions, and Economic Performance: The Legacy of Colonial Land Tenure Systems in India." *American Economic Review* 95 (4): 1190–1213.

Baron, Reuben M, and David A Kenny. 1986. "The Moderator--Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations." *Journal of Personality and Social Psychology* 51 (6): 1173. https://psycnet.apa.org/buy/1987-13085-001.

Becker, Sascha O, and Ludger Woessmann. 2009. "Was Weber Wrong? A Human Capital Theory of Protestant Economic History." *The Quarterly Journal of Economics* 124 (2): 531–96.

Bloom, Nicholas, Erik Brynjolfsson, Lucia Foster, Ron Jarmin, Megha Patnaik, Itay Saporta-Eksten, and John Van Reenen. 2019. "What Drives Differences in Management Practices?" *American Economic Review* 109 (5): 1648–83. https://doi.org/10.1257/aer.20170491.

Bloom, Nicholas, Aprajit Mahajan, David McKenzie, and John Roberts. 2020. "Do Management Interventions Last? Evidence from India." *American Economic Journal: Applied Economics* 12 (2): 198–219.

Bloom, Nicholas, Kalina Manova, John Van Reenen, Stephen Teng Sun, and Zhihong Yu. 2018. “Managing Trade: Evidence from China and the US.” https://doi.org/10.3386/w24718.

Bloom, Nicholas, and John Van Reenen. 2010. “Why Do Management Practices Differ across Firms and Countries?” *Journal of Economic Perspectives* 24 (1): 203–24. https://doi.org/10.1257/jep.24.1.203.

Bo, Yibo. 1991. “Review of Several Major Decisions and Events.” *The Chinese Communist Party School Press, Beijing*.

Boone, Peter. 1996. “Politics and the Effectiveness of Foreign Aid.” *European Economic Review* 40 (2): 289–329.

Burnside, Craig, and David Dollar. 2000. “Aid, Policies, and Growth.” *American Economic Review* 90 (4): 847–68.

Chen, Ting, James Kai-sing Kung, and Chicheng Ma. 2020. “Long Live Keju! The Persistent Effects of China’s Civil Examination System.” *The Economic Journal* 130 (631): 2030–64.

Chen, Xi. 2020. *Laying the Foundation*. Tiandi Press.

Chen, Yi, Ziying Fan, Xiaomin Gu, and Li-An Zhou. 2020. “Arrival of Young Talent: The Send-down Movement and Rural Education in China.” *American Economic Review* 110 (11): 3393–3430.

Clemens, Michael A, Steven Radelet, Rikhil R Bhavnani, and Samuel Bazzi. 2012. “Counting Chickens When They Hatch: Timing and the Effects of Aid on Growth.” *The Economic Journal* 122 (561): 590–617.

Cohen, Wesley M, and Daniel A Levinthal. 1989. “Innovation and Learning: The Two Faces of R \& D.” *The Economic Journal* 99 (397): 569–96.

Conley, T. 2008. “Spatial Econometrics. New Palgrave Dictionary of Economics, Eds

Durlauf SN, Blume LE.” Palgrave Macmillan, New York.

Conley, Timothy G. 1999. “GMM Estimation with Cross Sectional Dependence.” *Journal of Econometrics* 92 (1): 1–45.

DeLong, J Bradford, and Barry Eichengreen. 1991. “The Marshall Plan: History’s Most Successful Structural Adjustment Program.” National Bureau of Economic Research Cambridge, Mass., USA.

Dippel, Christian, Andreas Ferrara, and Stephan Heblich. 2020. “Causal Mediation Analysis in Instrumental-Variables Regressions.” *The Stata Journal* 20 (3): 613–26. https://doi.org/10.1177/1536867X20953572.

Dippel, Christian, Robert Gold, Stephan Heblich, and Rodrigo Pinto. 2019. “Mediation Analysis in IV Settings With a Single Instrument.” https://www.anderson.ucla.edu/faculty_pages/christian.dippel/DGHP-IVmediate.pdf.

