Can Migration Barriers Save Firm Productivity in a Developing Country?*

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Abstract

Migration barriers are often viewed as obstacles to productivity because they prevent labor from moving to its most efficient uses across firms and sectors. However, tighter labor markets may also encourage firms to adopt labor-saving organizational practices. This paper studies the long-run impact of rural–urban migration barriers on firm productivity in China, exploiting variation generated by the hukou-based "internal passport" system. Using an instrumental-variable approach, we find that a one-standard-deviation increase in migration barriers raises average labor productivity among urban manufacturing firms by about 22%. The effect is concentrated among domestic firms and is insignificant for foreign-owned firms. Evidence on mechanisms shows that the productivity gains arise primarily from increased adoption of management technologies, such as pay-for-performance incentive schemes, rather than from greater use of capital or skilled labor. Similar patterns emerge when productivity is measured using total factor productivity. These findings suggest that labor scarcity induced by migration barriers can encourage organizational upgrading, helping offset the productivity losses associated with labor misallocation.

Keywords: internal migration; labor scarcity; management practices; firm productivity; China

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1 Introduction

The long-run impact of migration barriers on firm productivity remains ambiguous. One strand of literature considers them as sources of labor misallocation and low productivity because they prevent workers from moving to more productive sectors and firms in destinations (Hsieh and Klenow, 2009; Tombe and Zhu, 2019; Bryan and Morten, 2019; Khanna *et al.*, 2025). However, another strand of literature suggests that migration barriers may enhance efficiency by inducing low-productivity sectors and firms in destinations to adopt labor-saving technologies (Acemoglu, 2010; Hornbeck and Naidu, 2014; Clemens *et al.*, 2018; Imbert *et al.*, 2022; Danzer *et al.*, 2024; Franck, 2024).[1] This article seeks to resolve this ambiguity by examining the long-run impact of migration barriers on firm productivity in migration destinations. Based on a prominent "internal passport" policy in China that controls rural–urban migration for more than half a century, we mainly address two questions: Have migration barriers affected long-run firm productivity in migration destinations, and, if so, what is the likely underlying mechanism for its effect?

The Chinese "internal passport" policy was formally implemented in 1958 and since then became an integral part of the household registration system (also known as the *hukou* system).[2] Owing to this policy, AH holders were prohibited from migrating to more productive urban destinations unless they successfully obtained a NAH, and access was strictly controlled by the central government through an annual quota system until the late 1990s.[3] In particular, the annual quota system in the pre-reform era required that the maximum number of AH holders who could obtain a NAH annually accounted for no more than 0.2 percent of the stocks of NAH holders in each locality, and local governments did not have the autonomy to change their local quotas until the late 1990s. By contrast, NAH holders were not prevented from migrating to rural destinations. These distinctive features of the "internal passport" policy allow us to quantify rural–urban migration barriers based on the prevalence of AH holders in the pre-reform era.[4] In this article, we define the extent of rural–urban migration barriers experienced by urban

[1] For example, according to the multitask theory of state enterprise reform, policies such as rural–urban migration barriers allow local state-owned enterprises to adopt more advanced management technology to improve financial performance rather than maintaining more employment to promote social stability (Bai *et al.*, 2000, 2006).

[2] Under the hukou system, individuals in rural areas were generally classified as agricultural hukou (AH) holders, while individuals in urban areas were generally classified as non-agricultural hukou (NAH) holders.

[3] Since the late 1990s, the Chinese authorities have slowly reformed the hukou system by making it easier for AH holders to migrate to small cities and towns. That said, migrating to medium and large cities remained difficult for most AH holders in the early 2000s because they had restricted access to local welfare benefits such as child education, the social security program, and so forth. In July 2014, the Chinese authorities announced a decree to make it easier for AH holders to migrate to the remaining urban areas, with the exception of several mega-cities such as Beijing and Shanghai. In the article, we define periods from the late 1990s as the reform era of migration barriers (or hukou system), and define periods before the late 1990s as the pre-reform era.

[4] Although a number of studies have measured migration barriers differently in the context of China by either

destinations as the percentage of AH holders in the local population in the pre-reform era, and compare long-run firm productivity in urban destinations exposed to higher and lower rural–urban migration barriers.

Such rural–urban migration barriers can persist largely because early reforms of the "internal passport" policy concentrated on facilitating labor migration without hukou conversion, also known as temporary migration. Specifically, although AH holders were allowed to migrate to urban destinations since the mid-1980s in the absence of a local hukou, most of them stayed temporarily due to denied access to public services in destinations. In other words, rural–urban migration barriers can continue affecting migration decisions by restricting migrants' access to public services in destinations. Indeed, a recent study by Jin and Zhang (2023) empirically shows that policies preventing rural migrants from obtaining a local hukou in urban destinations can substantially discourage rural–urban migration.

Conceptually, migration barriers may affect firm productivity through two opposing forces. On the one hand, restricting labor mobility prevents workers from moving toward more productive firms and sectors, thereby generating labor misallocation and reducing allocative efficiency. On the other hand, tighter migration barriers reduce the supply of migrant labor in urban destinations and increase labor costs. Facing a tighter labor market, firms may respond by adopting more labor-saving organizational practices, such as performance-based incentives or improved management systems. These adjustments can enhance firm-level productivity despite the presence of labor misallocation. The overall effect of migration barriers on observed firm productivity is therefore theoretically ambiguous and must ultimately be determined empirically.

To estimate the causal impact of rural–urban migration barriers, we employ an instrumental variable (IV) approach based on a plausibly exogenous shock on the stocks of NAH holders in the 1950s when the "internal passport" policy had not yet been implemented. Specifically, we construct an instrument using the geographical distance between each locality and Jinmen,[5] which is located only 2 kilometers from the mainland Chinese city of Xiamen but is controlled

relying on variations in the timing of relaxing the hukou system across regions (Sun *et al.*, 2011; Song and Li, 2014; Kinnan *et al.*, 2018; Jin, 2018; Jin and Zhang, 2023) or variations in the strictness of the hukou system across regions (Fan, 2019; Zhang *et al.*, 2019), these measures are only available in the reform era (i.e., after the late 1990s) and do not allow us to examine whether and how the consequences of migration barriers can persist for a long time. Moreover, these post-reform measures quantify the average migration barriers, including rural–urban and urban–urban migration barriers, while our pre-reform measure quantifies rural–urban migration barriers only. Finally, post-reform measures usually raise concerns owing to unspoken rules and mostly measure city-level rather than county-level migration barriers due to data limitations (Jin and Zhang, 2023), which can be mitigated by the pre-reform measure. To some extent, our county-level pre-reform measure is complementary to the existing city-level post-reform measures in quantifying Chinese internal migration barriers.

[5]Our IV approach shares the same spirit as previous valid instruments based on variations in geographical distance (Becker and Woessmann, 2009; Nunn and Wantchekon, 2011; Chen *et al.*, 2020a). For example, Becker and Woessmann (2009) use distance to Wittenberg, the hometown of Martin Luther, as an IV for Protestantism. Nunn and Wantchekon (2011) use the historical distance from the coast of an individual's ethnic group as an instrument for slave exports.

by Taiwan.[6] The rationale is that mainland Chinese cities closer to Jinmen were exposed to greater risks of armed conflict in the Taiwan Strait due to tensions between mainland China and Taiwan in the early 1950s,[7] and therefore probably received fewer industrial investments from the central government between 1949 and 1957. Because the stocks of NAH holders before 1958 were largely determined by industrial investments and the resulting labor demand in the industrial sector during that period, a shorter distance between a mainland Chinese city and Jinmen leads to fewer NAH holders and therefore higher rural–urban migration barriers in the pre-reform era due to the annual quota system. An important assumption for the validity of the instrument is that, conditional on observable characteristics such as exposure to foreign trade, exposure to policies enacted by the central government, industrial structures, and human capital stocks, firm-level outcomes are independent of the geographical distance between the mainland Chinese cities where these firms are located and Jinmen. We provide several empirical tests supporting this identification assumption.

The main findings of this study are as follows. First, rural–urban migration barriers in the pre-reform era substantially increase the long-run labor productivity of urban manufacturing firms. Our IV estimates indicate that a one-standard-deviation increase in the strength of migration barriers raises average labor productivity by about 22 percent. Second, this effect is concentrated among domestic firms and becomes insignificant for foreign-owned firms. Third, the productivity gains appear to arise primarily from increased adoption of management technologies—such as pay-for-performance incentive schemes—rather than from greater use of capital or skilled labor. Finally, we find that migration barriers also increase total factor productivity: a one-standard-deviation increase in migration barriers raises average TFP by approximately 10.8 percent. Taken together, these results suggest that labor scarcity induced by migration barriers can enhance firm efficiency by encouraging the adoption of performance-based management practices.

This study contributes to several strands of literature. First, it contributes to the literature on migration barriers and productivity. Existing studies typically emphasize the misallocation costs of restrictions on labor mobility, arguing that migration barriers prevent workers from moving to more productive firms and sectors and thereby reduce aggregate productivity (Hsieh and Klenow, 2009; Tombe and Zhu, 2019; Bryan and Morten, 2019; Khanna *et al.*, 2025). At the same time, a separate literature suggests that labor scarcity can induce technological or organizational upgrading, potentially improving productivity (Acemoglu, 2010; Hornbeck and Naidu, 2014;

[6] In 1949, after losing control of mainland China in the Chinese Civil War, the Republic of China (ROC) government under the Kuomintang (KMT) withdrew to Taiwan.

[7] In fact, two separate crises occurred in the Taiwan Strait during the 1950s, with the first occurring between 1954 and 1955.

Clemens *et al.*, 2018; Imbert *et al.*, 2022; Danzer *et al.*, 2024; Franck, 2024). We reconcile these two perspectives by providing firm-level evidence that migration barriers can increase productivity in the long run by inducing firms to adopt more efficient organizational practices. Using institutional variation from China's hukou-based migration system, we show that tighter migration barriers lead firms to strengthen performance-based management systems and improve productivity, suggesting that labor scarcity can trigger organizational upgrading that partly offsets the productivity losses associated with labor misallocation.

Second, this paper contributes to the literature on firm organization and management practices. While existing work documents substantial cross-firm and cross-country variation in management practices (Bloom and Van Reenen, 2010; Bloom *et al.*, 2019; Frederiksen and Manchester, 2020; Sadun *et al.*, 2025), relatively little is known about how labor market institutions shape firms' organizational choices. Our results show that tighter labor markets induced by migration barriers encourage firms to adopt stronger performance-based management systems, highlighting an important channel through which labor market institutions shape firms' internal organization.

Third, this study contributes to the literature on incentive systems and firm productivity. A large theoretical literature highlights the role of performance-based incentives in improving worker effort and firm efficiency (Stiglitz, 1975; Baker, 1992; Lazear, 2000; Hoffman and Stanton, 2025). However, empirical evidence on the productivity implications of such incentive systems remains limited, particularly in developing economies (Guiteras and Jack, 2018; Cai *et al.*, 2022). We provide new firm-level evidence that the adoption of performance-based incentives is associated with higher productivity, and show that these incentives constitute a key mechanism through which migration barriers translate into higher productivity.

The remainder of the paper is organized as follows. Section 2 provides institutional background on China's internal migration system and presents the conceptual framework. Section 3 describes the data and key variables used in the analysis. Section 4 introduces the empirical strategy and identification approach. Section 5 reports the main empirical results and explores the underlying mechanisms. Section 6 concludes.

2 Conceptual Framework

2.1 Institutional Background

Shortly after the founding of the People's Republic of China, the Chinese authorities established the household registration system (the *hukou* system) in urban areas in July 1951, which was extended to rural areas in June 1955. Under this system, individuals in rural areas were

classified as agricultural hukou (AH) holders, while individuals in urban areas were classified as non-agricultural hukou (NAH) holders. Both AH and NAH holders were generally free to migrate until 1958, when the Chinese authorities introduced an "internal passport" policy to control rural–urban migration. This policy became an integral part of the hukou system. AH holders were prohibited from migrating to urban destinations unless they obtained a NAH, access to which was strictly controlled by the central government through an annual quota system. In particular, the quota system required that the number of AH holders who could obtain a NAH each year accounted for no more than 0.2 percent of the stock of NAH holders in each locality.

Beginning in the mid-1980s, the system experienced some initial relaxations. Rural residents were *de jure* allowed to work temporarily in urban destinations without obtaining a NAH (or local hukou). However, migrants without a NAH were excluded from many local welfare benefits, including children's education, healthcare, and pensions. Obtaining a NAH remained difficult for most rural residents until the late 1990s, when Chinese authorities began to reform the "internal passport" policy in towns and small cities. These reforms replaced the rigid quota system with a quota-free system *de jure* and lowered entry requirements for NAH applications. Unlike the earlier regime, the new system no longer imposed numerical quotas on hukou conversion or strict age and education requirements. Similar reforms were gradually extended to medium and large cities in the 2000s and were eventually expanded to most remaining cities in July 2014, except for several mega-cities such as Beijing and Shanghai.

2.2 A Simple Framework

Migration barriers may influence firm productivity through two opposing mechanisms. First, by restricting workers from moving toward more productive firms and sectors, migration barriers distort the allocation of labor across firms and reduce aggregate efficiency. We refer to this mechanism as the *labor misallocation effect* (Hsieh and Klenow, 2009; Tombe and Zhu, 2019; Bryan and Morten, 2019; Khanna *et al.*, 2025). Second, migration barriers reduce the supply of migrant labor in urban destinations and increase labor costs. Facing a tighter labor market, firms may respond by adopting labor-saving technologies and organizational practices, such as performance-based incentives or improved management systems. We refer to this mechanism as the *organizational upgrading effect* (Acemoglu, 2010; Hornbeck and Naidu, 2014; Clemens *et al.*, 2018; Imbert *et al.*, 2022; Danzer *et al.*, 2024; Franck, 2024). These two forces operate in opposite directions. While migration barriers may reduce allocative efficiency through labor misallocation, they may also raise firm productivity by inducing firms to adopt productivity-enhancing organizational practices. As a result, the overall effect of migration barriers on observed firm productivity is theoretically ambiguous.

