Migrants and Firms: Evidence from China *

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Abstract

How does rural-urban migration shape urban production in developing countries? We use longitudinal data on Chinese manufacturing firms between 2001 and 2006, and exploit exogenous variation in rural-urban migration induced by agricultural price shocks for identification. We find that, when immigration increases, manufacturing production becomes more labor-intensive in the short run. In the longer run, firms innovate less, move away from capital-intensive technologies, and adopt final products that use low-skilled labor more intensively. We develop a model with endogenous technological choice, which rationalizes these findings, and we estimate the effect of migration on factor productivity and factor allocation across firms.

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1 Introduction

Firm productivity in developing countries is low (Hall and Jones, 1999) and highly heterogeneous, even within sectors (Hsieh and Klenow, 2009). A number of factors explain this pattern, such as a lack of capital (Banerjee and Duflo, 2014) or poor management (Bloom et al., 2013). Another potential factor is the abundance of migrant labor: the process of economic development induces large movements of rural workers from agriculture to manufacturing (Lewis, 1954), which could reduce firms' incentives to adopt productivity-enhancing technologies (Lewis, 2011). Despite its relevance, empirical evidence on the role of rural-urban migration in shaping urban production in developing countries is scarce. The main challenges are (i) to identify the effect of migration on urban production without confounding it with destination characteristics that attract migrants, and (ii) to observe the restructuring of production and technology adoption within production units.

This paper is the first to estimate the causal effect of rural migrant inflows on urban production during the process of structural transformation. We use longitudinal micro data on Chinese manufacturing firms between 2001 and 2006 and a population micro-census that allows us to measure rural-urban migration. We instrument migrant flows to Chinese cities using exogenous shocks to agricultural productivity in rural areas, which trigger rural-urban migration. We first identify the effect of migration on factor cost and factor use at destination. We better characterize changes in the structure of production through the analysis of investment, and, more importantly, directed technological change and product choice. We then develop a quantitative framework that models the choice of technology and accounts for complementarities between production factors. We use the model to estimate the effect of migration on productivity at destination and on the allocation of factors across heterogeneous firms.

Providing empirical evidence on the causal impact of labor inflows on manufacturing production requires large and exogenous migrant flows to cities. Our methodology proceeds in two steps. In the first step, we combine time-varying shocks to world prices for agricultural commodities with cross-sectional variation in cropping patterns to identify exogenous variation in agricultural labor productivity. We use agricultural productivity shocks at origin to predict rural emigration. In the second step, we combine predicted rural emigration with historical migration patterns between prefectures to predict urban immigration.[1] Migration predictions are orthogonal to factor demand in the urban sector, strongly predict migrant inflows, and

[1]Prefectures are the second administrative division in China, below the province. There were about 330 prefectures in 2000.

exhibit substantial variation across years and destinations.

We use these predictions to instrument rural-urban migration flows and estimate their short-term impact on manufacturing firms. We find that migration exerts a downward pressure on labor costs: the implied wage elasticity with respect to labor supply is -0.50. After an influx of migrants, manufacturing production becomes much more labor-intensive, as capital does not adjust to changes in employment. Value added per worker decreases sharply. Interestingly, these effects hold in the longer run: firms become even more labor-abundant and average labor productivity remains low. Our findings are robust to numerous sensitivity checks that test the exclusion restriction, e.g., controlling for agricultural shocks at destination and in neighboring prefectures, excluding industries that process agricultural goods, or omitting local migration flows. We also check that forward migration shocks have no effect on firm outcomes.

Changes in input mix in the medium run may reflect changes in technology. To better characterize the impact of labor inflows on the production process, we exploit textual information on the final product of manufacturing establishments and data on their patenting activity. We find that in response to immigration, firms adopt products that are labor-abundant and have low human capital intensity. Since labor costs are low, manufacturing firms become more profitable. But the short-term gain in profitability is achieved at the expense of innovation and technology adoption: there is a sharp decrease in patenting, which is concentrated in capital-intensive technologies. All categories of patents decline: changes in product design, shape and structure as well more fundamental innovation in production methods.

The restructuring of production within manufacturing establishments of the urban sector may have important implications for factor productivity. We develop a model in which production is characterized by sector-specific elasticities of substitution between factors, and technology is firm-specific and endogenous: establishments in the same sector can produce different product varieties that are more or less labor-intensive. We estimate the sector-specific elasticities of substitution between capital and labor following Oberfield and Raval (2014), using origin-driven migration shocks as an instrument for the relative factor cost. The quantitative framework rationalizes our previous findings, most notably the direction of technological change and its larger long-run impact on relative factor use.

Estimating production functions allows us to better characterize the effect of migration on productivity and the reallocation of factors across heterogeneous firms.[2]

[2] An important source of firm heterogeneity in China is the presence of state-owned firms and transformation of the public sector in the past decades (Hsieh and Song, 2015; Brandt et al., 2016). Our results do not seem to be driven by differences between public- and private-sector firms.