Djankov, Simeon, Jose G Montalvo, and Marta Reynal-Querol. 2008. “The Curse of Aid.” *Journal of Economic Growth* 13 (3): 169–94.

Dong, Zhikai, and Jiang Wu. 2004. *The Cornerstone of New China’s Industry-a Study of the 156 Projects 1950-2000*. Guangdong jingji chubanshe.

Dreher, Axel, Andreas Fuchs, Bradley Parks, Austin Strange, and Michael J Tierney. 2021. “Aid, China, and Growth: Evidence from a New Global Development Finance Dataset.” *American Economic Journal: Economic Policy* 13 (2): 135–74.

Easterly, William. 2003. “Can Foreign Aid Buy Growth?” *Journal of Economic Perspectives* 17 (3): 23–48.

———. 2007. “Was Development Assistance a Mistake?” *American Economic Review* 97 (2): 328–32.

———. 2009. “Can the West Save Africa?” *Journal of Economic Literature* 47 (2): 373–447.

Easterly, William, Ross Levine, and David Roodman. 2004. “Aid, Policies, and Growth:

Comment." *American Economic Review* 94 (3): 774–80.

Ederer, Florian, and Gustavo Manso. 2013. "Is Pay for Performance Detrimental to Innovation?" *Management Science* 59 (7): 1496–1513.

Eichengreen, Barry, and Marc Uzan. 1992. "The Marshall Plan: Economic Effects and Implications for Eastern Europe and the Former USSR." *Economic Policy* 7 (14): 13–75.

Fiszbein, Martin, Yeonha Jung, and Dietrich Vollrath. 2022. "Agrarian Origins of Individualism and Collectivism."

Foreman, Tim. 2020. "SPATIAL_HAC_IV: Stata Module to Estimate an Instrumental Variable Regression, Adjusting Standard Errors for Spatial Correlation, Heteroskedasticity, and Autocorrelation."

Frederiksen, Anders, and Colleen Manchester. 2020. "Personnel Practices and Regulation How Firm-Provided Incentives Respond to Changes in Mandatory Retirement Law." *Journal of Labor Economics*. https://doi.org/10.1086/712610.

Furman, Jeffrey L, Markus Nagler, and Martin Watzinger. 2021. "Disclosure and Subsequent Innovation: Evidence from the Patent Depository Library Program." *American Economic Journal: Economic Policy* 13 (4): 239–70.

Gangchalianke, Igor. 2002. "The Military Factors in the Separation between Soviet Union and China."

Giorcelli, Michela. 2019. "The Long-Term Effects of Management and Technology Transfers." *American Economic Review* 109 (1): 121–52.

Giorcelli, Michela, and Bo Li. 2021. "Technology Transfer and Early Industrial Development: Evidence from the Sino-Soviet Alliance." *Available at SSRN*.

Giuliano, Paola, and Nathan Nunn. 2021. "Understanding Cultural Persistence and Change." *The Review of Economic Studies* 88 (4): 1541–81.

Hau, Harald, Yi Huang, and Gewei Wang. 2020. "Firm Response to Competitive Shocks:

Evidence from China’s Minimum Wage Policy.” *The Review of Economic Studies* 87 (6): 2639–71. https://doi.org/10.1093/restud/rdz058.

He, Zi-Lin, Tony W Tong, Yuchen Zhang, and Wenlong He. 2018. “A Database Linking Chinese Patents to China’s Census Firms.” *Scientific Data* 5 (1): 1–16.

Heblich, Stephan, Marlon Seror, Hao Xu, and Yanos Zylberberg. 2019. “Industrial Clusters in the Long Run: Evidence from Million-Rouble Plants in China.”

Hu, Zhi-an, Jinghong Li, and Zhuo Nie. 2021. “Long Live Friendship? The Long-Term Impact of Soviet Aid on Sino-Russian Trade.” *The Long-Term Impact of Soviet Aid on Sino-Russian Trade (November 18, 2021)*.