To guide the empirical analysis, we develop a simple conceptual framework that highlights how migration barriers affect firms through labor scarcity, endogenous management upgrading, and product-market selection. The framework incorporates three key ingredients. First, migration barriers restrict firms' access to migrant labor and increase effective labor costs in urban destinations. Second, firms operate in a heterogeneous product-market environment in the spirit of Hopenhayn (1992) and Melitz (2003), where more productive firms are more likely to survive and expand in competitive markets. Third, firms can endogenously adopt productivity-enhancing organizational practices such as improved management incentives (Bloom and Van Reenen, 2007, 2010). When labor becomes more scarce or costly, firms may find it optimal to strengthen performance-based incentives or adopt more efficient management practices in order to economize on labor inputs.

The conceptual structure of the framework is summarized in Figure 1.

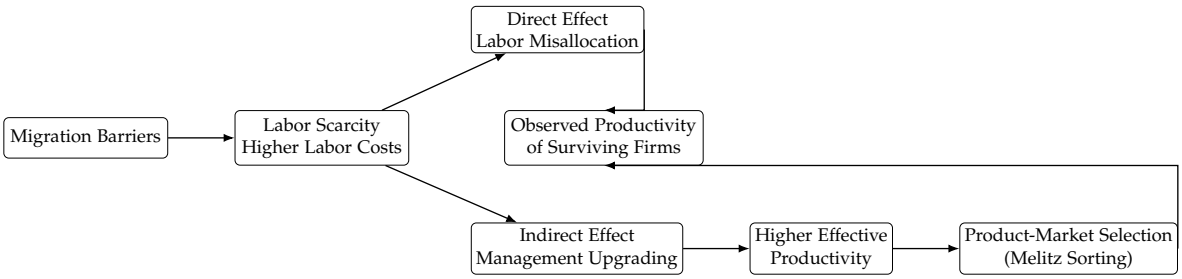


Figure 1: Conceptual Framework: Migration Barriers Affect Firm Productivity Through a Direct Misallocation Channel and an Indirect Technology-Choice Channel

2.3 Environment

Consider a continuum of firms indexed by baseline productivity ϕ, with cumulative distribution $G(\phi)$. Migration barriers are summarized by a parameter τ, where higher τ represents tighter restrictions on labor mobility. Tighter migration barriers reduce firms' access to migrant labor and increase effective labor costs:

$$w = w(\tau), \qquad w'(\tau) > 0. \tag{1}$$

Firms may serve either a local market L or an external market E. The external market is larger and more competitive but requires paying a fixed cost $F_E > 0$, while $F_L = 0$.

Firms can also choose whether to adopt an advanced management technology $m \in \{0, 1\}$. Let effective productivity be

$$\tilde{\phi} = \phi A(m), \tag{2}$$

where $A(1) > A(0) = 1$. Adopting advanced management requires paying a fixed cost $F_m > 0$.

Production is given by

$$y = \phi A(m) l^{\alpha_m}, \tag{3}$$

where l denotes labor input and $0 < \alpha_1 < \alpha_0 < 1$. The assumption $\alpha_1 < \alpha_0$ captures the idea that advanced management reduces firms' dependence on labor input.

Profits in market $j \in \{L, E\}$ are therefore

$$\Pi_j(\phi, m, \tau) = p_j \phi A(m) l^{\alpha_m} - w(\tau) l - F_m m - F_j. \tag{4}$$

2.4 Management Upgrading

Firms choose labor input optimally and compare profits under the two management regimes. Let

$$\Delta_j(\phi, \tau) = \Pi_j(\phi, 1, \tau) - \Pi_j(\phi, 0, \tau) \tag{5}$$

denote the gain from adopting advanced management.

Define the productivity cutoff $\phi_m^j(\tau)$ by

$$\Delta_j(\phi_m^j(\tau), \tau) = 0. \tag{6}$$

Proposition 1 (Management Upgrading). For each market j, there exists a productivity cutoff $\phi_m^j(\tau)$ such that firms with $\phi \geq \phi_m^j(\tau)$ adopt advanced management. Moreover, if advanced management is sufficiently labor-saving, tighter migration barriers reduce the adoption cutoff:

$$\frac{d\phi_m^j(\tau)}{d\tau} < 0.$$

Intuition. Migration barriers increase labor costs in urban destinations by restricting firms' access to migrant labor. When labor becomes more expensive, labor-saving management practices become more valuable because they reduce firms' dependence on labor input. As a result, adopting advanced management becomes profitable for a larger set of firms, lowering the productivity threshold required for management upgrading.

2.5 Market Sorting

Given effective productivity $\tilde{\phi} = \phi A(m)$, firms sort across markets. A firm enters the external market if

$$\Pi_E(\tilde{\phi}, \tau) \geq \Pi_L(\tilde{\phi}, \tau). \tag{7}$$

This condition defines an external-market productivity cutoff $\tilde{\phi}_E(\tau)$.

Proposition 2 (Market Selection). There exists an effective productivity cutoff $\tilde{\phi}_E(\tau)$ such that firms with $\tilde{\phi} \geq \tilde{\phi}_E(\tau)$ enter the external market. Moreover, tighter migration barriers increase the productivity threshold required for external-market participation.

Intuition. Entering the external market requires firms to cover fixed market-access costs. When migration barriers increase labor costs, production becomes more expensive and profits decline for low-productivity firms. As a result, only firms with sufficiently high effective productivity can profitably enter external markets. This generates a productivity cutoff that determines market participation.

2.6 Empirical Predictions

The framework generates several empirical predictions that guide the analysis. These predictions correspond directly to the mechanisms illustrated in Figure 1.

Prediction 1 (Management Upgrading). Cities facing tighter migration barriers should exhibit a higher likelihood that firms adopt labor-saving management practices.

Prediction 2 (Productivity Effects). Firms that adopt advanced management practices should exhibit higher productivity due to improved labor efficiency.

Prediction 3 (Market Participation and Selection). More productive firms should be more likely to participate in external markets. Consequently, tighter migration barriers may increase the average productivity of surviving firms through both organizational upgrading and stronger product-market selection.

Detailed derivations are provided in Appendix A.

3 Data Sources and Variables

To construct the rural-urban migration barriers variable, we use a 1% random sample of the 1982 Chinese Population Census, conducted by the National Bureau of Statistics of China. Specifically, we use the percentage of rural residents in the local population in 1982 to measure

rural-urban migration barriers in the pre-reform era across counties.[8] Counties with a higher percentage of rural residents in the local population experienced higher rural-urban migration barriers in the pre-reform era on average. An obvious advantage of using rural-urban migration barriers in the pre-reform era is that such migration barriers were directly regulated by the central government through an annual quota system aforementioned and the local governments did not have the autonomy to change the local migration barriers by themselves until the late 1990s.

To construct the firm-level variables, we use an investment climate survey for firm managers conducted by the World Bank between July and November 2005. The survey covers 12,400 Chinese manufacturing firms in 1,137 counties, located in all provinces, autonomous regions, and directly administrated cities, with the exception of Tibet.[9] The survey covers a broad range of firm-level information, including firm age, ownership, industry, employee wage components, labor conditions, financial statements, and labor statistics. We focus on two variables: pay for performance and firm productivity. We define the pay for performance variable as the extent to which each firm adopts bonuses and piece-rate wages for permanent workers. Firms with a higher percentage of bonuses and piece-rate wages in permanent workers' total compensation are identified as having greater adoption of pay for performance. We use total sales per worker to measure firm-level labor productivity in the benchmark analysis, combined with firm-level total factor productivity for additional checks (Levinsohn and Petrin, 2003; Ackerberg *et al.*, 2015).[10] After matching firm-level data in 2005 with the rural-urban migration barriers variable in 1982 through the adjusted county-level IDs, we identify a final sample of 11,100 firms, located in 1,036 counties.

We complement our main analysis with the Chinese Annual Survey of Industrial Firms (1999–2007), constructed by the National Bureau of Statistics of China. This survey includes all industrial firms that are owned by the state or have sales above 5 million RMB. It covers all industrial sectors, including the mining sector, and accounts for roughly 88% of the national industrial output. The survey contains extensive information about firm production, including total output, employment, wages, assets, total sales, exports, and so on, but little information on management

[8]The 1982 Chinese Population Census only provides information on whether or not an individual was residing in rural areas. Given that it was very difficult for AH holders to migrate to urban areas in the early 1980s, we use information on whether individuals were residing in rural areas or not to proxy for whether they were AH holders or not. In fact, less than 1% of the total population were living away from their registered places in 1982. We also use the 1990 Chinese Population Census and the 2000 Chinese Population Census, which provide information on whether an individual was an AH holder or not, to construct rural-urban migration barriers in 1990 and 2000 for robustness checks.

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

[10]We will further resort to another firm-level census data (i.e., Chinese Annual Survey of Industrial Firms, 1999–2007) for robustness checks, mitigating the concern regarding labor productivity measurement error.

practices.[11] We construct a balanced panel data set of 25,951 firms located in about 1,700 counties for each year from 1999 to 2007. These additional data help to mitigate the concern regarding error arising from measuring labor productivity based on survey data, and they also allow us to study the heterogeneous impacts of rural-urban migration barriers on firm productivity by groups or over time.[12]

Finally, we construct several other important variables as follows. (1) We use the *China City Statistical Yearbook* (1985–1986), also provided by the National Bureau of Statistics of China, to construct other city-level variables, such as industrial structures (e.g., ownership, size, type), local quality of infrastructure (e.g., railway passenger traffic, highway passenger traffic, number of subscribers of telephones), local human capital stocks (e.g., total registered population, number of scientists, number of social scientists), and foreign direct investments in 1984, and total exports in 1985, the earliest city-level official data available to us. (2) We 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) We 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 the civil war ended before October 1949 in each city. (4) We construct a measure of the severity of the Cultural Revolution at the county level following the literature (Walder and Lu, 2017; Chen, 2020). (5) We use geographic coordinates (i.e., latitude and longitude) of each location to generate geographical distance variables such as distance to Jinmen, distance to coastline, and distance to Beijing.

Table A1 reports summary statistics for the main variables.

4 Model Specification and Identification Strategy

To examine the causal impact of rural–urban migration barriers on long-run firm productivity, we use the following two-stage least squares model:

$$\ln(Productivity_{ic}) = \beta\, Barrier_c + \gamma X_{ic} + \epsilon_{ic} \tag{8}$$

$$Barrier_c = \delta Z_c + \theta X_c + u_c \tag{9}$$

[11] 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). However, the sample size of this data set is too small to conduct our analysis.

[12] In fact, we find similar results using different firm-level data sets, reducing the concern of measurement error regarding labor productivity.

where $Productivity_{ic}$ is the logarithm of total sales per worker (or total factor productivity) for each firm i in county c. $Barrier_c$ is the strength of rural–urban migration barriers in county c, defined as the percentage of rural residents in the local population in each county in 1982. Z_c is our IV, defined as the geographical distance between the centroid of each mainland Chinese city where county c is located and the centroid of Jinmen. X_{ic} refers to firm characteristics such as age, skill of the general manager, ownership dummies, 2-digit industry dummies for firm i in county c, the logarithm of the geographical distance between the county in which firm i is located and the coastline, and the logarithm of the geographical distance between the county in which firm i is located and Beijing. ϵ_{ic} and u_c are error terms. β is the parameter of interest. We cluster standard errors at the county level.[13]

Estimating the causal impact of rural–urban migration barriers on firm-level productivity presents some empirical challenges. Firms may self-select into localities exposed to different rural–urban migration barriers, resulting in reverse causality issues that consequently make the OLS estimate biased and inconsistent. Additionally, firms may differ in terms of production technology. If production technology is relevant for rural–urban migration barriers, omitting this variable also makes the OLS estimate biased and inconsistent.

Our IV approach takes advantage of plausible exogenous variations in the changes in the stocks of NAH holders prior to adopting the internal passport policy. Specifically, we use the geographical distance between the centroid of each mainland Chinese city and the centroid of Jinmen to capture the city-level exposure to the 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 more risks of armed conflict and probably received fewer industrial investments from the central government from 1949 to 1957. Given that industrial investments and the resulting labor demand in the industrial sector largely determine the changes in the stocks of NAH holders before 1958, a shorter distance between a mainland Chinese city and Jinmen leads to fewer numbers of NAH holders and in turn higher rural–urban migration barriers in the pre-reform era due to the annual quota system aforementioned.

The validity of the IV depends on two important assumptions. The first is that the geographical distance between the centroid of each mainland Chinese city where a firm is located and the centroid of Jinmen is negatively associated with the rural–urban migration barriers variable (relevance assumption). The second is that, conditional on observable characteristics (e.g., exposure to foreign trade, exposure to policies enacted by the central government, industrial structures, human capital stocks, etc.), the IV affects firm-level outcomes only through the rural–urban mi-

[13] To test whether our results are robust to alternative standard errors, we apply Conley standard errors to account for spatial autocorrelation (Conley, 1999, 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).

gration barriers variable (exclusion restriction assumption). While we can directly test the first assumption empirically,[14] testing 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 labor productivity, it is possible to test some of the most likely channels that may threaten the validity of our instrument. We provide some empirical validation of the IV assumption as follows.

First, regions with a high versus low distance from Jinmen may differ from one another in characteristics that are not observed. We address this concern by controlling for and investigating several likely factors through which the IV may affect labor productivity in the 2000s:

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 the geographical distance to coastline, we further control for total exports and foreign direct investments at the city level.