Based on the model, we construct measures of factor productivity, evaluated at the average sectoral technology. Labor productivity decreases sharply in the average firm due to (i) the substitution of capital with labor, responding to changes in labor cost in the short run, and (ii) the adoption of labor-intensive technologies in the longer run. Labor productivity falls by more than the wage: production appears too labor-abundant at destination. Migrant inflows also affect the allocation of resources across establishments. There is a large dispersion in factor productivity across firms at baseline, as in Hsieh and Klenow (2009), which in the context of our model reflects differences in firm-specific technology within sector. The capital-to-labor ratio declines the most in firms that produce more capital-intensive product varieties at baseline, thus reducing the dispersion in factor productivity.

One empirical observation cannot be rationalized by our stylized model of product choice: the allocation of resources across production units appears sub-optimal. First, migrant labor supply affects the selection of manufacturing plants at destination, notably allowing the least productive and profitable ones to survive. Second, production units with low total factor productivity expand relatively more, which further dampens aggregate productivity at destination.

This paper makes significant contributions to four main strands of the literature. First, our paper uses product-level information and patent data to estimate the effect of labor supply shocks on factor use, product choice and technological adoption at the establishment level. It relates to the growing literature that estimates the impact of immigration on factor use at destination (Peri, 2012; Accetturo et al., 2012; Olney, 2013; Dustmann and Glitz, 2015; Kerr et al., 2015; Mitaritonna et al., 2017), our results on directed technological adoption being closest to Lewis (2011). In contrast with a literature that mostly focuses on international migration to developed countries, we study a very different yet important context: an economy on the path to structural transformation with massive rural-urban migrant flows.

Our focus on the absorption of rural migrants in the urban sector of a fast-growing economy echoes a second, older literature that focuses on cities of the developing world (Harris and Todaro, 1970; Fields, 1975). This literature emphasizes the role of labor market imperfections, and associates rural migrants with unemployment, self-employment or informal wage employment at destination. In contrast, we show that migrants swiftly find their way into large, formal manufacturing firms. We document short-run wage adjustments and employment responses to labor supply shocks that are compatible with a relatively flexible labor market, although labor market frictions are likely pervasive in urban China.[3]

[3]Such labor market imperfections may be related to job search frictions (Abebe et al., 2016;

Our empirical investigation sheds light on disparities in productivity and factor allocation across firms of developing economies, which is the focus of a third strand of the literature (Hsieh and Klenow, 2009). This recent literature has documented the role of credit market imperfections in generating dispersion in factor returns across firms, even within the same sector and location (Song et al., 2011; Midrigan and Xu, 2014). In response to the labor supply shock, we find that the capital-to-labor ratio decreases more in firms with high marginal product of labor and low marginal product of capital, which suggests that rural-urban migration improves the relative allocation of factors across production units.[4]

Our study also relates to the literature on structural transformation, which describes the secular movement of factors from the traditional sector to the modern sector in developing economies (Lewis, 1954; Herrendorf et al., 2015). The finding that migration lowers wages and boosts urban employment relates to "labor push" models, which generally imply that, by releasing labor, agricultural productivity gains may trigger industrialization (Alvarez-Cuadrado and Poschke, 2011; Gollin et al., 2002; Bustos et al., 2016a).[5] In a recent contribution, Bustos et al. (2018) find that regions of Brazil that benefited from genetically-engineered soy specialized in low-productivity manufacturing, and argue that the effect is driven by the inflow of unskilled labor released by agriculture. Our paper contributes to this literature in two ways. First, we identify the effect of rural migrant labor supply on urban production independently from other factors such as consumer demand (Santangelo, 2016) and capital availability (Marden, 2015; Bustos et al., 2016b). Second, we exploit establishment-level data with information on product choice and technological adoption to document changes within firms and across firms within sectors.

Finally, our empirical analysis relates to the large literature on the effects of immigration on labor markets (Card and DiNardo, 2000; Card, 2001; Borjas, 2003), and more specifically to studies of internal migration (e.g., Boustan et al., 2010;

Alfonsi et al., 2017), informality (Meghir et al., 2015; Ulyssea, 2018) or institutional constraints, e.g., minimum wages (Mayneris et al., 2018; Hau et al., 2018).

[4]Our focus on productivity dispersion within sector within location sets our paper apart from the literature on internal migration and productivity gaps across space and sectors in developing countries (Gollin et al., 2014; Bryan and Morten, 2015), and China in particular (Brandt et al., 2013; Tombe and Zhu, 2019).

[5]In order to identify migration inflows that are exogenous to labor demand at destination, our paper takes the opposite approach to "labor pull" models, in which rural migrants are attracted by increased labor productivity in manufacturing (see Facchini et al., 2015, using trade shocks). One difference with the traditional "labor push" interpretation is that migration from rural areas is triggered, in our context, by a *negative* shock to agricultural productivity (as in Gröger and Zylberberg, 2016; Feng et al., 2017; Minale, 2018, for instance). Worse economic conditions at origin lower the opportunity cost of migrating, an effect which dominates the opposite effect operating through tightening liquidity constraints (Angelucci, 2015; Bazzi, 2017).

El Badaoui et al., 2017; Imbert and Papp, 2016; Kleemans and Magruder, 2018). Since internal migrants are usually closer substitutes to resident workers than international migrants to natives, the literature on internal migration tends to find larger negative effects on wages at destination. In China, the evidence is mixed: De Sousa and Poncet (2011), Meng and Zhang (2010) and Combes et al. (2015) respectively find a negative effect, no effect and a positive impact on local wages. In a more structural approach, Ge and Yang (2014) show that migration depressed unskilled wages in urban areas by at least 20% throughout the 1990s and 2000s, which would be comparable to our own estimates.