Jia, Ruixue. 2014. “The Legacies of Forced Freedom: China’s Treaty Ports.” *Review of Economics and Statistics* 96 (4): 596–608.

Knack, Stephen. 2004. “Does Foreign Aid Promote Democracy?” *International Studies Quarterly* 48 (1): 251–66.

Lazear, Edward P. 2000. “Performance Pay and Productivity.” *American Economic Review* 90 (5): 1346–61. https://doi.org/10.1257/aer.90.5.1346.

Lerner, Josh, and Julie Wulf. 2007. “Innovation and Incentives: Evidence from Corporate R&D.” *The Review of Economics and Statistics* 89 (4): 634–44.

Li, Bo, and Michela Giorcelli. 2022. “Technology Transfer and Early Industrial Development: Evidence from the Sino-Soviet Alliance.”

Lowes, Sara, and Eduardo Montero. 2021. “The Legacy of Colonial Medicine in Central Africa.” *American Economic Review* 111 (4): 1284–1314.

MacKinnon, David Peter. 2008. *Introduction to Statistical Mediation Analysis*. Routledge. https://books.google.com/books?hl=zh-CN&lr=&id=vHUVYKfrdtYC&oi=fnd&pg=PP2&dq=Introduction+to+Statistical+Mediation+Analysis&ots=QD0WN3mdFv&sig=v6hZpwV_lM076aZtMmkT6P-

TemE#v=onepage&q=Introduction to Statistical Mediation Analysis&f=false.

Markevich, Andrei, and Ekaterina Zhuravskaya. 2018. “The Economic Effects of the Abolition of Serfdom: Evidence from the Russian Empire.” *American Economic Review* 108 (4–5): 1074–1117.

Meng, Xin, Nancy Qian, and Pierre Yared. 2015. “The Institutional Causes of China’s Great Famine, 1959--1961.” *The Review of Economic Studies* 82 (4): 1568–1611.

Moss, Todd J, Gunilla Pettersson Gelander, and Nicolas de Walle. 2006. “An Aid-Institutions Paradox? A Review Essay on Aid Dependency and State Building in Sub-Saharan Africa.” *Center for Global Development Working Paper*, no. 74: 5–11.

Nunn, Nathan. 2009. “The Importance of History for Economic Development.” *Annu. Rev. Econ.* 1 (1): 65–92.

Nunn, Nathan, and Leonard Wantchekon. 2011. “The Slave Trade and the Origins of Mistrust in Africa.” *American Economic Review* 101 (7): 3221–52.

Olea, José Luis Montiel, and Carolin Pflueger. 2013. “A Robust Test for Weak Instruments.” *Journal of Business \& Economic Statistics* 31 (3): 358–69.

Rajan, Raghuram G, and Arvind Subramanian. 2008. “Aid and Growth: What Does the Cross-Country Evidence Really Show?” *The Review of Economics and Statistics* 90 (4): 643–65.

Rajan, Raghuram, and Arvind Subramanian. 2007. “Does Aid Affect Governance?” *American Economic Review* 97 (2): 322–27.

Shearer, Bruce. 2004. “Piece Rates, Fixed Wages and Incentives: Evidence from a Field Experiment.” *The Review of Economic Studies* 71 (2): 513–34.

Sutton, Anthony C. 1973. *Western Technology and Soviet Economic Development. Vol. 3. 1945 to 1965*. Hoover Institution.

Talhelm, Thomas, and Alexander S English. 2020. “Historically Rice-Farming Societies

Have Tighter Social Norms in China and Worldwide.” *Proceedings of the National Academy of Sciences* 117 (33): 19816–24.

UNCATAD. 2007. “Least Developed Countries Report 2007.” https://unctad.org/system/files/official-document/ldc2007_en.pdf.

Walder, Andrew G, and Q Lu. 2017. “China Political Events Dataset, 1966-1971.”

Williams, Heidi L. 2013. “Intellectual Property Rights and Innovation: Evidence from the Human Genome.” *Journal of Political Economy* 121 (1): 1–27.