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, we further control for a dummy variable indicating whether the armed conflict of civil war ended before October 1, 1949. Intuitively, the central government may be in favor of cities ending the armed conflict of civil war at an earlier point in time.

3. Industrial structures. The government may have enacted other industrial policies to support the military industry or related industries in locations close to Taiwan, and firms closer to Taiwan may be more likely to be state-owned or in different industries. To mitigate these concerns, we control for industrial structures (e.g., state-owned versus non-state-owned, heavy industry versus light industry, large firms versus small firms) at the city level.

4. Human capital stocks. To allow for the possibility that distance to Jinmen affects human capital stocks and therefore labor productivity, we control for the number of universities and colleges in each mainland city in 1949 accumulated prior to the establishment of the PRC, the number of scientists, the number of social scientists, and the total population.

5. Quality of infrastructure. To allow for the possibility that distance to Jinmen affects investments in local infrastructure and therefore labor productivity, we control for railway

[14] In addition to testing the overall relationship between the IV and the rural–urban migration barriers variable, we further check whether or not this relationship occurs over a plausible distance.

passenger traffic per capita, highway passenger traffic per capita, and the number of telephone subscribers per capita at the city level.

6. Cultural Revolution. To allow for the possibility that distance to Jinmen affects the Cultural Revolution and therefore labor productivity, we control for the local intensity of the Cultural Revolution (Walder and Lu, 2017; Chen *et al.*, 2020b).

If including all of these control variables does not significantly affect our parameter of interest, then the IV exclusion restriction assumption is more likely to be satisfied in our context. As an additional test, we further regress the measure of past human capital stocks, timing of ending the armed conflict of civil war, and local intensity of the Cultural Revolution on the IV with included controls, respectively. If the instrument is valid, we should not find significant impacts of the IV on these variables.

Second, to mitigate the concern that the IV may affect local firm productivity through other unobservable factors, e.g., the rapid development of coastal areas in China due to global trade, we construct two counterfactual IVs based on the geographical distance between each mainland Chinese city and major Chinese coastal ports that are adjacent to Hong Kong (e.g., Shenzhen port) or Macau (e.g., Zhuhai Port) for placebo analyses. Unlike Taiwan, neither Hong Kong (under British rule until 1997) nor Macau (under Portuguese rule until 1999) was exposed to risks of armed conflict with mainland China. If our benchmark estimates, that is, using distance to Jinmen as the IV, are mainly driven by unobservable factors correlated to the rapid development of coastal areas in China due to global trade, then it is very likely that we will find similar estimates when using these placebo IVs. Otherwise, the IV exclusion restriction assumption is less likely to be a concern in our context.

Third, to allow for the possibility that the placebo IVs do not entirely address the concern that the exclusion restriction assumption is not satisfied (e.g., the risk of war itself causes nearby places to be different from faraway places in other unobserved ways), we propose a new IV based on city-level access to the 156 Projects,[15] through which the Soviet Union helped China to establish the initial foundation of its socialist industrialization during its "First Five-Year Plan" period (1953–1957). The 156 Projects were unevenly adopted across Chinese cities, largely determined by factors such as proximity to resources, the ability to change economically underdeveloped areas, and military considerations (Bo, 1991).

[15]The 156 Projects Soviet aid program was intended to develop China's economy and to organize it along Soviet lines. As part of its First Five-Year Plan (1953–1957), China was the recipient of the most comprehensive technology transfer in modern industrial history. The Soviet Union provided aid for 156 major industrial projects concentrated in mining, power generation, and heavy industry. Following the Soviet model of economic development, these projects were large-scale, capital-intensive undertakings. By the late 1950s, China had made substantial progress in such fields as electric power, steel production, basic chemicals, and machine tools, as well as in the production of military equipment such as artillery, tanks, and jet aircraft (Worden *et al.*, 1987).

To measure a mainland Chinese city's access to the 156 Projects, we manually extract a dataset from a number of historical studies (Dong and Wu, 2004; Chen, 2020). This dataset contains information such as the name, industry, geographical location (city-level), and total amounts of investments received from the central government for each industrial project. We then construct a dummy variable to capture whether a city had any access to the 156 Projects from 1953 to 1957. Differing from our main IV (i.e., distance to Jinmen), the new IV takes advantage of a plausible exogenous policy shock on industrial investments aided by the Soviet Union. Based on our data, the correlation between the distance to Jinmen IV and the 156 Projects IV is 0.4432, suggesting that a shorter distance to Jinmen is associated with a lower probability of having access to the 156 Projects. The additional IV allows us to (a) estimate and compare the parameter of interest using different IVs and (b) test the validity of instruments through the Hansen overidentification test.[16]

5 Empirical Results

This section presents the empirical evidence on how migration barriers affect firm productivity and examines the mechanisms underlying this relationship. The empirical analysis in this section corresponds directly to the predictions derived from the conceptual framework in Section 2. Guided by the conceptual framework developed in Section 2, the empirical analysis proceeds in several steps. We first estimate the baseline effect of migration barriers on firm productivity. We then investigate the mechanisms through which migration barriers influence firm performance, focusing on organizational upgrading and firm dynamics. Finally, we explore heterogeneous effects across firms and conduct additional analyses to assess the persistence and robustness of the results.

5.1 Baseline Productivity Effects

We begin by estimating the baseline relationship between migration barriers and firm productivity. Table 1 reports the main results. Columns 1 and 2 show the OLS estimate of the impact of rural-urban migration barriers in the pre-reform era on firm productivity. Without controlling for additional variables, we find that the coefficient of interest is -0.0006. After we control for other firm-level characteristics, the coefficient increases slightly to -0.0004. Neither coefficient is statistically significant at the conventional level.

[16] An alternative approach is using heteroscedasticity to construct an additional IV (Lewbel, 2012); however, this approach does not work in our context. As Baum and Lewbel (2019) indicate, it is almost always preferable to use any available external instruments rather than constructed instruments such as those of Lewbel (2012), owing to the greater difficulty of confirming that constructed instruments are valid.

As discussed above, the OLS estimate may be biased owing to endogeneity problems. Column 3 shows the IV estimate. We find that the coefficient of interest increases substantially to 0.0052, suggesting that a one-standard-deviation increase in the strength of rural-urban migration barriers improves the average firm productivity by 22%. The OLS estimate is biased downward for at least two reasons. First, the more-productive firms are more likely to relocate to where rural-urban migration barriers are lower to improve access to labor resources, resulting in reverse causality issues. Second, firms differ in their production technology, and omitting this variable causes the OLS estimate to be biased downward.

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 rural-urban migration barriers that are 13.3 units lower on average, which accounts for about 22.8% of the average rural-urban migration barriers across counties. 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 57, leading us to reject the null hypothesis that the IV suffers from weak identification problems. Moreover, the p-values from the endogeneity test of endogenous regressors lead to rejecting the null hypothesis that the OLS estimator is consistent and efficient at the 5% level. This evidence collectively does not reject the validity of our IV approach.

To rule out the possibility that the IV may not be plausible beyond or below a limited number of kilometers from Jinmen, we 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, we focus on cities that are at least 300, 500, and 800 km from Jinmen, respectively (Columns 1–6 of Table 2). Second, we 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, we 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).

To mitigate the concern that regions with a high versus low distance from Jinmen differ from one another in characteristics that are not observed, we control for and investigate some of the mostly likely channels (see Section 4) through which the IV may affect labor productivity. After controlling for all of the factors that are observable, we find that the coefficient of interest changes slightly from 0.0052 to 0.0054 (Columns 1 to 7 of Table 3), suggesting that omitting these factors have minimal impact on our main findings.

We further regress the measures of timing of ending the armed conflict of civil war, past human capital stocks, and local intensity of Cultural Revolution on the IV with the included controls, respectively. We find that the distance to Taiwan had no obvious impact on all of these variables (Columns 8 to 10 of Table 3), further mitigating concern that the IV assumption is

violated.

Considering that the IV may affect local firm productivity through other factors that are unobservable (e.g., the rapid development of coastal area in China due to global trade), we move a little further by constructing two counterfactual IVs based on the geographical distance between each mainland Chinese city and major Chinese coastal ports that are adjacent to Hong Kong (e.g., Shenzhen port) or Macau (e.g., Zhuhai Port) for placebo analyses. Using these placebo IVs, we find that the coefficient of interest is 0.0012 for Hong Kong and 0.0006 for Macau.[17] Both values are much smaller than the benchmark result, and neither is statistically significant at the conventional level (Columns 11 and 12 of Table 3). These findings further mitigate the concern that the IV exclusion restriction assumption is violated in our context due to some unobservable factors.

Given that the placebo IVs do not entirely address the concern that the exclusion restriction assumption may be violated, we propose a new IV based on a plausible exogenous policy shock on industrial investments aided by the Soviet Union (i.e., the 156 Projects) from 1953 to 1957. We start by comparing the coefficient of interest using two different IVs. Using the adoption of the 156 Projects as an instrument, we find that the coefficient of interest is 0.0031 (Column 13 of Table 3), which is close to the benchmark result. The first stage and reduced-form results also confirm that the adoption of the 156 Projects leads to lower rural-urban migration barriers and long-term labor productivity, respectively (Columns 14 and 15 of Table 3). Additionally, we exploit both instruments to test the validity of IVs. We find that the coefficient of interest is 0.0039 (Column 16 of Table 3). The bottom row of Table 3 reports results of the Hansen overidentification test (p-value is 0.3181), which fails to reject the null hypothesis that the instruments are valid. All of these exercises suggest that the exclusion restriction assumption is not likely to be violated in our context.

Overall, we provide consistent evidence that rural-urban migration barriers in the pre-reform era substantially increase firm productivity, which contradicts the conventional wisdom that considers migration barriers as sources of labor misallocation and low productivity, particularly in developing countries (Hsieh and Klenow, 2009; Tombe and Zhu, 2019; Bryan and Morten, 2019) but aligns with the argument that labor scarcity could potentially drive technological progress if new (management) technologies are strongly labor-saving (Acemoglu, 2010; Danzer *et al.*, 2024). These findings are consistent with the conceptual framework presented in Section 2. While migration barriers may reduce allocative efficiency through labor misallocation, the positive IV estimate suggests that firms may respond to tighter labor markets by upgrading their organizational practices, allowing the organizational upgrading channel to dominate in the long run.

[17] We also find no significant effect of these counterfactual IVs on labor productivity (the reduced form estimates).

Up to now, our analysis concentrates on whether and how migration barriers affect the optimization of labor input within manufacturing firms. It remains unclear whether or not the labor productivity gains of migration barriers also apply to the use of other inputs within firms. To address this issue, we construct measures of total factor productivity following Ackerberg *et al.* (2015), and estimate the impact of migration barriers on total factor productivity using similar empirical strategies. Our findings show that a one-standard-deviation increase in migration barriers leads to an increase in total factor productivity by 10.8%. As a result, migration barriers optimize the use of all inputs within manufacturing firms. Further details on the estimation results can be found in Table A5. Having established a positive causal effect of migration barriers on firm productivity, we next investigate the mechanisms underlying this relationship.

Table 1: Impact of Rural–Urban Migration Barriers on Labor Productivity

	(1) OLS	(2) OLS	(3) IV	(4) First Stage	(5) Reduced Form
Rural–urban migration barriers	-0.0006	-0.0004	0.0052***		
	(0.0006)	(0.0006)	(0.0019)		
IV: Distance to Jinmen				-0.0217***	-0.0001***
				(0.0029)	(0.0000)
Observations	11,100	11,095	11,095	11,095	11,195
R-squared	0.0005	0.2400	0.2060	0.1606	0.2402
F-stat	1.1174	57.0912	52.5534	13.8274	57.2673
Weak IV test (*F*)			57.3129		
Endogeneity test (*p*-value)			0.0007		
Control variables	NO	YES	YES	YES	YES

Notes: This table reports the impact of rural–urban migration barriers on labor productivity. Columns (1) and (2) report the OLS results without and with control variables, respectively. Columns (3) to (5) report the IV, first-stage, and reduced-form estimates. Control variables consist of firm-level variables such as age, skill of the general manager, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the mainland Chinese county in which firms are located and the coastline, and the logarithm of the distance between the mainland Chinese county in which firms are located and Beijing. The rural–urban migration barriers variable is constructed using China's population census in 1982. Firm-level variables come from the World Bank Enterprise Survey in 2005. Standard errors are clustered at the county level. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2 Mechanisms: Organizational Upgrading

5.2.1 Pay-for-Performance Adoption

The conceptual framework developed in Section 2 predicts that higher migration barriers tighten local labor supply and increase the relative cost of labor. In response, firms may ad-

Table 2: First-stage and Reduced-form Results in More Detail

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	≥800 km		≥500 km		≥300 km		≤3,500 km
	First Stage	Reduced Form	First Stage	Reduced Form	First Stage	Reduced Form	First Stage
IV: Distance to Jinmen	-0.0319***	-0.0002***	-0.0244***	-0.0002***	-0.0239***	-0.0001***	-0.0234***
	(0.0034)	(0.0001)	(0.0029)	(0.0000)	(0.0029)	(0.0000)	(0.0034)
Observations	7,796	7,796	9,995	9,995	10,495	10,495	10,995
R-squared	0.2263	0.2627	0.1790	0.2525	0.1733	0.2459	0.1537
F-stat	14.7801	54.4400	16.9693	61.2144	16.2672	60.4402	12.8027