The remainder of the paper is organized as follows. Section 2 presents data sources and the estimation strategy. Section 3 describes reduced-form results on production at destination. Section 4 provides a quantitative framework to derive implications for factor productivity at destination. Section 5 briefly concludes.

2 Data and empirical strategy

This section describes the data sources and our empirical strategy. We first explain how we measure migration flows in the data. Next, we construct an instrument for migration inflows to urban areas based on shocks to agricultural labor productivity. We then present the firm data and describe our main estimation strategy.

2.1 Migration flows

To construct migration flows, we use the representative 2005 1% Population Survey (hereafter, "2005 Mini-Census"), collected by the National Bureau of Statistics.[6] The sampling frame of the 2005 Mini-Census covers the entire population at current places of residence, including migrants and anyone who is not registered locally. The survey collects information on occupation, industry, income, ethnicity, education level, housing characteristics and, crucially, migration history. First, we observe the household registration type or *hukou* (agricultural or non-agricultural), place of registration, and place of residence at the prefecture level. Second, migrants are asked the main reason for leaving their places of registration and which year they left (censored above five years before the interview). We combine these two pieces of information to create a matrix of yearly rural-urban migration spells "for labor reasons" between all Chinese prefectures from 2000 to 2005.[7]

[6] These data are widely used in the literature (Combes et al., 2015; Facchini et al., 2015; Meng and Zhang, 2010; Tombe and Zhu, 2019, among others).

[7] During our period of interest, barriers to mobility come from restrictions due to the registration system (*hukou*). These restrictions do not impede rural-urban migration but limit the benefits of

A raw measure of migration flows would not account for two types of migration spells: step and return migration. *Step migration* occurs when migrants transit through another city before reaching their destination. In such cases, we mistake the date of departure from the place of registration for the date of arrival at the current destination. When there is *return migration*, migrants may leave their places of registration within the last five years and come back before 2005. We then miss the entire migration episode. Fortunately, the 2005 Mini-Census collects information on the place of residence one and five years before the interview, which allows us to partly measure return and step migration. We adjust migration flows allowing for variation in destination- and duration-specific rates of return.[8]

Let M_{odt} denote the number of workers migrating between origin o (rural areas of prefecture o) and destination d (urban areas of prefecture d) in a given year $t = 2000, \ldots, 2005$. The emigration rate, O_{ot}, is obtained by dividing the sum of migrants who left origin o in year t by the number of working-age residents in o in 2000, which we denote with N_o:

$$O_{ot} = \frac{\sum_d M_{odt}}{N_o}.$$

The probability that a migrant from origin o migrates to destination d at time t, λ_{odt}, verifies:

$$\lambda_{odt} = \frac{M_{odt}}{\sum_d M_{odt}}.$$

The immigration rate, m_{ot}, is obtained by dividing the sum of migrants who arrived in destination d in year t by the number of residents (non-migrants) in d at baseline, in 2000, which we denote with N_d, rescaled by the employment rate in manufacturing ($\mu \approx 14.5\%$),

$$m_{dt} = \frac{\sum_o M_{odt}}{N_d \times \mu}.$$

To estimate the causal effect of migrant inflows on urban destinations, we need variation in immigration that is unrelated to potential destination outcomes. The next section describes our strategy, based on shocks to rural livelihoods.

rural migrants' long-term settlement in urban areas. See Appendix A.1 for more details about how mobility restrictions are applied in practice and the rights of rural migrants in urban China.

[8] We show in Appendix A that, while return migration is substantial, step migration is negligible. See Appendix A.2 for more details about the correction for return migration. Results presented in the baseline empirical analysis are corrected for return migration but remain robust to using the non-adjusted flows (see a sensitivity analysis in Appendix D and Appendix Table D21).

2.2 Migration predictions

Our empirical strategy relies on a shift-share instrument (Card, 2001). We interact two sources of exogenous variation to isolate a supply (or push) component in migrant inflows. First, we use changes in agricultural productivity at origin as exogenous determinants of migrant outflows from the rural areas of each prefecture. We construct shocks to labor productivity in agriculture as an interaction between origin-specific cropping patterns and exogenous price fluctuations. Second, we use the settlement patterns of earlier migration waves to allocate rural migrants to urban destinations. This two-step method yields a prediction of migrant inflows to urban areas that is exogenous to variation in urban factor demand.

Potential agricultural output We first construct potential output for each crop in each prefecture as the product of harvested area (2000 World Census of Agriculture) and potential yield (Global Agro-Ecological Zones Agricultural Suitability and Potential Yields, GAEZ). These data are provided by the Food and Agriculture Organization (FAO) and the International Institute for Applied Systems Analysis (IIASA).[9] We use the geo-coded map of harvested areas to construct total harvested area h_{co} for a given crop c in a given prefecture o. Information on potential yield per hectare, y_{co}, is similarly collapsed at the prefecture level. We compute potential agricultural output for each crop in each prefecture as the product of total harvested area and average potential yield, $q_{co} = h_{co} \times y_{co}$. By construction, the potential agricultural output, q_{co}, is time-invariant and captures cropping patterns at origin. It is measured at the beginning of the study period and thus arguably exogenous to future migration changes in response to price shocks.[10] Figure 1 displays potential output q_{co} for rice and cotton by prefecture, and illustrates the wide cross-sectional variation in agricultural portfolios. Appendix B provides summary statistics about the variation in cropping patterns across prefectures and regions.