Zhang, Baichun, Jiuchun Zhang, and Fang Yao. 2006. “Technology Transfer from the Soviet Union to the People’s Republic of China: 1949-1966.” *Comparative Technology Transfer and Society* 4 (2): 105–67.

Zhu, Jiong, James B Ang, and Per G Fredriksson. 2019. “The Agricultural Roots of Chinese Innovation Performance.” *European Economic Review* 118: 126–47.

Supplementary Appendix: Can Technology Transfers Save Innovation? Evidence from China

A1 Summary Statistics for Main Variables

Table A1 Summary statistics for main variables

Variables	N	Mean	Median	Std. Dev.	min	max
RD or not (0/1)	11200.00	0.56	1.00	0.50	0.00	1.00
RD intensity (%)	11200.00	1.04	0.04	3.00	0.00	64.34
Percentage of piece rate wage plus bonuses among permanent workers (%)	10942.00	42.07	38.95	33.98	0.00	100.00
Percentage of piece rate wage among permanent workers (%)	10942.00	29.54	0.00	36.48	0.00	100.00
Percentage of bonuses among permanent workers (%)	10942.00	12.53	5.00	17.07	0.00	100.00
Percentage of fixed salary among permanent workers (%)	10942.00	46.91	50.00	35.17	0.00	100.00
Firm age	11195.00	13.76	9.00	13.64	3.00	140.00
State-owned firms (0/1)	11200.00	0.09	0.00	0.29	0.00	1.00
Non-State-owned firms (0/1)	11200.00	0.73	1.00	0.44	0.00	1.00
Foreign-owned firms (0/1)	11200.00	0.18	0.00	0.38	0.00	1.00
Total employment in log	11200.00	5.58	5.51	1.48	1.79	13.50
Total assets in log	11200.00	16.27	16.31	2.32	0.00	25.61
Percentage of exports to other countries (%)	11199.00	15.95	0.00	31.23	0.00	100.00
Percentage of exports to other cities (%)	11199.00	60.63	73.00	36.65	0.00	100.00
Percentage of workers with high school degree and above (%)	11198.00	48.97	49.00	27.47	0.00	100.00
Percentage of workers with college degree and above (%)	11198.00	17.80	12.00	17.19	0.00	100.00
The distance between each mainland Chinese county in which firms are located and coastline (km)	11200.00	399.85	293.58	401.38	0.04	2575.14
The distance between each mainland Chinese county to the nearest port (km)	11200.00	392.95	288.09	401.33	2.12	2581.37
The geographical distance between each mainland Chinese city and Jinmen (km)	11200.00	1189.79	1139.95	613.16	35.65	3507.98
Cultivated land per capita (mu)	11000.00	1.59	1.31	1.00	0.41	6.96
Whether the armed conflict of civil war ended before October 1, 1949 (0/1)	11200.00	0.77	1.00	0.42	0.00	1.00
Number of universities and colleges in each mainland city in 1949	11200.00	1.13	0.00	2.45	0.00	13.00
Local severity of the Cultural Revolution	11200.00	0.02	0.01	0.04	0.00	0.49
Local severity of the Great Famine	10800.00	0.45	0.44	0.40	0.04	6.00
Natural suitability of rice-farming	11200.00	0.27	0.09	0.33	0.00	1.46

relative to wheat-farming						
Access to 156 projects (0/1)	11200.00	0.23	0.00	0.42	0.00	1.00
Exposure to the 156 projects (in 10,000 RMB)	11200.00	14300.18	0.00	39951.63	0.00	268500.00

Notes: Firm-level variables come from the Enterprise Survey in 2005.