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	≤3,500 km	≤3,000 km		≤2,500 km		800–2,500 km	
	Reduced Form	First Stage	Reduced Form	First Stage	Reduced Form	First Stage	Reduced Form
IV: Distance to Jinmen	-0.0002***	-0.0234***	-0.0002***	-0.0230***	-0.0002***	-0.0390***	-0.0003***
	(0.0000)	(0.0034)	(0.0000)	(0.0039)	(0.0001)	(0.0043)	(0.0001)
Observations	10,995	10,995	10,995	10,795	10,795	7,496	7,496
R-squared	0.2430	0.1537	0.2430	0.1408	0.2433	0.2125	0.2675
F-stat	56.9309	12.8027	56.9309	11.1544	55.6123	15.5869	53.3162

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

Table 3: Tests of the IV Exclusion Restriction Assumption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Foreign trade	Armed conflict	Industrial structures	Human capital	Infrast-ructure	Cultural revolution	All	Regress armed conflict on IV
Rural–urban migration barriers	0.0059***	0.0050***	0.0055**	0.0054**	0.0062**	0.0050***	0.0054*	
	(0.0019)	(0.0018)	(0.0027)	(0.0024)	(0.0025)	(0.0019)	(0.0031)	
Instrument								-0.0000
								(0.0001)
Observations	11,095	11,095	11,095	11,095	11,095	11,095	11,095	11,195
R-squared	0.1984	0.2101	0.2105	0.2285	0.1952	0.2083	0.2376	0.3662
F-stat	50.3910	51.2588	49.7794	56.3362	50.3927	51.2404	47.1244	3.3402
Weak IV test (*F*)	60.6319	59.4055	29.6035	44.4926	40.9419	58.1195	26.5593	
Endogeneity test (*p*-value)	0.0001	0.0009	0.0093	0.0095	0.0005	0.0009	0.0378	

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	HC on IV	CR on IV	Placebo IV			New IV		Both IVs
			Hong Kong	Macau	IV	First Stage	Reduced Form	
Rural–urban migration barriers			0.0012	0.0006	0.0031**			0.0039***
			(0.0014)	(0.0013)	(0.0015)			(0.0013)
Instrument	-0.0002	0.0000				-31.7373***	-0.1050**	
	(0.0004)	(0.0000)				(3.9021)	(0.0477)	
Observations	11,195	11,195	11,095	11,095	11,095	11,095	11,195	11,095
R-squared	0.0927	0.0496	0.2371	0.2388	0.2266	0.1827	0.2395	0.2198
F-stat	1.6436	2.0662	56.0922	56.3772	55.6876	14.5754	57.8621	55.0231
Weak IV test (*F*)			97.0664	103.6567	66.1522			54.5994
Endogeneity test (*p*-value)					0.0167			0.0002
Hansen test (*p*-value)								0.3181

Notes: This table tests the validity of the IV exclusion restriction assumption. Columns (1) to (7) report IV estimates controlling for other likely channels through which the IV may affect local labor productivity. Columns (8) to (10) regress the timing of the end of the armed conflict in the civil war, past human capital stocks in 1949, and local intensity of the Cultural Revolution on the IV with included controls, respectively. Columns (11) and (12) report IV estimates using two counterfactual instruments based on the geographical distance between each mainland Chinese city and major Chinese coastal ports adjacent to Hong Kong and Macau, respectively. Columns (13) to (15) report the IV, first-stage, and reduced-form estimates using a new IV, namely access to the 156 Projects. Column (16) reports the IV estimate using both instruments simultaneously. The main IV refers to the distance to Jinmen. Standard errors are clustered at the county level. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

just their production organization by adopting more labor-saving management practices. Such organizational upgrading allows firms to maintain production efficiency when labor becomes scarce.

A growing literature documents that firms respond to labor scarcity by adopting labor-saving technologies or more efficient organizational practices (Acemoglu, 2010; Hornbeck and Naidu, 2014; Clemens *et al.*, 2018; Danzer *et al.*, 2024). Among these practices, performance-based incentive schemes have been shown to substantially increase worker productivity (Lazear, 2000; Shearer, 2004). These incentive systems are widely viewed as an important component of modern management technologies (Bloom *et al.*, 2016).

Guided by the model's prediction, we examine whether firms located in areas with higher rural-urban migration barriers are more likely to adopt performance-based compensation systems. In environments with tighter labor supply, firms may strengthen performance incentives in order to improve labor productivity.

We now estimate the causal impact of rural-urban migration barriers in the pre-reform era on firms' adoption of pay for performance, where

$$Payforperformance_{ic} = \beta Barrier_c + \gamma X_{ic} + \epsilon_{ic} \tag{10}$$

is identical to Equation 8, except $Payforperformance_{ic}$ replaces $Productivity_{ic}$. The first-stage Equation 9 remains the same as before. $Payforperformance_{ic}$ is the intensity of pay for performance adopted by firm i in county c, defined as the percentage of bonuses and piece-rate wages in total compensation given to permanent workers. β is the parameter of interest. We cluster standard errors at the county level.

Table 4 reports the main results. Columns 1 and 2 show the OLS estimate of the impact of rural-urban migration barriers on firms' adoption of pay for performance. The coefficient of interest is 0.0989, without any control variables. After we control for other variables, the coefficient of interest is 0.0920. As discussed earlier, the OLS estimates are still likely to be biased due to endogeneity problems. With the use of the same IV approach, the coefficient of interest increases substantially to 0.4080 (Column 3 of Table 4), suggesting that a one-standard-deviation increase in the strength of rural-urban migration barriers leads to an increase of 17.6 units in the intensity of pay for performance on average. Further details on the first-stage results, reduced-reform results, and relevant tests for the IV are presented in Table 4.

Taken together, the results suggest that firms facing stronger rural-urban migration barriers are more likely to adopt performance-based incentive schemes. These results provide direct empirical support for the organizational upgrading mechanism proposed in Session 2. When

migration barriers tighten local labor markets, firms respond by adopting stronger performance-based incentive systems in order to improve worker effort and productivity.

5.2.2 Mediation Analysis

While these findings are consistent with the organizational upgrading mechanism proposed in the conceptual framework, they do not directly reveal how much of the productivity effect operates through this channel. To quantify the contribution of this mechanism, we next conduct a mediation analysis. 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 a "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 are endogenous.

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

$$Y_{ic} = \beta_Y^M M_{ic} + \beta_Y^I T_c + \gamma X_{ic} + \epsilon_{ic} \tag{11}$$

$$M_{ic} = \gamma_M^Z Z_c + \gamma_M^T T_c + \theta X_{ic} + u_{ic} \tag{12}$$

The estimation procedure associated with Equations 8 and 9 is the standard IV approach. By contrast, the estimation procedure associated with Equations 11 and 12 is novel to the framework of Dippel *et al.* (2019), where Z is our IV to identify the causal effect of M on Y when conditioned on T. All variables are the same as before. β_Y^M and β_Y^I are the coefficients of interest. We cluster standard errors at the county level.

According to Dippel *et al.* (2019), identifying β_Y^M and β_Y^I using a single instrument variable Z requires an additional partial confounding assumption; that is, unobserved confounding variables that jointly cause the treatment and the intermediate outcomes (first causal relation) are independent of the confounders that cause the intermediate and the final outcomes (second causal relation). In our context, confounders in the first causal relation capture unobserved characteristics of people who work in the industrial sector. The greater adoption of pay for performance could be due to workers' values and beliefs (e.g., collectivism versus individualism) or to rural-urban migration barriers. By contrast, the confounders in the second causal relation represent firms' production technology that supports both pay for performance adoption and firm productivity. If workers' values and beliefs are uncorrelated with firms' production technology, the

Table 4: Impact of Rural–Urban Migration Barriers on the Adoption of Pay for Performance

	(1) OLS	(2) OLS	(3) IV	(4) First Stage	(5) Reduced Form
Rural–urban migration barriers	0.0989***	0.0920***	0.4080***		
	(0.0127)	(0.0112)	(0.0570)		
IV: Distance to Jinmen				-0.0214***	-0.0086***
				(0.0029)	(0.0009)
Observations	10,843	10,839	10,839	10,839	10,938
R-squared	0.0159	0.0864	-0.0594	0.1576	0.0890
F-stat	60.8439	20.6479	11.5406	13.3601	22.0923
Weak IV test (*F*)			55.2853		
Endogeneity test (*p*-value)			0.0000		
Control variables	NO	YES	YES	YES	YES

	(6) Control likely channels	(7) IV	(8) First Stage	(9) Reduced Form	(10) Two IVs
Rural–urban migration barriers	0.4542***	0.2763***			0.3257***
	(0.0914)	(0.0407)			(0.0373)
IV: Access to 156 Projects			-31.8092***	-8.9650***	
			(3.9333)	(1.1238)	
Observations	10,839	10,839	10,839	10,938	10,839
R-squared	-0.0759	0.0369	0.1808	0.0842	0.0067
F-stat	9.3989	14.7992	14.1962	20.1765	14.0063
Weak IV test (*F*)	25.8594	65.4022			53.8292
Endogeneity test (*p*-value)	0.0000	0.0000			0.0000
Hansen test (*p*-value)					0.0198
Control variables	YES	YES	YES	YES	YES

Notes: This table reports the impact of rural–urban migration barriers on the adoption of pay for performance. Columns (1) and (2) report the OLS results without and with control variables, respectively. Columns (3) to (5) report the IV, first-stage, and reduced-form estimates using the distance to Jinmen as an instrument. Column (6) controls for other likely channels through which the IV may affect pay for performance. Columns (7) to (9) report IV estimates using a new instrument: access to the 156 Projects. Column (10) reports the IV estimate using both instruments simultaneously. Standard errors clustered at the county level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

partial confounding assumption is likely to hold.

Table 5 reports the main results. Panel A presents the results of the second-stage Equation 11. Column 1 assesses the mediating effect changes in the adoption of pay for performance. The point estimate β_Y^M in column 1 indicates that a 10-percentage-point increase in the intensity of pay for performance improves the average firm productivity by 17.6%. This is the overall effect of the adoption of pay for performance on firm productivity, whether caused by rural-urban migration barriers or not. This result provides direct empirical support for the mechanism proposed in the conceptual framework: firms that adopt performance-based management practices achieve higher productivity through stronger worker incentives and improved labor efficiency.

The real importance of the point estimates β_Y^M lies in generating the indirect effect IE. Panel B of Table 5 reports this, along with the other relevant parameters of the mediation model. The β_M^T of rural-urban migration barriers on the adoption of pay for performance is estimated in Table 5 to be 0.41. IE represents the effect of changing the adoption of pay for performance, which was caused by rural-urban migration barriers, on firm productivity. If the strength of rural-urban migration barriers increases by one standard deviation, the intensity of pay for performance also increases, which in turn increases firm productivity by 31%. Relating this to the total effect of rural-urban migration barriers on firm productivity estimated in Table 5, the adoption of pay for performance can, as mediator M, explain around 140% of the overall effect of rural-urban migration barriers on firm productivity.[18] IE and DE add up to the effect estimated in Table 5 (i.e., $DE + IE = TE$).

The indirect effect of rural-urban migration barriers being larger than the total effect implies a moderating direct effect, whereby larger rural-urban migration barriers cause lower firm productivity through channels unrelated to the adoption of pay for performance (e.g., labor misallocation). This suggests that rural-urban migration barriers would have a stronger efficiency-enhancing effect if they affected the adoption of pay for performance alone. But the effect would be different: rural-urban migration barriers would not positively affect or might even adversely affect firm productivity if the impact of rural-urban migration barriers on the adoption of pay for performance could be mitigated (e.g., widespread adoption of performance-based reward systems across firms).

5.2.3 Additional Management Practices

While pay-for-performance provides a useful proxy for management upgrading, it captures only one dimension of management technology adoption within firms. Modern management

[18] We find similar results when using total factor productivity as the alternative outcome.

Table 5: Estimates of the mediation model

Mediating Variables	(1)
Panel A: Second Stage in Equation (11)	
β_Y^M	0.0176***
	(0.0060)
DE: β_Y^T	-0.0021***
	(0.0007)
F-stat Instruments	67.424
Panel B: Model Parameters	
β_M^T	0.4079
IE: $\beta_M^T \cdot \beta_Y^M$	0.0071
TE	0.0051
IE+DE	0.0051
S = IE / TE	1.40
S = IE / (IE+DE)	1.40
Panel C: First Stage in Equation (12)	
γ_M^Z	-0.0072***
	(0.0008)
γ_M^T	0.0698***
	(0.0110)
Observations	10,839
R-squared	0.0967

Notes: This table reports estimates of the mediation model. Panel A reports the second-stage results based on Equation 11. Panel C reports the first-stage results based on Equation 12. Panel B reports the main parameters of the mediation model. We use the STATA code `ivmediate` to estimate the mediation effects (Dippel *et al.*, 2020). Control variables are the same as those used in Table 1. The rural-urban migration barriers variable is constructed using China's population census in 1982. Firm-level variables come from the World Bank Enterprise Survey in 2005. Standard errors are clustered at the county level. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

practices also involve other incentive and personnel management mechanisms, such as promotion and demotion policies. To assess whether our results reflect a broader pattern of organizational upgrading rather than a single compensation practice, we examine additional management practice outcomes.

Specifically, we observe four management practice variables that can be used to assess the management technology adoption mechanism:

1. Percentage of bonuses and piece-rate wages among permanent workers,
2. Whether or not the general manager (GM)'s annual income is directly related to the company's performance,
3. Whether or not mid-level managers have been demoted in the past 3 years, and
4. For employees who received a wage increase, the percentage of employees who received a promotion in the previous year.

Each of those variables could qualify as a mediator, but our empirical approach allows for identifying the mediating effect of one mediator per regression and only.[19]

We therefore aggregate the observed management practice variables into principal components and focus on the mediating effects of management practices adoption in the aggregate. A principal component analysis is attractive because it generates indices that are purely statistical measurements based on the total variation in management practice outcomes, and are orthogonal to one another by construction. We label the principal components as "Management Technology Components" (MTCs).