Price fluctuations The time-varying component of our push shock is fluctuations in international commodity prices. We collect monthly commodity prices on international market places from the World Bank Commodities Price Data ("The Pink Sheet").[11] We use monthly prices per kg in constant 2010 USD between 1990 and

[9]The data are available online from http://www.fao.org/nr/gaez/about-data-portal/en/.
[10]To the extent that price shocks are anticipated, changes in cropping patterns should attenuate their effect on income and migration, which would bias our first stage coefficients toward zero.
[11]The data are freely available online at http://data.worldbank.org/data-catalog/commodity-price-data.

2010 for 17 commodities.[12] These crops account for the lion's share of agricultural production over the period of interest: 90% of total agricultural output in 1998 and 80% in 2007. We apply a Hodrick-Prescott filter to the logarithm of nominal monthly prices and compute the average annual deviation from the long-term trend, d_{ct}. Changes in d_{ct} capture short-run fluctuations in international crop prices.[13]

For these shocks to influence migration decisions, there should be a significant pass-through from international prices to the domestic prices faced by rural farmers. In Appendix B, we use producer prices and production as reported by the FAO between 1990 and 2010 for China and show that fluctuations in international prices strongly affect the average Chinese farmer.

Push Shocks We combine the variations in crop prices with cropping patterns to construct the excess value of crop production in each prefecture o and year t. The *residual agricultural income*, p_{ot}, is the average of the crop-specific deviations from long-term trend, $\{d_{ct}\}_c$, weighted by the expected share of agricultural revenue for crop c in prefecture o:

$$p_{ot} = \left(\sum_c q_{co} \bar{P}_c d_{ct}\right) / \left(\sum_c q_{co} \bar{P}_c\right) \tag{1}$$

where $\bar{P}_c$ denotes the international price for each crop at baseline.

The *residual agricultural income* exhibits time-varying volatility coming from world demand and supply, but also large cross-sectional differences due to the wide variety of harvested crops across China.[14] Fluctuations in the measure p_{ot} exhibit part of the persistence already present in international crop prices. A negative shock does not only affect labor productivity in the same year but also expected labor productivity, which helps trigger emigration.[15]

[12]These 17 crops are banana, cassava, coffee, cotton, groundnut, maize, millet, pulses, rapeseed, rice, sorghum, soybean, sugar beet, sugar cane, sunflower, tea and wheat. We exclude from our analysis tobacco, for which China has a dominant position on the international market.

[13]We apply a Hodrick-Prescott filter with a parameter of 14,400 in order to exclude medium-run fluctuations in prices. We provide in Appendix B descriptive statistics on the magnitude of fluctuations across crops. The residual fluctuations in prices behave as an auto-regressive process, but the amplitude of innovation shocks is non-negligible.

[14]As an example, Appendix Figure B7 displays the spatial dispersion in p_{ot} in 2001, when the rice price decreased sharply, and in 2002, after recovery. Appendix Table B16 decomposes the variation in the measure p_{ot} between time-series and cross-sectional variations.

[15]We show in Appendix B.4 (and Appendix Table D20) that we find similar results when we use fluctuations in agricultural output due to rainfall shocks, which are not serially correlated.

Exogenous variation in migrant outflows We now generate an instrument for migrant flows based on the measure of residual agricultural income and exogenous to local demand conditions. A migration spell recorded at date $t = 2005$, for instance, corresponds to a migrant worker who moved between October 2004 and October 2005. Emigration is likely to be determined not only by prices at the time of harvest, but also by prices at the time of planting, which determine expected agricultural revenues, and by prices in previous years due to lags in migration decisions. As a measure of shock to rural livelihood, s_{ot}, we thus use the average residual agricultural income p_{ot} between $t-1$ and $t-2$.

We regress rural migrant outflows, O_{ot}, on shocks to agricultural income. Formally, we estimate the following equation:

$$O_{ot} = \beta_0 + \beta_1 s_{ot} + \delta_t + \nu_o + \varepsilon_{ot}, \tag{2}$$

where o indexes the origin and t indexes time $t = 2000, \ldots, 2005$, δ_t are year fixed effects, and ν_o denotes origin fixed effects and captures any time-invariant characteristics of origins, e.g., barriers to mobility.[16] We use baseline population (N_o) as a weight to generate consistent predictions in the number of emigrants.

We present the estimation of Equation (2) in Panel A of Table 1, including and excluding short-distance migration spells. Between 2000 and 2005, emigration was negatively correlated with price fluctuations. A 10% lower return to agriculture, as measured by the residual agricultural income, is associated with a $0.9-1$ p.p. higher migration incidence. Equivalently, a one standard deviation increase in the shock to rural livelihood decreases migration incidence by about 0.10 standard deviations. In theory, fluctuations in agricultural labor productivity may have two opposite effects on migration (Angelucci, 2015; Bazzi, 2017). A negative shock to agricultural productivity widens the gap between urban and rural labor productivity and should push rural workers toward urban centers (an *opportunity cost* effect). Low agricultural productivity reduces household wealth and its ability to finance migration to urban centers (a *wealth* effect). The negative relationship between agricultural income shocks and migration suggests that migration decisions are mostly driven by the opportunity cost of migrating.[17] Based on these estimates, we compute the

[16] Incorporating price trends in the analysis does not change the results. We also estimate the same specification using forward shocks, i.e., the average residual agricultural income at the end of period t, to show that shocks are not anticipated (Appendix D and Appendix Table D20). Finally, we validate the relationship between emigration and local shocks using night-time luminosity (Appendix Figure D11).