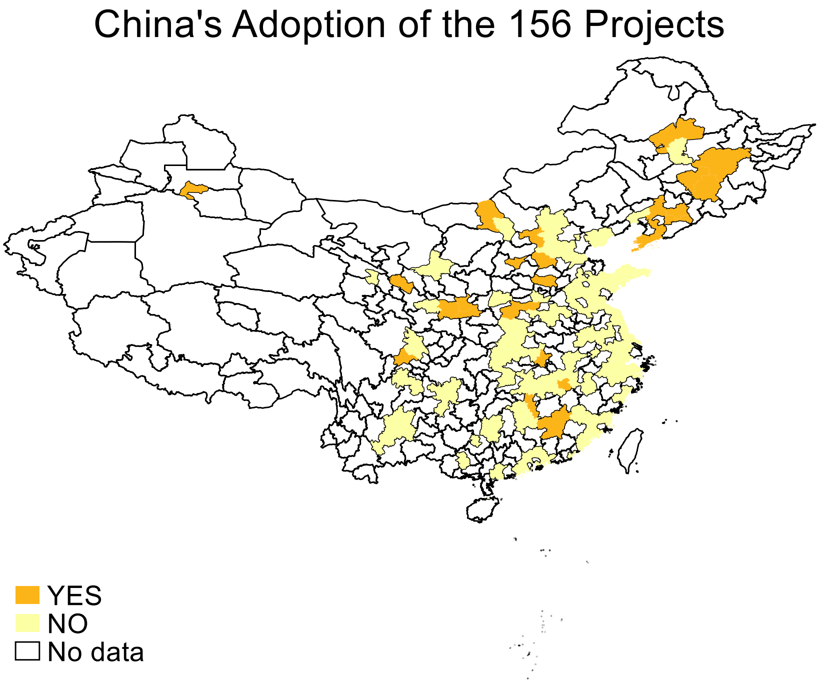

Figure A1 The adoption of the 156 Projects across Chinese cities

Notes: YES=adopted the 156 Projects; No=did not adopt the 156 Projects. I only focus on cities that can be matched with World Bank's Enterprise Survey in 2005.

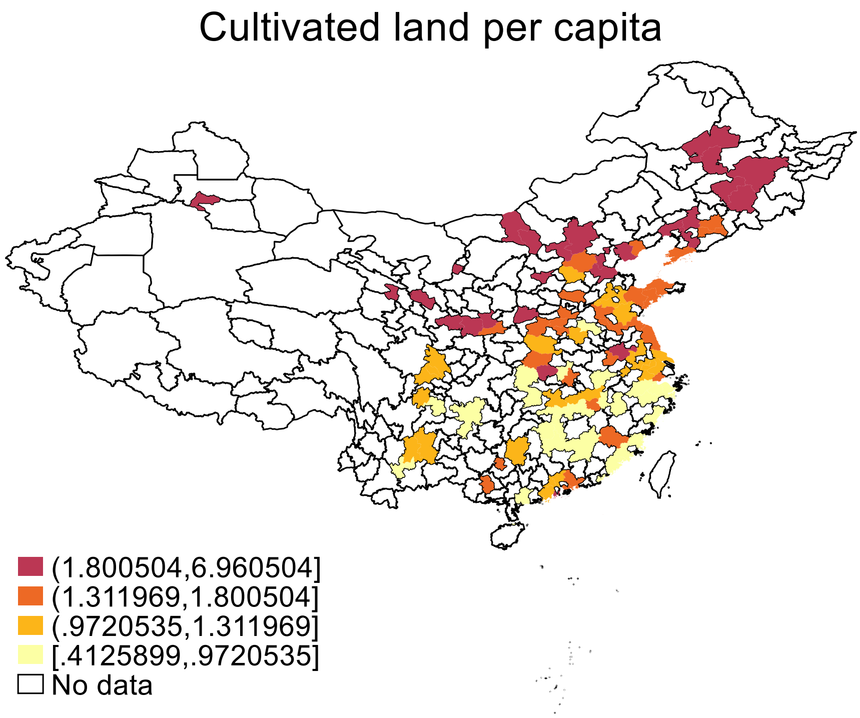

Figure A2 The cultivated land per capita across cities

A2 Robustness Checks

A2.1 Alternative Measure of the 156 Projects

Table A2 Estimates of the mediation model using an alternative measure of the 156 Projects