One can best interpret the MTCs through their relation to the observed management practice outcomes, i.e., their factor loadings reported in Table A7. By construction, there are as many MTCs as variables, but following the Kaiser–Guttman criterion it is common to regard only principal components with an eigenvalue larger than 1. This holds for the first MTC. In our data, MTC1 explains about 34% of the variation in the management practice data. Therefore, we focus on MTC1 as our key mechanism that plausibly captures the core management practice adjustments to migration barriers.

Using a similar empirical approach, we show that a one-standard-deviation increase in the strength of migration barriers increases MTC1 by 0.51, equivalent to 43% of its standard deviation. Moreover, the adoption of management technology can, as mediator M, explain around

[19]Causally disentangling the mediating effects of different variables would require additional instruments, while omitting mediating channels from the model does not bias the estimates for the main treatment effect (Dippel *et al.*, 2019).

120% of the overall effect of rural–urban migration barriers on firm productivity. Further details on the estimation results can be found in Table A7.

Taken together, these results provide empirical support for the mechanism highlighted in Section 2: migration barriers tighten labor markets, induce organizational upgrading within firms, and ultimately affect firm productivity.

5.3 Firm Dynamics and Product-Market Selection

We next examine whether the productivity improvements associated with rural–urban migration barriers translate into changes in firm dynamics and product-market selection. In the conceptual framework, migration barriers may increase firms' effective productivity through management upgrading. If this channel is important, more productive firms should expand, new firms may enter, and sales may be reallocated toward more competitive external markets, consistent with a Melitz-type sorting mechanism.

Our empirical analysis shows that a one-standard-deviation increase in the strength of rural–urban migration barriers leads to a 39.7 percent increase in firm employment. In addition, the same increase raises the probability of new firm creation (i.e., firms established within the past three or five years) by approximately 0.8 to 1.2 percentage points. These findings suggest that migration barriers are associated with greater firm expansion and firm entry, consistent with stronger market selection forces. Further details on these results are provided in Tables A10, A11, and A12.

We further explore how migration barriers affect firms' product-market orientation. If migration barriers increase firms' effective productivity through management upgrading, more productive firms may expand their presence in competitive external markets rather than relying on protected local demand. Consistent with this interpretation, we find that a one-standard-deviation increase in the strength of rural–urban migration barriers leads to a 16.9 percentage-point increase in the share of products sold to other cities and foreign markets, representing a 22% increase from the sample mean. At the same time, the share of products sold to government entities and state-owned enterprises declines by 15.7 percentage points, accounting for about 69% of the sample mean. These patterns suggest a shift toward more competitive product markets, consistent with a Melitz-style sorting process. Further details on these results are reported in Tables A8 and A9.

Overall, these results provide additional support for the mechanism proposed in the conceptual framework. By increasing firms' effective productivity through management upgrading, migration barriers strengthen market selection forces, allowing more productive firms to expand, encouraging the entry of new firms, and shifting sales toward more competitive external markets.

These patterns are consistent with a Melitz-style sorting process in which higher-productivity firms grow and gain market share.

Taken together, these findings suggest that migration barriers not only affect firm productivity through organizational upgrading but also reshape market outcomes through a productivity-driven sorting mechanism.

5.4 Heterogeneous Effects

If the productivity-enhancing effect of rural-urban migration barriers operates through organizational upgrading within firms, the magnitude of this effect should vary across firms with different baseline management practices. In particular, firms that already employ modern management practices, such as performance-based incentive systems, should benefit less from the labor-scarcity-induced organizational upgrading channel.

To explore this implication, we use the Chinese Annual Survey of Industrial Firms (1999–2007) and construct a balanced panel dataset of 25,951 firms located in about 1,700 counties in each year from 1999 to 2007. Panel A of Table 6 reports the baseline results using this alternative dataset. Using the same IV approach, we find that the effects of rural-urban migration barriers on firm productivity remain robust over time. These similar results also alleviate concerns regarding potential measurement error in firm productivity.

We then examine heterogeneity by firm ownership type. Panels B to D of Table 6 report the dynamic impacts of rural-urban migration barriers on firm productivity for private firms, state-owned enterprises (SOEs), and foreign-owned firms, respectively. The results reveal notable differences across ownership types. Among private Chinese firms (Panel B), the impact of migration barriers on productivity declines slightly over time. By contrast, the impact becomes larger over time among state-owned enterprises (Panel C). These contrasting findings are consistent with the well-documented fact that SOEs lag behind private firms in adopting performance-based reward systems and modern management practices. For foreign-owned firms (Panel D), the estimated effects are generally negative and statistically insignificant. This result is consistent with the earlier adoption of performance-based incentive systems and more advanced management practices among foreign firms operating in China during this period. This pattern is consistent with the conceptual framework, which predicts that firms that have already adopted modern management practices have less scope for additional organizational upgrading.

Taken together, these heterogeneous effects provide additional evidence supporting the organizational upgrading mechanism. Firms with weaker baseline management practices appear to benefit more from the labor-scarcity pressures induced by rural-urban migration barriers, which encourage the adoption of more efficient management technologies.

Table 6: Heterogeneous impacts of rural–urban migration barriers on labor productivity over time

Variables	(1) 1999	(2) 2000	(3) 2001	(4) 2002	(5) 2003	(6) 2004	(7) 2005	(8) 2006	(9) 2007
Panel A: All firms									
Rural–urban migration barriers	0.0063***	0.0058***	0.0064***	0.0075***	0.0081***	0.0078***	0.0077***	0.0071***	0.0072***
	(0.0021)	(0.0022)	(0.0022)	(0.0022)	(0.0023)	(0.0024)	(0.0024)	(0.0023)	(0.0023)
Observations	25,255	25,363	25,328	25,333	25,429	25,410	25,426	25,401	25,355
R-squared	0.2076	0.2161	0.1841	0.1447	0.1184	0.1137	0.1169	0.1278	0.1271
F-stat	94.9656	95.4085	83.1613	80.7108	69.0830	100.9563	79.2818	81.4649	78.5958
Weak IV test (*F*)	33.9870	31.2134	33.1527	34.8444	31.0215	28.3517	30.0989	29.0164	28.5343
Firm controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Panel B: Private Chinese firms									
Rural–urban migration barriers	0.0093***	0.0083***	0.0073***	0.0081***	0.0086***	0.0081***	0.0079***	0.0080***	0.0079***
	(0.0025)	(0.0025)	(0.0023)	(0.0021)	(0.0022)	(0.0022)	(0.0021)	(0.0022)	(0.0021)
Observations	12,791	13,170	13,437	13,668	13,957	14,158	14,248	14,438	14,423
Panel C: State-owned enterprises									
Rural–urban migration barriers	0.0052***	0.0048**	0.0064***	0.0070***	0.0088***	0.0093***	0.0090***	0.0086***	0.0100***
	(0.0020)	(0.0020)	(0.0020)	(0.0021)	(0.0022)	(0.0024)	(0.0024)	(0.0025)	(0.0026)
Observations	5,058	4,766	4,432	4,217	4,016	3,744	3,683	3,507	3,433
Panel D: Foreign-owned firms									
Rural–urban migration barriers	-0.0094	-0.0098	-0.0069	-0.0041	-0.0100	-0.0104	-0.0079	-0.0089	-0.0109
	(0.0082)	(0.0095)	(0.0071)	(0.0061)	(0.0112)	(0.0109)	(0.0086)	(0.0090)	(0.0116)
Observations	7,406	7,427	7,459	7,448	7,456	7,508	7,495	7,456	7,499

Notes: This table reports the heterogeneous impacts of rural–urban migration barriers on labor productivity over time. Panel A reports estimates for all firms. Panel B reports estimates for private Chinese firms only. Panel C reports estimates for state-owned enterprises only. Panel D reports estimates for foreign-owned firms only. Columns (1)–(9) report the impact of rural–urban migration barriers on labor productivity from 1999 to 2007. Control variables are the same as those used in Table 1. The indicator of rural–urban migration barriers is constructed using China's population census in 1982. Firm-level variables come from the Chinese Annual Survey of Industrial Firms (1999–2007). Standard errors are clustered at the county level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.5 Persistence of Early Migration Barriers

A natural concern is whether migration barriers measured in the early reform period can have persistent effects on firms observed many years later. We therefore discuss several institutional and empirical reasons suggesting that early migration barriers remained highly persistent over time.

First, early reforms of the "internal passport" (hukou) system primarily aimed to facilitate temporary labor migration without granting migrants local hukou status. As documented by Jin and Zhang (2023), policies that prevent rural migrants from obtaining a local hukou in urban destinations can substantially discourage rural–urban migration, thereby sustaining migration barriers even when temporary migration becomes more common.

Second, the relaxation of hukou entry requirements occurred very gradually and spanned more than two decades. Our data also confirm the persistence of migration barriers over time. For example, the correlation between migration barriers measured in 1982 and those measured in 2000 is 0.69, which is consistent with the gradual nature of hukou reforms.

Third, to address the concern that firms exposed to similar migration barriers may experience different degrees of labor scarcity due to heterogeneous labor demand shocks following China's accession to the WTO, we examine whether migration barriers are associated with firms' reported labor shortages. Our results show that a one-standard-deviation increase in the strength of migration barriers raises the probability that manufacturing firms report labor shortages by 3.3 percentage points. This finding further supports the idea that the labor supply consequences of early migration barriers can persist for a prolonged period. Further details on these estimation results are reported in Table A6.

5.6 Robustness Checks

We conduct several robustness checks to verify the stability of our main findings. First, we use alternative measures of rural–urban migration barriers. Specifically, we construct two additional indicators based on the percentage of agricultural hukou (AH) holders in the local population in 1990 and 2000, respectively, using data from the 1990 and 2000 Chinese population censuses.[20]

Second, we employ alternative measures of pay-for-performance practices to capture firms' adoption of performance-based reward systems. These include: (i) the percentage of bonuses in total compensation (excluding piece-rate wages) paid to permanent workers; (ii) the percentage of piece-rate wages in total compensation (excluding bonuses) paid to permanent workers; (iii) the

[20]The correlation between migration barriers measured in 1982 and 2000 is 0.675, suggesting substantial persistence of migration barriers over time.

percentage of bonuses and piece-rate wages in total compensation paid to all workers (including temporary workers); and (iv) a dummy variable indicating whether the general manager's annual income is directly linked to firm performance. Across all specifications, the estimated effects remain qualitatively unchanged. Detailed results of these robustness checks are reported in Tables A2–A3.

6 Conclusion

To the best of our knowledge, this study provides the first causal evidence on the long-run impact of migration barriers on firm productivity in urban destinations in a developing economy. Exploiting variation generated by China's rural–urban migration restrictions under the hukou system, we show that stronger migration barriers increase the long-run productivity of urban manufacturing firms.

Our results highlight an important mechanism behind this relationship. The productivity gains appear to arise primarily from increased adoption of management technologies—such as pay-for-performance incentive schemes—rather than from greater use of capital or skilled labor within firms. These findings are consistent with the idea that tighter labor markets can induce firms to adopt labor-saving organizational practices that improve labor efficiency.

More broadly, our findings illustrate two opposing forces through which migration barriers may affect productivity. On the one hand, restricting labor mobility can generate labor misallocation by preventing workers from moving toward more productive firms and sectors. On the other hand, tighter migration barriers reduce the supply of migrant labor in urban destinations, raise labor costs, and strengthen firms' incentives to adopt productivity-enhancing management practices. Our evidence suggests that in some contexts the latter force may dominate, leading to higher observed productivity among surviving firms.

These results complement recent evidence by Imbert *et al.* (2022), which shows that rural–urban migration can induce labor-oriented technological change and reduce productivity in developing economies. Together, these studies highlight the central role of labor market conditions in shaping firms' technological and organizational choices.

Given that large differences in management technology persist across countries and firms (Bloom *et al.*, 2019), our findings suggest that labor scarcity may encourage firms—particularly low-productivity domestic firms—to adopt improved management practices such as performance-based reward systems.

At the same time, our results do not imply that migration barriers are welfare improving overall. Migration restrictions may still generate substantial allocative distortions in the broader

economy. Rather, our findings highlight a firm-level channel through which labor scarcity can stimulate organizational upgrading and productivity improvements. An important policy challenge for developing economies such as China is therefore how to liberalize migration while preserving firms' incentives to improve management practices and productivity in destination regions.

References

Acemoglu, D. (2010). When does labor scarcity encourage innovation? *Journal of Political Economy*, **118** (6), 1037–1078.

Ackerberg, D. A., Caves, K. and Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, **83** (6), 2411–2451.

Bai, C.-E., Li, D. D., Tao, Z. and Wang, Y. (2000). A multitask theory of state enterprise reform. *Journal of Comparative Economics*, **28** (4), 716–738.

—, Lu, J. and Tao, Z. (2006). The multitask theory of state enterprise reform: Empirical evidence from china. *American Economic Review*, **96** (2), 353–357.

Baker, G. P. (1992). Incentive contracts and performance measurement. *Journal of Political Economy*, **100** (3), 598–614.

Baron, R. M. and Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research. *Journal of Personality and Social Psychology*, **51** (6), 1173–1182.

Baum, C. F. and Lewbel, A. (2019). Advice on using heteroskedasticity-based identification. *Stata Journal*, **19** (4), 757–767.

Becker, S. O. and Woessmann, L. (2009). Was weber wrong? a human capital theory of protestant economic history. *Quarterly Journal of Economics*, **124** (2), 531–596.

Bloom, N., Brynjolfsson, E., Foster, L., Jarmin, R., Patnaik, M., Saporta-Eksten, I. and Van Reenen, J. (2019). What drives differences in management practices? *American Economic Review*, **109** (5), 1648–1683.

—, Manova, K., Van Reenen, J., Sun, S. T. and Yu, Z. (2018). Managing trade: Evidence from china and the us. *NBER Working Paper*, (24718).