[17] In the Chinese context, workers migrate without their families, low-skill jobs in cities are easy to find, and the fixed cost of migration is relatively low. Chinese households also have high savings, so that the impact of short-term fluctuations in agricultural prices on wealth is small.

predicted emigration rate $\widehat{O_{ot}}$ from origin o in year t:

$$\widehat{O_{ot}} = \widehat{\beta_0} + \widehat{\beta_1} s_{ot} + \widehat{\nu_o},$$

from which we remove the year fixed effects to avoid correlation between migrant flows and trends in outcomes at destination.

Exogenous variation in migration inflows We combine the predicted emigration rate, $\widehat{O_{ot}}$, and probabilities to migrate from each origin to each destination for earlier cohorts, λ_{od}.[18] The predicted immigration rate to destination d in year t is:

$$z_{dt} = \frac{\sum_{o \neq d} \widehat{O_{ot}} \times N_o \times \lambda_{od}}{N_d \times \mu}, \tag{3}$$

where N_o is the rural population at origin, N_d is the working-age urban population at destination in 2000, rescaled by the employment rate in manufacturing in China in 2000, μ. To alleviate concerns that migrant inflows are correlated with destination outcomes, we exclude intra-prefecture migrants. This procedure provides supply-driven migrant inflows that are orthogonal to labor demand at destination.

The construction of the instrument z_{dt} follows a shift-share procedure with a panel dimension. The exogenous variation in migration inflows into every prefecture of destination comes from crop $\times$ year price shocks weighted by cropping patterns in every prefecture of origin and by migration patterns between every origin and every destination. Since we use 17 crops and 6 years, the identifying variation results from 102 independent realizations (Borusyak et al., 2018; Goldsmith-Pinkham et al., 2018). There is some spatial auto-correlation due to the geographic determinants of cropping patterns at origin.[19] The shocks however display large cross-sectional and time-varying fluctuations.

We regress the actual immigration rate on the predicted, supply-driven immigration rate and report the results in Panel B of Table 1. The relationship is positive and significant: the origin-based variation in the arrival of recent immigrants, z_{dt}, is a strong predictor of observed labor inflows.[20] This relationship is the first stage of

[18] Alternatively, in Appendix D and Appendix Table D22, we use a gravity model of migration flows to predict λ_{od} as in Boustan et al. (2010). The advantage of using λ_{od} is that it includes idiosyncratic variation in migrant networks in addition to geographical factors (Kinnan et al., 2018).

[19] We provide in Appendix B an illustration of this spatial auto-correlation. Appendix Figure B8, shows the geographical distribution of z_{dt} in 2001 (left panel) and 2004 (right panel), after taking out prefecture fixed effects.

[20] The effects are robust to excluding migrant flows within 300km of a destination's centroid to alleviate spatial auto-correlation concerns. Appendix B.3 explains the choice of this threshold based on the Global Moran's I.

our empirical analysis.

2.3 Description of the firm data

We use firm-level data spanning 2001–2006 from the National Bureau of Statistics (NBS).[21] The NBS implements every year a census of all state-owned manufacturing enterprises and all non-state manufacturing firms with sales exceeding RMB 5 million or about $600,000. While small firms are not included in the census, the sample accounts for 90% of total manufacturing output. Firms can be matched across years, and the main analysis will be performed on the balanced panel (about 50,000 firms). The NBS census collects information on location, industry, ownership type, exporting activity, number of employees, and a wide range of accounting variables (sales, inputs, value added, wage bill, fixed assets, financial assets, etc.). We divide total compensation (to which we add housing and pension benefits) by employment to compute the compensation rate and construct real capital as in Brandt et al. (2014).

We complement these outcomes with product-level information, extracted from the textual information provided by manufacturing firms about their main final goods. We also exploit the bridge constructed by He et al. (2018) to match firms with all patents submitted to the State Intellectual Property Office (SIPO).

There are three potential issues with the NBS census. First, matching firms over time is difficult because of frequent changes in identifiers. We extend the fuzzy algorithm (using name, address, phone number, etc.) developed by Brandt et al. (2014) to the period 1992–2009 to detect "identifier-switchers." Second, although we may use the term "firm" in this paper, the NBS data cover "legal units" (*faren danwei*), which roughly correspond to the definition of "establishments" in the United States.[22] Third, the RMB 5 million threshold that defines whether a non-publicly owned firm belongs to the NBS census is not sharply implemented. Hence, some private firms may enter the database a few years after having reached the sales cut-off or continue to participate in the survey even if their annual sales fall below the threshold. We cannot measure delayed entry into the sample, but delayed exit of firms below the threshold is negligible, as Figure 2 shows.

[21] The following discussion partly borrows from Brandt et al. (2014), and a detailed description of construction choices is provided in Appendix C.