Mediating Variables	(1)
Panel A: Second Stage (Equation 5)	
β_Y^M	0.0131***
	(0.0028)
DE: β_Y^T	0.0061*
	(0.0034)
F-Stat Instruments	25.681
Panel B: Model Parameters	
β_M^T	-3.0311***
IE: $\beta_M^T \cdot \beta_Y^M$	-0.0397
TE	-0.0336
IE+DE	-0.0336
S=IE/TE	1.18
S=IE/(IE+DE)	1.18
Panel C: First Stage Equation (Equation 4)	
γ_M^Z	-0.00***
	(0.00)
γ_M^T	-0.60***
	(0.15)
Observations	10938
R-Squared	0.09

Notes: This table shows the estimates of the mediation model using an alternative measure of the 156 Projects, defined as the logarithm of total amounts of investments received from the central government for the 156 Projects in each locality. Panel A reports the second stage results, based on equation (5). Panel C reports the first stage results based on equation (4). Panel B reports main parameters of the mediation model. I use the STATA code *ivmediate* to estimate the main results above (Dippel, Ferrara, and Heblich 2020). Firm-level Control variables consist of firm-level variables such as age, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the county in which firms are located and the coastline, and the logarithm of the distance between the county in which firms are located and Beijing. Firm-level variables come from World Bank's Enterprise Survey in 2005. Standard errors are clustered at the city level. Standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

A2.2 Alternative Measures of Performance-based Reward Systems

Table A3 Estimates of the mediation model using alternative measures of performance-based reward systems

Mediating Variables	(1) Bonuses	(2) Piece-rate wages	(3) All employees	(4) General manager
Panel A: Second Stage (Equation 5)				
β_Y^M	0.0302***	0.0136***	0.0157***	1.4140***
	(0.0081)	(0.0038)	(0.0039)	(0.2904)
DE: β_Y^T	0.0054	0.0810	0.1070	0.0018
	(0.0295)	(0.0498)	(0.0538)	(0.0263)
F-Stat Instruments	17.219	15.220	24.213	26.998
Panel B: Model Parameters				
β_M^T	-11.8492	-31.7832	-29.3753	-0.2574
IE: $\beta_M^T \cdot \beta_Y^M$	-0.3590	-0.4349	-0.4618	-0.3640
TE	-0.3517	-0.3543	-0.3552	-0.3622
IE+DE	-0.3517	-0.3543	-0.3552	-0.3622
S=IE/TE	1.02	1.22	1.30	1.00
S=IE/(IE+DE)	1.02	1.22	1.30	1.00
Panel C: First Stage Equation (Equation 4)				
γ_M^Z	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
γ_M^T	-1.04	-7.28***	-8.00***	-0.01
	(0.92)	(1.80)	(1.59)	(0.01)
Observations	10305	10922	10938	11069
R-Squared	0.01	0.11	0.11	0.02

Notes: This table shows the estimates of the mediation model using alternative measures of performance-based reward systems. Panel A reports the second stage results, based on equation (5). Panel C reports the first stage results based on equation (4). Panel B reports main parameters of the mediation model. I use the STATA code *ivmediate* to estimate the main results above (Dippel, Ferrara, and Heblich 2020). Firm-level Control variables consist of firm-level variables such as age, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the county in which firms are located and the coastline, and the logarithm of the distance between the county in which firms are located and Beijing. Columns (1) to (4) use the percentage of bonuses in total compensation (excluding piece-rate wages) among permanent workers, the percentage of piece-rate wages in total compensation (excluding bonuses) among permanent workers, the percentage of bonuses and piece-rate wages in total compensation among all workers (including temporary workers), a dummy variable on whether the general manager's annual income is directly related to the company's performance, to measure firms' intensity of incentive pay, respectively. Firm-level variables come from World Bank's Enterprise Survey in 2005. Standard errors are clustered at the city level. Standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

A2.3 Alternative Measure of Innovation Inputs

Table A4 Estimates of the mediation model using alternative measures of innovation inputs