—, Sadun, R. and Van Reenen, J. (2016). *Management as a Technology?* NBER Working Paper 22327, National Bureau of Economic Research.

— and Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. *Quarterly Journal of Economics*, **122** (4), 1351–1408.

— and — (2010). Why do management practices differ across firms and countries? *Journal of Economic Perspectives*, **24** (1), 203–224.

Bo, Y. (1991). *Review of Several Major Decisions and Events*. Beijing: The Chinese Communist Party School Press.

Bryan, G. and Morten, M. (2019). The aggregate productivity effects of internal migration. *Journal of Political Economy*, **127** (5), 2229–2268.

Cai, X., Jiang, W., Song, H. and Xie, H. (2022). Pay for performance schemes and manufacturing worker productivity: Evidence from a kinked design in china. *Journal of Development Economics*, **156**, 102840.

Chen, T., Kung, J. K.-s. and Ma, C. (2020a). Long live keju! the persistent effects of china's civil examination system. *Economic Journal*, **130** (631), 2030–2064.

Chen, X. (2020). *Laying the Foundation*. Tiandi Press.

Chen, Y., Fan, Z., Gu, X. and Zhou, L.-A. (2020b). Arrival of young talent: The send-down movement and rural education in china. *American Economic Review*, **110** (11), 3393–3430.

Clemens, M. A., Lewis, E. G. and Postel, H. M. (2018). Immigration restrictions as active labor market policy. *American Economic Review*, **108** (6), 1468–1487.

Conley, T. (2008). Spatial econometrics. In *The New Palgrave Dictionary of Economics*, New York: Palgrave Macmillan.

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of Econometrics*, **92** (1), 1–45.

Danzer, A. M., Feuerbaum, C. and Gaessler, F. (2024). Labor supply and automation innovation: Evidence from an allocation policy. *Journal of Public Economics*, **235**, 105136.

Dippel, C., Ferrara, A. and Heblich, S. (2020). Causal mediation analysis in instrumental-variables regressions. *Stata Journal*, **20** (3), 613–626.

—, Gold, R., Heblich, S. and Pinto, R. (2019). Mediation analysis in iv settings with a single instrument. Working paper.

Dong, Z. and Wu, J. (2004). *The Cornerstone of New China's Industry: A Study of the 156 Projects, 1950–2000*. Guangdong jingji chubanshe.

Fan, J. (2019). Internal geography, labor mobility, and the distributional impacts of trade. *American Economic Journal: Macroeconomics*, **11** (3), 252–288.

Foreman, T. (2020). Spatial_hac_iv: Stata module to estimate an instrumental variable regression, adjusting standard errors for spatial correlation, heteroskedasticity, and autocorrelation. Statistical software component.

Franck, R. (2024). Labor scarcity, technology adoption and innovation: evidence from the cholera pandemics in 19th century france. *Journal of Economic Growth*, **29** (4), 543–583.

Frederiksen, A. and Manchester, C. (2020). Personnel practices and regulation: How firm-provided incentives respond to changes in mandatory retirement law. *Journal of Labor Economics*.

Guiteras, R. P. and Jack, B. K. (2018). Productivity in piece-rate labor markets: Evidence from rural malawi. *Journal of Development Economics*, **131**, 42–61.

Hau, H., Huang, Y. and Wang, G. (2020). Firm response to competitive shocks: Evidence from china's minimum wage policy. *Review of Economic Studies*, **87** (6), 2639–2671.

Hoffman, M. and Stanton, C. T. (2025). People, practices, and productivity: A review of new advances in personnel economics. *Handbook of Labor Economics*, **6**, 729–818.

Hopenhayn, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica*, **60** (5), 1127–1150.

Hornbeck, R. and Naidu, S. (2014). When the levee breaks: Black migration and economic development in the american south. *American Economic Review*, **104** (3), 963–990.

Hsieh, C.-T. and Klenow, P. J. (2009). Misallocation and manufacturing tfp in china and india. *Quarterly Journal of Economics*, **124** (4), 1403–1448.

Imbert, C., Seror, M., Zhang, Y. and Zylberberg, Y. (2022). Migrants and firms: Evidence from china. *American Economic Review*, **112** (6), 1885–1914.

Jin, Z. (2018). *China's Reform of the Hukou System and Consequences for Workers and Firms*. Ph.D. thesis, University of Nottingham.

— and Zhang, J. (2023). Access to local citizenship and internal migration in a developing country. *Journal of Comparative Economics*, **51** (1), 181–215.

Khanna, G., Liang, W., Mobarak, A. M. and Song, R. (2025). The productivity consequences of pollution-induced migration in china. *American Economic Journal: Applied Economics*, **17** (2), 184–224.

Kinnan, C., Wang, S. and Wang, Y. (2018). Access to migration for rural households. *AEJ: Applied Economics*, **10** (4), 79–119.

Lazear, E. P. (2000). Performance pay and productivity. *American Economic Review*, **90** (5), 1346–1361.

Levinsohn, J. and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *Review of Economic Studies*, **70** (2), 317–341.

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics*, **30** (1), 67–80.

MacKinnon, D. P. (2008). *Introduction to Statistical Mediation Analysis*. Routledge.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, **71** (6), 1695–1725.

Nunn, N. and Wantchekon, L. (2011). The slave trade and the origins of mistrust in africa. *American Economic Review*, **101** (7), 3221–3252.

Sadun, R., Schuh, R. J., Hartley, J. S., Van Reenen, J. and Bloom, N. (2025). *Management and firm dynamism*. Tech. rep., National Bureau of Economic Research.

Shearer, B. (2004). Piece rates, fixed wages and incentives. *Review of Economic Studies*, **71** (2), 513–534.

Song, J. and Li, S. (2014). Hukou's impact on labor occupation segmentation. *China Agricultural Economic Review*.

Stiglitz, J. E. (1975). Incentives, risk, and information: Notes towards a theory of hierarchy. *Bell Journal of Economics*, **6** (2), 552–579.

Sun, W., Bai, C. and Xie, P. (2011). The effect of rural mobility from registration system reform in china. *Economic Research Journal*, **1**, 28–41.

Tombe, T. and Zhu, X. (2019). Trade, migration, and productivity. *American Economic Review*, **109** (5), 1843–1872.

Walder, A. G. and Lu, Q. (2017). China political events dataset, 1966–1971. Dataset.

Worden, R. L., Savada, A. M. and Dolan, R. E. (1987). China: A country study. Country study.

Zhang, J., Wang, R. and Lu, C. (2019). A quantitative analysis of hukou reform in chinese cities: 2000–2016. *Growth and Change*, **50** (1), 201–221.

Supplementary Appendix: Can Migration Barriers Save Productivity in a Developing Country?

A Model Derivations

This appendix provides the formal derivations underlying the simple framework presented in Section 2. The purpose of the framework is to illustrate how migration barriers may affect firm productivity through labor scarcity, endogenous management upgrading, and product-market selection.

A.1 Setup

Consider a firm with baseline productivity $\phi > 0$. Firms may adopt a management technology $m \in \{0,1\}$, where $m = 1$ denotes advanced management and $m = 0$ denotes basic management. Management affects effective productivity through

$$\tilde{\phi} = \phi A(m), \tag{13}$$

where

$$A(1) > A(0) = 1. \tag{14}$$

Adopting advanced management requires paying a fixed organizational cost $F_m > 0$.

Production is given by

$$y = \phi A(m) l^{\alpha_m}, \tag{15}$$

where l denotes labor input and

$$0 < \alpha_1 < \alpha_0 < 1. \tag{16}$$

The assumption $\alpha_1 < \alpha_0$ captures the idea that advanced management reduces firms' dependence on labor input, making production more labor-saving.

Firms can serve either a local market L or an external market E. Let $j \in \{L, E\}$ index the market served. Firms face output price p_j and incur a market-specific fixed cost F_j, with

$$F_E > F_L \geq 0. \tag{17}$$

Migration barriers are summarized by a parameter τ, which affects firms through the wage rate:

$$w = w(\tau), \qquad w'(\tau) > 0. \tag{18}$$

Thus tighter migration barriers increase labor costs by restricting firms' access to migrant labor.

Profits in market j are given by

$$\Pi_j(\phi, m, \tau) = p_j \phi A(m) l^{\alpha_m} - w(\tau) l - F_j - F_m m. \tag{19}$$

A.2 Optimal Labor Demand

For a given market j, management choice m, and migration barrier level τ, the firm chooses labor input l to maximize profits. The first-order condition is

$$\alpha_m p_j \phi A(m) l^{\alpha_m - 1} = w(\tau). \tag{20}$$

Solving for optimal labor demand yields

$$l_j^*(\phi, m, \tau) = \left(\frac{\alpha_m p_j \phi A(m)}{w(\tau)} \right)^{\frac{1}{1-\alpha_m}}. \tag{21}$$

Substituting optimal labor demand back into the profit function gives maximized variable profits:

$$\pi_j(\phi, m, \tau) = B_m \left(p_j \phi A(m) \right)^{\frac{1}{1-\alpha_m}} w(\tau)^{-\frac{\alpha_m}{1-\alpha_m}}, \tag{22}$$

where

$$B_m = (1 - \alpha_m) \alpha_m^{\frac{\alpha_m}{1-\alpha_m}} > 0. \tag{23}$$

Total profits are therefore

$$\Pi_j(\phi, m, \tau) = B_m \left(p_j \phi A(m) \right)^{\frac{1}{1-\alpha_m}} w(\tau)^{-\frac{\alpha_m}{1-\alpha_m}} - F_j - F_m m. \tag{24}$$

A.3 Management Adoption

Define the gain from adopting advanced management in market j as

$$\Delta_j(\phi, \tau) \equiv \Pi_j(\phi, 1, \tau) - \Pi_j(\phi, 0, \tau). \tag{25}$$

Using equation (24), we obtain

$$\begin{aligned} \Delta_j(\phi, \tau) = {} & B_1 \left(p_j \phi A(1) \right)^{\frac{1}{1-\alpha_1}} w(\tau)^{-\frac{\alpha_1}{1-\alpha_1}} \\ & - B_0 \left(p_j \phi A(0) \right)^{\frac{1}{1-\alpha_0}} w(\tau)^{-\frac{\alpha_0}{1-\alpha_0}} - F_m. \end{aligned} \tag{26}$$

A firm adopts advanced management if and only if

$$\Delta_j(\phi, \tau) \geq 0. \tag{27}$$

A.4 Proof of Proposition 1

We first show that management adoption follows a cutoff rule. Under the maintained assumption that the profit gain from advanced management is increasing in firm productivity,[21] $\Delta_j(\phi, \tau)$ is strictly increasing in ϕ. Therefore, there exists a productivity cutoff $\phi_m^j(\tau)$ defined implicitly by

$$\Delta_j(\phi_m^j(\tau), \tau) = 0, \tag{28}$$

such that firms with

$$\phi \geq \phi_m^j(\tau) \tag{29}$$

adopt advanced management.

We next examine how migration barriers affect the adoption cutoff. Differentiating equation (26) with respect to the wage w gives

$$\begin{aligned}\frac{\partial \Delta_j}{\partial w} = &-\frac{\alpha_1}{1-\alpha_1} B_1 \left(p_j \phi A(1)\right)^{\frac{1}{1-\alpha_1}} w^{-\frac{1}{1-\alpha_1}} \\ &+ \frac{\alpha_0}{1-\alpha_0} B_0 \left(p_j \phi A(0)\right)^{\frac{1}{1-\alpha_0}} w^{-\frac{1}{1-\alpha_0}}.\end{aligned} \tag{30}$$

Because $\alpha_1 < \alpha_0$, profits under advanced management are less sensitive to wage increases. Under the sufficient condition that advanced management is sufficiently labor-saving, the gain from adopting advanced management rises with wages:

$$\frac{\partial \Delta_j}{\partial w} > 0. \tag{31}$$

Since $w'(\tau) > 0$, the chain rule implies

$$\frac{\partial \Delta_j}{\partial \tau} = \frac{\partial \Delta_j}{\partial w} w'(\tau) > 0. \tag{32}$$

Applying the implicit function theorem to the cutoff condition $\Delta_j(\phi_m^j(\tau), \tau) = 0$ yields

$$\frac{d\phi_m^j(\tau)}{d\tau} = -\frac{\partial \Delta_j / \partial \tau}{\partial \Delta_j / \partial \phi} < 0, \tag{33}$$

[21] This condition is satisfied under standard parameter restrictions ensuring that the productivity-enhancing effect of advanced management dominates the associated fixed organizational cost for sufficiently productive firms.

because $\partial \Delta_j / \partial \phi > 0$ by assumption. Thus tighter migration barriers reduce the productivity threshold for management adoption, implying that a larger set of firms finds it optimal to adopt advanced management.

A.5 Market Participation and Selection

Given effective productivity

$$\tilde{\phi} = \phi A(m), \tag{34}$$

firms choose whether to serve only the local market or also the external market. A firm enters the external market if

$$\Pi_E(\tilde{\phi}, \tau) \geq \Pi_L(\tilde{\phi}, \tau). \tag{35}$$

Define

$$G(\tilde{\phi}, \tau) \equiv \Pi_E(\tilde{\phi}, \tau) - \Pi_L(\tilde{\phi}, \tau). \tag{36}$$

The external-market participation condition can be written as

$$G(\tilde{\phi}, \tau) \geq 0. \tag{37}$$

A.6 Proof of Proposition 2

Because profits are increasing in effective productivity $\tilde{\phi}$, the difference $G(\tilde{\phi}, \tau)$ is increasing in $\tilde{\phi}$. Therefore, there exists an effective productivity cutoff $\tilde{\phi}_E(\tau)$ defined implicitly by

$$G(\tilde{\phi}_E(\tau), \tau) = 0, \tag{38}$$

such that firms with

$$\tilde{\phi} \geq \tilde{\phi}_E(\tau) \tag{39}$$

enter the external market.