[22] Different subsidiaries of the same enterprise may indeed be surveyed, provided they meet a number of criteria, including having their own names, being able to sign contracts, possessing and using assets independently, assuming their liabilities, and being financially independent (see Appendix C). In 1998, 89% of firms reported a single production plant. In 2007, the share of single-plant firms increased to 97% (Brandt et al., 2014).

Our baseline outcomes include compensation per worker, employment, capital-to-labor ratio, and value added per worker. Table 2 provides descriptive statistics of our key outcomes in 2001 and 2006. There is substantial heterogeneity in firm outcomes across locations, but most of the variation is within locations—especially so for relative factor use.[23]

2.4 Empirical strategy

We use two main specifications, depending on whether we estimate the short-term effect or longer-run effects using cumulative migration between 2001 and 2006.

Short-run effects We first exploit yearly variation within the full panel. The unit of observation is a firm i in year t, sector s and prefecture d. We estimate an IV specification and regress the dependent variable y_{isdt} on the immigration rate m_{dt}:

$$y_{isdt} = \alpha + \beta m_{dt} + \eta_i + \nu_{st} + \varepsilon_{isdt} \tag{4}$$

where η_i and ν_{st} are firm and sector $\times$ year fixed effects, and m_{dt} is instrumented by the supply-driven predicted immigration rate, z_{dt}. Standard errors are clustered at the level of the prefecture.

Longer-run effects To estimate the longer-run impact of migration on urban production, we estimate the effect of cumulative migration shocks between 2001 and 2006 on changes in firm outcomes over the period. Letting $\overline{m}_d$ (resp. $\overline{z}_d$) denote the average yearly immigration rate (resp. the average yearly supply-driven predicted immigration rate) in destination d between 2001 and 2006, and Δy_{isd} denote the difference in outcomes between 2001 and 2006 for firm i in sector s, we estimate:

$$\Delta y_{isd} = \alpha + \beta \overline{m}_d + \zeta_s + \varepsilon_{isd} \tag{5}$$

where $\overline{m}_d$ is instrumented by $\overline{z}_d$, and ζ_s are industry fixed effects. Standard errors are clustered at the level of the prefecture of destination. In order to identify heterogeneous effects, we estimate:

$$\Delta y_{isd} = \alpha + \beta \overline{m}_d + \gamma \overline{m}_d \times X_i + \zeta_s + \varepsilon_{isd}, \tag{6}$$

[23] We leave the analysis of general trends in China and differences across establishments of the sample to Appendix C, and Appendix Tables C18 and C19 in particular. This analysis shows that manufacturing growth is very unequally shared across prefectures, and that there is substantial variation within sectors and locations (as already shown in Hsieh and Klenow, 2009).

where X_i is a time-invariant characteristic of firm i. The time-invariant characteristics, X_i, are variables capturing relative factor use and factor productivity at baseline within a sector $\times$ prefecture. Cumulative migration, $\overline{m}_d$, is instrumented by $\overline{z}_d$, and its interaction $\overline{m}_d \times X_i$ is instrumented by $\overline{z}_d \times X_i$.

3 Migration, labor cost, and factor demand

This section first quantifies the effect of migrant labor supply on labor cost and factor demand, both on impact and in the longer run. It then analyzes how production changes within firm, through the adoption of new products and technologies. Finally, it estimates heterogeneous responses and the aggregate implications at destination.

3.1 Average effect on labor cost and factor demand

Short-run effects An important and debated consequence of migration is its short-run effect on wages at destination. We estimate specification (4) on the subsample of firms present all years between 2001 and 2006 and use total compensation per employee (including fringe benefits) as a proxy for labor cost. The first column of Table 3 displays the OLS estimate (Panel A) and the IV estimate (Panel B); observations are weighted by the inverse of the number of establishments at baseline such that each prefecture equally contributes to the estimated elasticities.[24] An inflow of rural migrants is negatively associated with labor cost at destination. Since migrants are attracted to cities that offer higher wages, one would expect the OLS estimate to be biased upwards. We indeed find a more negative price elasticity of labor demand when we instrument the immigration rate by exogenous migration predictions. A one percentage point increase in the immigration rate induces a 0.50% decrease in compensation per employee.[25]

Our findings are in line with recent studies that argue that rural-urban migration has tempered wage growth in urban China (De Sousa and Poncet, 2011; Ge and Yang, 2014). The magnitude of the wage response to immigration is comparable with other studies of internal migration in developing economies (see, e.g., Kleemans and Magruder, 2018) but much larger than in the literature on international migrants in developed countries (see, e.g., Borjas, 2003). Internal migrants are more substi-

[24] We provide in Appendix D the results without any weights.