Mediating Variables	(1)	(2)	(3)
Panel A: Second Stage (Equation 5)			
β_Y^M	0.1159***	0.0110***	0.0127***
	(0.0287)	(0.0024)	(0.0028)
DE: β_Y^T	0.5949*	0.0359	0.0600*
	(0.3566)	(0.0286)	(0.0354)
F-Stat Instruments	25.016	25.016	25.016
Panel B: Model Parameters			
β_M^T	-31.9968	-31.9968	-31.9968
IE: $\beta_M^T \cdot \beta_Y^M$	-3.7098	-0.3539	-0.4069
TE	-3.1196	-0.3184	-0.3474
IE+DE	-3.1196	-0.3184	-0.3474
S=IE/TE	1.18	1.11	1.17
S=IE/(IE+DE)	1.18	1.11	1.17
Panel C: First Stage Equation (Equation 4)			
γ_M^Z	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)
γ_M^T	-6.16***	-6.16***	-6.16***
	(1.59)	(1.59)	(1.59)
Observations	10938	10938	10938
R-Squared	0.09	0.09	0.09

Notes: This table shows the estimates of the mediation model using an alternative measure of innovation inputs. Column 1 defines innovation inputs as the ratio of R&D expenditure to total sales in the survey year. Column 2 defines innovation inputs as a dummy variable indicating positive R&D growth from 2002 to 2004. Column 3 defines innovation inputs as a dummy variable indicating positive R&D by aggregating R&D across multiple years (2002-2004) for each firm. Panel A reports the second stage results, based on equation (5). Panel C reports the first stage results based on equation (4). Panel B reports main parameters of the mediation model. I use the STATA code *ivmediate* to estimate the main results above (Dippel, Ferrara, and Heblich 2020). Firm-level Control variables consist of firm-level variables such as age, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the county in which firms are located and the coastline, and the logarithm of the distance between the county in which firms are located and Beijing. Firm-level variables come from World Bank’s Enterprise Survey in 2005. Standard errors are clustered at the city level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A2.3 Alternative Estimation Approaches

Given that the main variable of interest is a dummy variable, we further resort to Poisson Pseudo-Maximum Likelihood (PPML) to estimate the main results in order to enhance the credibility of the findings.

Table A5 Impact of the adoption of the 156 Projects on firms' innovation inputs using Poisson Pseudo-Maximum Likelihood (PPML) estimation approach

Variables	(1) PPML	(2) PPML	(3) PPML+IV	(4) First Stage
Access to 156 Projects	-0.0786	-0.1160***	-0.6952***	
	(0.0496)	(0.0424)	(0.2146)	
IV: Distance to Jinmen (km)			0.0003***	0.0003***
			(0.0001)	(0.0000)
Observations	11200	11195	11195	11195
Control variables	NO	YES	YES	YES

Notes: This table reports the impact of the adoption of the 156 Projects on firms' innovation inputs using Poisson Pseudo-Maximum Likelihood (PPML) estimation approach. Columns 1 and 2 report the PPML results, with and without control variables, respectively. Columns 3 and 4 report the IV estimates and first-stage results. Control variables consist of firm-level variables such as age, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the county in which firms are located and the coastline, and the logarithm of the distance between the county in which firms are located and Beijing. The 156 Projects variable is constructed based on a city's access to the 156 Projects in the 1950s. Firm-level variables come from World Bank's Enterprise Survey in 2005. Standard errors are clustered at the city level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A3 Effects of the 156 Projects by Firm Ownership

Table A6 Impact of the adoption of the 156 Projects by firm ownership

	(1)	(2)	(3)	(4)
Variables	R&D		Pay for performance	
	SOE	Non-SOE	SOE	Non-SOE
Access to 156 Projects	-0.1463*	-0.4419***	-16.3107***	-36.6664***
	(0.0777)	(0.1338)	(5.5118)	(11.4774)
Observations	2039	9156	2034	8904
R-squared	0.0796	-0.0188	0.0308	-0.0009
F-stat	17.8876	7.6636	4.4443	12.4388
Weak IV test (F statistic)	15.8934	13.0067	15.9411	12.3726
Endogeneity test (p-value)	0.0979	0.0001	0.0054	0.0007
Control variables	NO	YES	YES	YES