To characterize the effect of migration barriers on market selection, note that tighter migration barriers increase labor costs through $w'(\tau) > 0$. Holding effective productivity fixed, higher wages reduce profits in both markets. When serving the external market involves higher fixed or variable costs than serving only the local market, the profitability of external-market participation declines more sharply for firms with low effective productivity. Under the maintained assumption that this cost effect dominates any offsetting gains from management upgrading at the participation margin, we have

$$\frac{\partial G(\tilde{\phi}, \tau)}{\partial \tau} < 0. \tag{40}$$

Applying the implicit function theorem to the cutoff condition yields

$$\frac{d\tilde{\phi}_E(\tau)}{d\tau} = -\frac{\partial G/\partial \tau}{\partial G/\partial \tilde{\phi}} > 0, \tag{41}$$

since $\partial G/\partial \tilde{\phi} > 0$. Thus tighter migration barriers raise the effective productivity threshold for external-market participation and strengthen product-market selection.

An immediate implication is that firms with higher effective productivity are more likely to participate in external markets. Since management upgrading increases effective productivity through $A(1) > A(0)$, firms adopting advanced management are more likely to cross the external-market cutoff.

A.7 Implications for Average Productivity

The model highlights two distinct channels through which tighter migration barriers may affect observed average productivity among surviving firms.

First, tighter migration barriers raise labor costs and induce more firms to adopt advanced, labor-saving management practices. This management-upgrading channel increases effective productivity at the firm level.

Second, tighter migration barriers strengthen product-market selection by raising the productivity threshold required for external-market participation. As a result, low-productivity firms are less likely to survive in more competitive markets, and the average productivity of participating firms rises.

Taken together, these two forces imply that regions facing tighter migration barriers may exhibit higher observed average productivity among surviving firms, even though migration barriers also generate labor misallocation.

A.8 Connection to the Empirical Predictions

The derivations above motivate the empirical predictions tested in the main text.

First, tighter migration barriers should increase the likelihood that firms adopt labor-saving management practices.

Second, firms that adopt advanced management should exhibit higher productivity because advanced management raises effective productivity and reduces dependence on labor input.

Third, more productive firms should be more likely to participate in external markets, and tighter migration barriers may increase the average productivity of surviving firms through both management upgrading and stronger product-market selection.

B Summary Statistics for Main Variables

Table A1: Summary statistics for main variables

Variables	N	Mean	Median	Std. Dev.	min	max
Sales per capita in log	11200.00	12.19	12.15	1.24	5.31	21.30
Percentage of piece rate wage plus bonuses (%)	10942.00	42.07	38.95	33.98	0.00	100.00
Percentage of piece rate wage (%)	10942.00	29.54	0.00	36.48	0.00	100.00
Percentage of bonuses (%)	10942.00	12.53	5.00	17.07	0.00	100.00
Percentage of fixed salary (%)	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 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
General manager with master degree (0/1)	11200.00	0.15	0.00	0.36	0.00	1.00
General manager with undergraduate degree (0/1)	11200.00	0.42	0.00	0.49	0.00	1.00
General manager with college degree (0/1)	11200.00	0.28	0.00	0.45	0.00	1.00
General manager with high school degree or below (0/1)	11200.00	0.14	0.00	0.35	0.00	1.00
The distance between each mainland Chinese county in which firms are located and the coastline (km)	11200.00	399.85	293.58	401.38	0.04	2575.14
Total population (in 10,000 person)	11200.00	273.02	219.64	232.62	14.06	867.73
Foreign direct investment (in 10,000 dollars)	11200.00	1490.02	9.50	6761.35	0.00	58906.00
Total exports (in 10,000 dollars)	11200.00	16003.74	0.00	71023.94	0.00	546725.00
Percentage of heavy industry (%)	11200.00	53.01	55.53	19.04	2.08	91.71
Percentage of state-owned industry (%)	11200.00	73.36	79.69	16.13	29.62	98.73
Percentage of large-size industry (%)	11200.00	21.51	15.65	21.46	0.00	93.20
Number of subscribers of telephones	11200.00	20511.66	15281.00	20240.66	940.00	91191.00
Railway passenger traffic (in 10,000 person)	11200.00	592.92	337.50	813.60	0.00	4393.00
Highway passenger traffic (in 10,000 person)	11200.00	1720.37	1191.50	2057.00	0.00	16456.00
Number of scientists	11200.00	23029.19	14440.00	26188.91	765.00	144738.00
Number of social scientists	11200.00	16450.84	12381.00	15221.64	20.00	78963.00
Access to "156 projects" (0/1)	11200.00	0.23	0.00	0.42	0.00	1.00
Rural-urban migration barriers (1982)	11100.00	58.19	87.90	43.24	0.00	100.00

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

Table A1: Summary statistics for main variables (continued)

Variables	N	Mean	Median	Std. Dev.	min	max
The geographical distance between each mainland Chinese city and Jinmen (km)	11200.00	1189.79	1139.95	613.16	35.65	3507.98
Distance to the capital of the PRC (km)	11200.00	1097.51	1028.35	554.67	55.25	2426.82
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

C Robustness Checks

C.1 Alternative Measures of Rural-Urban Migration Barriers

In our main analysis, we use the percentage of rural residents in the local population in 1982 to measure rural-urban migration barriers, given the fact that AH holders were not allowed to migrate to urban areas unless they successfully obtained NAH and that it was very difficult for AH holders to migrate to urban areas in early 1980s.[22] We use two different measures of rural-urban migration barriers for robustness checks. First, to reduce the concern that the percentage of rural residents in the local population may be different from the percentage of AH holders in the local population, we further use the percentage of AH holders in the local population in 1990, provided by the 1990 Chinese population census, to measure rural-urban migration barriers in 1990. Second, to reduce the concern that rural-urban migration barriers in 1982 may not fully capture rural-urban migration barriers exposed to local firms in 2005, we further use the percentage of AH holders in the local population in 2000, provided by the 2000 Chinese population census, to measure rural-urban migration barriers in 2000.[23] Results shown in Table A2 do not reject our main findings.

C.2 Alternative Measures of Incentive Pay

In our main analysis, we use the percentage of bonuses and piece-rate wages in total compensation among permanent workers to measure the intensity of incentive pay. We use four different measures of incentive pay for robustness checks. The first one is the percentage of bonuses in total compensation (excluding piece-rate wages) among permanent workers. The second one is the percentage of piece-rate wages in total compensation (excluding bonuses) among permanent workers. The third one is the percentage of bonuses and piece-rate wages in total compensation among all workers (including temporary workers). Finally, we use 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. Results shown in Table A3 do not reject our main findings.

[22] According to the Chinese Population Census, less than 1% of the total population were living away from their registered places in 1982.

[23] In fact, the correlation between rural-urban migration barriers in 1982 and rural-urban migration barriers in 2000 is 0.675, suggesting the persistence of rural-urban migration barriers over time.

Table A2: Estimates of the mediation model using alternative measures of rural-urban migration barriers

	(1) Migration barriers (1990)	(2) Migration barriers (2000)
Panel A: Second Stage in Equation (11)		
β_{YM}	0.0134**	0.0251***
	(0.0059)	(0.0078)
DE: β_{YT}	-0.0023***	-0.0049**
	(0.0008)	(0.0015)
F-Stat Instruments	65.581	44.281
Panel B: Model Parameters		
β_{MT}	0.6010	0.5309
IE: $\beta_{MT} \times \beta_{YM}$	0.0080	0.0133
TE	0.0057	0.0084
IE+DE	0.0057	0.0084
S = IE/TE	1.413	1.581
S = IE/(IE+DE)	1.413	1.581
Panel C: First Stage in Equation (12)		
γ_{MZ}	-0.0071***	-0.0058***
	(0.0008)	(0.0008)
γ_{MT}	0.0824***	0.1421***
	(0.0120)	(0.0166)
Observations	10,448	10,640
R-Squared	0.0908	0.0984

Notes: This table reports estimates of the mediation model using alternative measures of rural-urban migration barriers. Panel A reports the second-stage results based on Equation 11. Panel C reports the first-stage results based on Equation 12. Panel B reports the main parameters of the mediation model. We use the STATA code *ivmediate* to estimate the main results above (Dippel *et al.*, 2020). Control variables consist of age, skill composition of general managers, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the mainland Chinese county in which firms are located and the coastline, and the logarithm of the distance between the mainland Chinese county in which firms are located and Beijing. The rural-urban migration barriers variable in Column (1) is constructed using China's population census in 1990. The rural-urban migration barriers variable in Column (2) is constructed using China's population census in 2000. Firm-level variables come from the World Bank Enterprise Survey in 2005. Standard errors are clustered at the county level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Estimates of the mediation model using alternative measures of incentive pay

	(1) Bonuses	(2) Piece-rate wages	(3) All employees	(4) General manager
Panel A: Second Stage in Equation (11)				
β_{YM}	0.0347***	0.0214***	0.0208***	1.5330***
	(0.0115)	(0.0080)	(0.0077)	(0.5430)
DE: β_{YT}	-0.0009*	-0.0030***	-0.0024***	-0.0006
	(0.0005)	(0.0011)	(0.0009)	(0.0005)
F-Stat Instruments	35.330	38.086	56.022	57.541
Panel B: Model Parameters				
β_{MT}	0.1767	0.3823	0.3615	0.0037
IE: $\beta_{MT} \times \beta_{YM}$	0.0061	0.0081	0.0075	0.0057
TE	0.0051	0.0051	0.0050	0.0050
IE+DE	0.0051	0.0051	0.0050	0.0050
S = IE/TE	1.204	1.607	1.482	1.132
S = IE/(IE+DE)	1.204	1.607	1.482	1.132
Panel C: First Stage in Equation (12)				
γ_{MZ}	-0.0036***	-0.0059***	-0.0060***	-0.0000***
	(0.0006)	(0.0009)	(0.0008)	(0.0000)
γ_{MT}	0.0044	0.1044***	0.0768***	-0.0001
	(0.0073)	(0.0118)	(0.0105)	(0.0001)
Observations	10,215	10,823	10,839	10,970
R-Squared	0.0333	0.1396	0.1278	0.0434

Notes: This table reports estimates of the mediation model using alternative measures of incentive pay. Panel A reports the second-stage results based on Equation 11. Panel C reports the first-stage results based on Equation 12. Panel B reports the main parameters of the mediation model. We use the STATA code *ivmediate* to estimate the main results above (Dippel *et al.*, 2020). Control variables consist of age, skill composition of general managers, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the mainland Chinese county in which firms are located and the coastline, and the logarithm of the distance between the mainland Chinese 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), and 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 the World Bank Enterprise Survey in 2005. Standard errors are clustered at the county level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D The Reforms of Wage Payment System in China

China's transformation into a more market-oriented economic system is accompanied with substantial changes in wage payment system over the past four decades. The reforms of wage payment systems started with the introduction of the Household Responsibility System (HRS) to the agricultural sector. After the massive collective movement in the 1950s, China's agricultural sector worked under the production team system for about 20 years. Under this system, agricultural workers got work points for the jobs they performed every day. At the end of each year, the net income of production team was distributed based on the work points that each one earned during the year. Although various systems of work points had been adopted to reflect the quality and quantity of work performed by each worker, it is extremely difficult to supervise agricultural work because of the nature of agricultural production. An agricultural worker received fixed work points for a day's work regardless of his work output. Consequently, the incentive to work was low, and productivity was stagnant (Lin 1988).

The HRS was introduced to deal with problems associated with the collective system of the late 1970s. Under the new system, the individual peasant, rather than the production team, became the basic decision-making unit for agricultural production. The HRS involves contracts signed between the production team and each household, which regulate the taxes and delivery quotas payable to the state, and the welfare and investment funds payable to the team. Any production above the delivery quota is retained by the household, which can sell it and receive the proceeds. Some significant studies have assessed the effectiveness of the HRS (McMillan, Whalley, and Zhu 1989; Lin 1988; 1992; Wen 1993). These studies consistently provide evidence that introducing the HRS significantly increases agricultural productivity through changing wage payment systems.

The second stage introduces the "managerial responsibility system" to state-owned firms in the industrial sector, which transferred the responsibility of production decisions from the state to the firm and increased the fraction of profits that the firm could retain. As a result, firm managers respond to these increases in autonomy by strengthening workers' performance incentives, such as paying more in bonuses and hiring more workers on fixed-term contracts. A number of studies have confirmed that introducing the "managerial responsibility system" significantly increases productivity of the state-owned firms through increased bonuses (Groves et al. 1994; Li 1997).

The third stage is the prevalence of the non-state-owned firms in the industrial sector since the late 1990s. Since non-state-owned firms adopt more flexible wage payment systems than their state-owned counterparts, the increased proportion of non-state-owned firms significantly

alters the wage payment systems of the industrial sector. For example, while state-owned firms used to recruit permanent (contract) workers, it is very common for non-state-owned firms to recruit temporary (contract) workers. As a result, more flexible wage payment systems such as piece rates have been adopted intensively by non-state-owned firms than their state-owned counterparts.

E Effects of Rural-Urban Migration Barriers on Other Outcomes

In order to highlight the management technology channel, we further analyze the effects of rural-urban migration barriers on other firm-level outcomes such as capital-labor ratio, skill composition of employees, and technological adoption in terms of computer use. Table A4 shows the main results.