[25] The average compensation per employee may decrease due to an outward shift in labor supply but also to the replacement of native workers by less productive migrants. The NBS data do not provide yearly information on the composition of the workforce by skill or migrant status. To shed light on the issue, we exploit the Urban Household Survey (2002–2006), a representative survey of urban "natives" (see Appendix D.3). We find that natives do experience a significant wage decline, and conclude that compositional effects cannot explain more than a third of the wage response.

tutable with “natives” than international migrants, and labor markets are relatively less regulated in developing countries.[26]

Following a positive labor supply shock and a decline in wages, one would expect manufacturing firms to expand. Our estimates of the impact of migration on factor demand are presented in columns 2 and 3 of Table 3. An additional percentage point in the immigration rate increases employment in the average manufacturing firm by 0.33%.[27] Since we normalize the migration rate by the population working in the manufacturing sector, one would expect the coefficient to be one if all newly-arrived immigrants were absorbed by the manufacturing sector and if they were allocated uniformly to firms in the NBS sample and to other (smaller) manufacturing firms. The coefficient lower than one suggests that migrant workers are more likely to be hired by smaller firms, work in other sectors (e.g., construction), or transit through unemployment or self-employment (Giulietti et al., 2012; Zhang and Zhao, 2015).

Migrant labor supply shocks strongly affect relative factor use at destination. As shown in column 3 of Table 3, the capital-to-labor ratio decreases by 0.28% following a one percentage point increase in the migration rate, which suggests that capital positively adjusts to the increase in employment but moderately so. There are two possible reasons for this finding. First, firms that expand may belong to sectors with relatively high substitutability between capital and labor. A moderate adjustment of capital would then be an optimal response. Second, there may be credit constraints or adjustment costs that prevent firms from reaching the optimal use of production factors in the short run. We will shed light on these interpretations by investigating treatment heterogeneity and longer-run effects in this section, and by modeling the degree of substitutability between factors in Section 4.

The average product of labor appears to fall sharply in response to migrant inflows. An additional percentage point in the immigration rate decreases value added per worker by 0.30% (column 4 of Table 3). Since employment increases by 0.33%, the coefficient implies that the labor supply shock has only modest positive effects on value added at the firm level. Firm expansion may come at a short-run cost; for instance, new hires may need to be trained and production lines adjusted before the expansion of production factors translates into higher output. We will test the persistence of this effect using the long-run specification below.

[26]For instance, minimum wage regulations in China only came into force toward the end of our observation period (Mayneris et al., 2018; Hau et al., 2018).

[27]We find little differences between the OLS and IV estimates for employment and capital-to-labor ratio. Unlike for wages, the direction of the bias is not clear for these outcomes.

Sensitivity analysis An important threat to the identification strategy is that agricultural prices affect the urban sector through other channels than the arrival of immigrants in cities, notably through markets for goods. Specifically, changes in the price of agricultural output may affect local industries that use agricultural products as intermediate inputs. Cities and their surroundings are also integrated through final goods markets, so that changes in agricultural income in rural hinterlands affects demand for manufactured products in cities (Bustos et al., 2016a; Santangelo, 2016). More generally, one may worry that the spatial distribution of manufacturing sectors correlates with migration flows in such a way that we attribute to migration the effect of other macroeconomic shocks or trends.

To alleviate these concerns, we carry out five robustness checks, which are presented in Table 4. In Panel A, we control for the agricultural income shock in the prefecture of destination. In Panel B, we control for this shock in neighboring prefectures, weighting by the inverse of travel time computed using the existing transportation network. To further alleviate concerns about spatial autocorrelation in agricultural revenue shocks, we exclude from the analysis migration flows between prefectures that are less than 300-km apart (Panel C). In Panel D, we exclude industries that use agricultural products as intermediate inputs (food processing and beverage manufacturing industries). In Panel E, we control for a measure of market access—the sum of the rural population in all prefectures weighted by the inverse of the distance to the prefecture where the firm is located—fully interacted with year dummies. In all these instances, the estimates are similar to the main results.

Finally, we perform a placebo test in which we regress firm outcomes on the immigration rate in the next period, instrumented by the migration predictions. As Panel F of Table 4 shows, the placebo estimates are all much smaller than our main estimates. The sensitivity analysis supports our interpretation that agricultural price shocks affect manufacturing firms through a shift in migrant labor supply.

Longer-run effects The longer-run effect of migrant inflows may differ from their immediate impact. Labor markets at destination may adjust through worker mobility across prefectures, e.g., if prefectures that experience a wage decrease due to a sudden migrant inflow receive fewer migrants in subsequent years (Monras, 2018). Within a destination, local labor supply may also respond to the arrival of low-skill workers (Llull, 2018). Moreover, capital and investment could adjust over time, and production lines could be re-optimized to accommodate the arrival of new workers.

We use specification (5) and report longer-run effects of migration on factor cost, factor demand, and value added per worker in Table 5. The price elasticity of labor demand in the longer run is -0.22, lower than the short-run estimate. This wage adjustment occurs in spite of a higher absorption of migrants within manufacturing firms: An additional percentage point in the immigration rate between 2001 and 2006 increases employment by 0.52%. The impact of migrant inflows on labor cost and employment strongly affects relative factor demand. Firms located in prefectures that receive more migration remain labor-abundant even in the longer run; capital adjustments remain marginal. Finally, the effect of migration on value added per worker is less negative in the longer run and suggests an increased positive effect of migration on output at destination. The differences between the short- and longer-run impacts of immigration are consistent with (i) slow labor market adjustments, (ii) low levels of complementarity between capital and labor, a shift toward labor-intensive production technologies or non-negligible frictions in access to capital, and (iii) some disruption of production on impact.