Notes: This table reports the impacts of the adoption of the 156 Projects by firm ownership. Columns 1 and 2 report the impact of the adoption on innovation inputs for state-owned firms (SOEs) and non-sate-owned firms (non-SOEs), respectively. Columns 3 and 4 report impact of the adoption on pay for performance for state-owned firms and non-sate-owned firms, respectively. We distinguish between SOEs and non-SOEs based on ownership structure. We define SOEs as those firms partly owned by the state. Control variables consist of firm-level variables such as age, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the county in which firms are located and the coastline, and the logarithm of the distance between the county in which firms are located and Beijing. The 156 Projects variable is constructed based on a city's access to the 156 Projects in the 1950s. Firm-level variables come from World Bank's Enterprise Survey in 2005. Standard errors are clustered at the city level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A4 Effects of the 156 Projects on Other Outcomes

Table A7 Effects of the 156 Projects on Other Outcomes

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employment (log)		Capital (log)		Capital-labor ratio (log)		Exports (%)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Access to 156 Projects	0.0510	-0.4471	0.0627	-0.2990	0.0198	0.1784	0.6444	-5.8056
	(0.0876)	(0.3163)	(0.1538)	(0.4172)	(0.0917)	(0.2390)	(1.0061)	(3.5686)
Observations	11195	11195	11195	11195	11195	11195	11194	11194
R-squared	0.1695	0.1519	0.1354	0.1317	0.0839	0.0821	0.2931	0.2865
F-stat	34.5212	34.7092	30.9358	31.6355	27.8371	28.4746	37.6951	34.7002
Weak IV test (F statistic)		14.4622		14.4622		14.4622		14.4604
Endogeneity test (p-value)		0.1036		0.3562		0.4494		0.0206
Variables	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	High school or above (%)		College or above (%)		Formal training (%)		Computer use (%)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Access to 156 Projects	6.0077***	8.7131**	5.1530***	9.4794***	1.8893	-5.3871	2.4113**	1.8068
	(1.4742)	(3.8635)	(1.1671)	(3.2408)	(1.4449)	(4.8457)	(1.1352)	(4.0330)
Observations	11193	11193	11193	11193	11195	11195	11195	11195
R-squared	0.1337	0.1322	0.1339	0.1241	0.0450	0.0388	0.1113	0.1111
F-stat	37.7870	37.0781	20.7214	20.7062	16.9613	16.2860	23.2975	22.9933
Weak IV test (F statistic)		14.4472		14.4472		14.4622		14.4622
Endogeneity test (p-value)		0.4694		0.1578		0.1007		0.8637

Notes: this table reports the effects of adopting the 156 Projects on other outcomes. Columns 1 and 2 report the OLS and IV estimates for the effect of the 156 Projects on total employment (in log). Columns 3 and 4 report the OLS and IV estimates for the effect of the 156 Projects on total capital (in log). Columns 5 and 6 report the OLS and IV estimates for the effect of the 156 Projects on capital-labor ratio (in log). Columns 7 and 8 report the OLS and IV estimates for the effect of the 156 Projects on the percentage of exports. Columns 9 and 10 report the OLS and IV estimates for the effect of the 156 Projects on the percentage of employees with high school education or above. Columns 11 and 12 report the OLS and IV estimates for the effect of the 156 Projects on the percentage of employees with college education or above. Columns 13 and 14 report the OLS and IV estimates for the effect of the 156 Projects on the percentage of employees received formal training. Columns 15 and 16 report the OLS and IV estimates for the effect of the 156 Projects on the percentage of employees who regularly use computers. The instrumental variable refers to the geographical distance between each mainland Chinese city and Jinmen. Firm-level variables come from World Bank's Enterprise Survey in 2005. Standard errors are clustered at the city level. Standard errors are in parentheses. *** p < .01, ** p < .05, * p < .1.