Table A4: Effects of rural-urban migration barriers on other outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Capital-labor ratio		College and above (%)		High school and above (%)		Computer use (%)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Rural–urban migration barriers	0.0001	-0.0000	-0.0597***	-0.0893***	-0.0667***	-0.0604*	-0.0472***	0.0087
	(0.0006)	(0.0019)	(0.0058)	(0.0246)	(0.0084)	(0.0337)	(0.0065)	(0.0311)
Observations	11,095	11,095	11,093	11,093	11,093	11,093	11,095	11,095
R-squared	0.1265	0.1264	0.2303	0.2253	0.2130	0.2129	0.1828	0.1680
F-stat	34.5117	34.3765	52.6513	49.6108	64.9628	65.1069	41.2225	39.0833
Weak IV test (*F*)	.	57.3129	.	57.2014	.	57.2014	.	57.3129
Endogeneity test (*p*-value)	.	0.9336	.	0.2348	.	0.8525	.	0.0392

Notes: This table reports the effects of rural-urban migration barriers on other outcomes. Columns (1) and (2) show the effect of rural-urban migration barriers on the capital-labor ratio (in log). Columns (3) and (4) show the effect of rural-urban migration barriers on the percentage of employees with college education or above. Columns (5) and (6) show the effect of rural-urban migration barriers on the percentage of employees with high school education or above. Columns (7) and (8) show the effect of rural-urban migration barriers on the percentage of employees who regularly use computers. Columns (1), (3), (5), and (7) report OLS estimates. Columns (2), (4), (6), and (8) report IV estimates. Control variables consist of age, skill composition of general managers, ownership dummies, 2-digit industry dummies, and the logarithm of the distance between the mainland Chinese county in which firms are located and the coastline, and the logarithm of the distance between the mainland Chinese county in which firms are located and Beijing. The rural-urban migration barriers variable is constructed using China's population census in 1982. The instrumental variable refers to the geographical distance between each mainland Chinese city and Jinmen. Firm-level variables come from the World Bank Enterprise Survey in 2005. Standard errors are clustered at the county level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

F Effects of Rural-Urban Migration Barriers on Total Factor Productivity

In order to check whether or not migration barriers optimize the use of other inputs within firms, we examine the impact of migration barriers on total factor productivity using similar empirical approaches.

Table A5: Impact of migration barriers on total factor productivity

	(1) OLS	(2) OLS	(3) IV	(4) First Stage	(5) Reduced Form
Rural–urban migration barriers	-0.0002	-0.0002	0.0025**		
	(0.0003)	(0.0003)	(0.0012)		
IV: Distance to Jinmen				-0.0217***	-0.0001**
				(0.0029)	(0.0000)
Observations	10,844	10,839	10,839	11,095	10,936
R-squared	0.0001	0.0414	0.0289	0.1606	0.0418
F-stat	0.3115	10.7419	10.3220	13.8274	11.0876
Weak IV test (*F* statistic)	.	.	56.0436	.	.
Endogeneity test (*p*-value)	.	.	0.0227	.	.
Control variables	NO	YES	YES	YES	YES

Notes: This table reports the impact of rural-urban migration barriers on total factor productivity. Columns (1) and (2) report the OLS results, without and with control variables, respectively. Columns (3) to (5) report the IV, first-stage, and reduced-form estimates. Control variables consist of firm-level variables such as age, skill of the general manager, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the mainland Chinese county in which firms are located and the coastline, and the logarithm of the distance between the mainland Chinese county in which firms are located and Beijing. The rural-urban migration barriers variable is constructed using China's population census in 1982. Firm-level variables come from the World Bank Enterprise Survey in 2005. Standard errors are clustered at the county level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

G Effects of Rural-Urban Migration Barriers on Firms' Probability of Experiencing Labor Shortage

In order to confirm the persistence of early migration barriers experienced by current firms, we examine the impact of migration barriers on the probability of experiencing labor shortage among manufacturing firms.

Table A6: Impact of migration barriers on firms' probability of experiencing labor shortage

	(1) OLS	(2) OLS	(3) IV	(4) First Stage	(5) Reduced Form
Rural–urban migration barriers	0.0002**	-0.0001	0.0008**		
	(0.0001)	(0.0001)	(0.0004)		
IV: Distance to Jinmen				-0.0217***	-0.0000**
				(0.0029)	(0.0000)
Observations	11,100	11,095	11,095	11,095	11,195
R-squared	0.0007	0.0872	0.0772	0.1606	0.0877
F-stat	4.1357	22.3514	18.8745	13.8274	23.0143
Weak IV test (*F* statistic)	.	.	57.3129	.	.
Endogeneity test (*p*-value)	.	.	0.0059	.	.
Control variables	NO	YES	YES	YES	YES

Notes: This table reports the impact of rural-urban migration barriers on firms' probability of experiencing labor shortage. Columns (1) and (2) report the OLS results, without and with control variables, respectively. Columns (3) to (5) report the IV, first-stage, and reduced-form estimates. Control variables consist of firm-level variables such as age, skill of the general manager, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the mainland Chinese county in which firms are located and the coastline, and the logarithm of the distance between the mainland Chinese county in which firms are located and Beijing. The rural-urban migration barriers variable is constructed using China's population census in 1982. Firm-level variables come from the World Bank Enterprise Survey in 2005. Standard errors are clustered at the county level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

H Effects of Rural-Urban Migration Barriers on Firms' Management Technology Adoption

In order to mitigate the concern that the pay for performance variable may be insufficient to capture management technology adoption, we resort to the principle component analysis to construct a measure of 'management technology', which considers management practices such as pay for performance, promotion and demotion.

Table A7: Estimates of the mediation model

	(1)
Panel A: Second Stage in Equation (11)	
β_{YM}	0.5129***
	(0.1920)
DE: β_{YT}	-0.0010*
	(0.0005)
F-Stat Instruments	54.807
Panel B: Model Parameters	
β_{MT}	0.0118
IE: $\beta_{MT} \times \beta_{YM}$	0.0061
TE	0.0051
IE+DE	0.0051
S = IE/TE	1.20
S = IE/(IE+DE)	1.20
Panel C: First Stage in Equation (12)	
γ_{MZ}	-0.0002***
	(0.0000)
γ_{MT}	0.0003
	(0.0003)
Observations	10,228
R-Squared	0.0864

Notes: This table reports estimates of the mediation model. Panel A reports the second-stage results based on Equation 11. Panel C reports the first-stage results based on Equation 12. Panel B reports the main parameters of the mediation model. We use the STATA code *ivmediate* to estimate the main results above (Dippel *et al.*, 2020). Control variables are the same as those used in Table 1. The rural-urban migration barriers variable is constructed using China's population census in 1982. Firm-level variables come from the World Bank Enterprise Survey in 2005. Standard errors are clustered at the county level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

I Effects of Rural-Urban Migration Barriers on Sales to Other Cities and Countries

Table A8: Impact of rural-urban migration barriers on sales to other cities and countries

	(1) OLS	(2) OLS	(3) IV	(4) First Stage	(5) Reduced Form
Rural–urban migration barriers	0.0573***	0.0791***	0.3919***		
	(0.0132)	(0.0108)	(0.0575)		
IV: Distance to Jinmen				-0.0217***	-0.0084***
				(0.0029)	(0.0010)
Observations	11,099	11,094	11,094	11,095	11,194
R-squared	0.0060	0.1284	-0.0327	0.1606	0.1337
F-stat	18.8543	25.3976	15.7133	13.8274	26.9192
Weak IV test (*F* statistic)	.	.	57.3421	.	.
Endogeneity test (*p*-value)	.	.	0.0000	.	.
Control variables	NO	YES	YES	YES	YES

Notes: This table reports the impact of rural-urban migration barriers on the percentage of sales to other cities and countries. Columns (1) and (2) report the OLS results, without and with control variables, respectively. Columns (3) to (5) report the IV, first-stage, and reduced-form estimates. Control variables consist of firm-level variables such as age, skill of the general manager, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the mainland Chinese county in which firms are located and the coastline, and the logarithm of the distance between the mainland Chinese county in which firms are located and Beijing. The rural-urban migration barriers variable is constructed using China's population census in 1982. Firm-level variables come from the World Bank Enterprise Survey in 2005. Standard errors are clustered at the county level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

J Effects of Rural-Urban Migration Barriers on Sales to the Government and SOEs

Table A9: Impact of rural-urban migration barriers on sales to the government and SOEs

	(1) OLS	(2) OLS	(3) IV	(4) First Stage	(5) Reduced Form
Rural–urban migration barriers	-0.1373***	-0.0793***	-0.3634***		
	(0.0162)	(0.0112)	(0.0572)		
IV: Distance to Jinmen				-0.0217***	0.0078***
				(0.0029)	(0.0011)
Observations	11,100	11,095	11,095	11,095	11,195
R-squared	0.0293	0.2052	0.0923	0.1606	0.2082
F-stat	71.9100	53.0901	36.8478	13.8274	56.6419
Weak IV test (*F* statistic)	.	.	57.3129	.	.
Endogeneity test (*p*-value)	.	.	0.0000	.	.
Control variables	NO	YES	YES	YES	YES

Notes: This table reports the impact of rural-urban migration barriers on the percentage of sales to the government and state-owned enterprises (SOEs). Columns (1) and (2) report the OLS results, without and with control variables, respectively. Columns (3) to (5) report the IV, first-stage, and reduced-form estimates. Control variables consist of firm-level variables such as age, skill of the general manager, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the mainland Chinese county in which firms are located and the coastline, and the logarithm of the distance between the mainland Chinese county in which firms are located and Beijing. The rural-urban migration barriers variable is constructed using China's population census in 1982. Firm-level variables come from the World Bank Enterprise Survey in 2005. Standard errors are clustered at the county level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

K Effects of Rural-Urban Migration Barriers on Firm Employment

Table A10: Impact of rural-urban migration barriers on firm employment

	(1) OLS	(2) OLS	(3) IV	(4) First Stage	(5) Reduced Form
Rural–urban migration barriers	-0.0021***	0.0011**	0.0092***		
	(0.0007)	(0.0005)	(0.0025)		
IV: Distance to Jinmen				-0.0217***	-0.0002***
				(0.0029)	(0.0000)
Observations	11,100	11,095	11,095	11,095	11,195
R-squared	0.0038	0.2602	0.2091	0.1606	0.2620
F-stat	9.8123	73.6784	63.4336	13.8274	75.0057
Weak IV test (*F* statistic)	.	.	57.3129	.	.
Endogeneity test (*p*-value)	.	.	0.0029	.	.
Control variables	NO	YES	YES	YES	YES

Notes: This table reports the impact of rural-urban migration barriers on firm employment. Columns (1) and (2) report the OLS results, without and with control variables, respectively. Columns (3) to (5) report the IV, first-stage, and reduced-form estimates. Control variables consist of firm-level variables such as age, skill of the general manager, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the mainland Chinese county in which firms are located and the coastline, and the logarithm of the distance between the mainland Chinese county in which firms are located and Beijing. The rural-urban migration barriers variable is constructed using China's population census in 1982. Firm-level variables come from the World Bank Enterprise Survey in 2005. Standard errors are clustered at the county level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

L Effects of Rural-Urban Migration Barriers on New Firm Creation

Table A11: Impact of rural-urban migration barriers on the probability of new firm creation (created within the past three years)

	(1) OLS	(2) OLS	(3) IV	(4) First Stage	(5) Reduced Form
Rural–urban migration barriers	0.0003***	0.0002***	0.0002		
	(0.0001)	(0.0001)	(0.0003)		
IV: Distance to Jinmen				-0.0217***	-0.0000
				(0.0029)	(0.0000)
Observations	11,095	11,095	11,095	11,100	11,195
R-squared	0.0028	0.0182	0.0180	0.1576	0.0166
F-stat	19.4960	10.4629	10.6245	13.1731	11.3653
Weak IV test (*F* statistic)	.	.	57.0871	.	.
Endogeneity test (*p*-value)	.	.	0.7449	.	.
Control variables	NO	YES	YES	YES	YES

Notes: This table reports the impact of rural-urban migration barriers on the probability of new firm creation (created within the past three years). Columns (1) and (2) report the OLS results, without and with control variables, respectively. Columns (3) to (5) report the IV, first-stage, and reduced-form estimates. Control variables consist of firm-level variables such as age, skill of the general manager, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the mainland Chinese county in which firms are located and the coastline, and the logarithm of the distance between the mainland Chinese county in which firms are located and Beijing. The rural-urban migration barriers variable is constructed using China's population census in 1982. Firm-level variables come from the World Bank Enterprise Survey in 2005. Standard errors are clustered at the county level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A12: Impact of rural-urban migration barriers on the probability of new firm creation (created within the past five years)

	(1) OLS	(2) OLS	(3) IV	(4) First Stage	(5) Reduced Form
Rural–urban migration barriers	0.0005***	0.0003**	0.0006		
	(0.0001)	(0.0001)	(0.0005)		
IV: Distance to Jinmen				-0.0217***	-0.0000
				(0.0029)	(0.0000)
Observations	11,095	11,095	11,095	11,100	11,195
R-squared	0.0022	0.0441	0.0432	0.1576	0.0433
F-stat	14.3991	512.2129	534.1065	13.1731	371.3001
Weak IV test (*F* statistic)	.	.	57.0871	.	.
Endogeneity test (*p*-value)	.	.	0.4640	.	.
Control variables	NO	YES	YES	YES	YES

Notes: This table reports the impact of rural-urban migration barriers on the probability of new firm creation (created within the past five years). Columns (1) and (2) report the OLS results, without and with control variables, respectively. Columns (3) to (5) report the IV, first-stage, and reduced-form estimates. Control variables consist of firm-level variables such as age, skill of the general manager, ownership dummies, 2-digit industry dummies, the logarithm of the distance between the mainland Chinese county in which firms are located and the coastline, and the logarithm of the distance between the mainland Chinese county in which firms are located and Beijing. The rural-urban migration barriers variable is constructed using China's population census in 1982. Firm-level variables come from the World Bank Enterprise Survey in 2005. Standard errors are clustered at the county level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.