While our study cannot provide direct evidence on the consequences of large rural-urban migration in the very long run, the behavior of manufacturing firms in China is consistent with Lewis's (2011) findings for the 1980s and 1990s in the United States. Firms may choose not to mechanize due to the availability of cheap labor. They shift investment and technology adoption decisions toward a more labor-intensive mode of production, a choice that may have important long-term consequences. We provide additional support for this interpretation below.

3.2 Restructuring of production and innovation

Profitability and investment We first estimate the effect of migration on profits and investment. We use the longer-run specification (5) and consider as outcomes the ratio of profits to revenues (profitability), a dummy equal to one if profits are positive, a dummy equal to one if short-term investment is positive, and a dummy equal to one if long-term investment is positive. Table 6 presents the estimates. The arrival of low-skill workers does not affect profitability in the average establishment (see column 1); it does however increase the probability that an establishment reports net profits (see column 2), thus mostly benefiting low-profitability establishments. A ten percentage points increase in the immigration rate increases the probability that firms make profit by 1.9 percent. Short- and long-term investments increase slightly, which suggests that profits may be partly reinvested, but the coefficients are not significant (columns 3 and 4). These results show that cheaper labor makes the least profitable firms break even, but does not have any positive effect on investment.

Innovation We next explore the effect of migration on innovation. We exploit a match between establishment × year observations in the NBS firm census and all the patents submitted to the State Intellectual Property Office (He et al., 2018). The data cover three main categories of patents: design (external appearance of the final product), innovation (fundamental innovations in methods) and utility (e.g., changes in processing, shape or structure of products). It also provides a more detailed classification of the technological content of each patent. We use this classification to qualify the nature of technological innovation, using average characteristics of firms that submitted a patent within each subcategory at baseline. Specifically, we classify a patent as high-education if the share of the workforce with a high-school degree in the average establishment that submitted a patent in this subcategory at baseline is above the median. Similarly, we classify a patent as high-capital-to-labor ratio if the capital-to-labor ratio in the average establishment that submitted a patent in this subcategory at baseline is above the median.

We estimate the longer-run specification (5) at the establishment-level between 2001 and 2006, and regress the difference in the probability to submit a patent application between 2001 and 2006 on the labor supply shift, instrumented by our origin-based shock. Panel A of Table 7 shows that the probability to submit a patent decreases by 0.04 percentage point after a one percentage point increase in the immigration rate. One standard deviation in the immigration rate between 2001 and 2006 lowers the probability to patent by one percentage point (from an average of 4 percentage points). The effect is similar across official patent categories (see columns 2 to 4): the arrival of low-skilled workers reduces technological innovation along the whole production line. These results suggest that the response to the outward shift in labor supply, while increasing profitability in the short run, may be detrimental to their productivity in the longer run.

Rural-urban migration does not only affect the pace of technological progress, but also its direction. The drop in patenting is most pronounced for high-education patent subcategories, and almost entirely explained by capital-intensive technologies (see Panel B of Table 7). Manufacturing establishments appear to shift along the technological frontier toward more labor-intensive production methods.

Restructuring of production Since rural-urban migration biases technological development toward labor-intensive technologies, it may induce a similar change in the goods produced by manufacturing establishments.

This section explores changes in the production structure of manufacturing establishments as implied by changes in the (main) end product. The NBS collects each year a textual description of final products. We use this description to detect any change between 2001 and 2006 and determine the direction of the change using the characteristics of the average establishment producing the same good at baseline. We proxy human capital intensity by the average share of the workforce with a high-school degree and (physical) capital-abundance by the average capital to labor ratio. Establishments in prefectures experiencing large immigration flows are more likely to report different final products in 2001 and 2006 (see column 1 of Table 8); a one percentage point increase in the immigration rate raises the probability to change products by 0.23 percentage points, which is equivalent to a standardized effect of 0.08. The effect is driven by products with low human capital and low physical capital intensity. These results are reminiscent of the slower adoption of machinery in U.S. manufacturing plants subject to similar labor supply shocks (Lewis, 2011).

Taken together, these findings paint a consistent picture. The arrival of low-skill labor is associated with an increase in short-term profitability, a decline in innovation and technology adoption, and a change in the structure of production away from technologies that are intensive either in human or physical capital.

3.3 Heterogeneity and aggregation

Our analysis so far has focused on average changes within establishments. It may underestimate the extent to which the local economy responds to migrant labor supply shocks, as the shift toward a more labor-intensive production structure may involve a reallocation of resources across establishments (Dustmann and Glitz, 2015). We now provide evidence on the heterogeneous absorption of migrants in the urban economy and its aggregate implications.

Heterogeneity in factor demand We study the heterogeneous response in factor demand by interacting migrant inflows with firm characteristics at baseline (see Equation 6). We label as capital-abundant all firms with a capital-to-labor ratio at baseline above the median in their sector and prefecture. We label as labor-productive all firms with a value added per worker at baseline above the median in their sector and prefecture. Table 9 presents the heterogeneous response in labor cost and labor demand. In columns 1 and 3, we test for the existence of heterogeneous effects of migrant inflows on labor cost. The reduction in labor cost is remarkably homogeneous across firms; all firms seem to face similar labor market conditions. In response to the labor supply shift, we do not find that capital-abundant firms recruit more than the average firm (column 2). However, firms with higher average labor productivity are less likely to expand in response to the migration shock: a one percentage point increase in the migration rate increases employment in firms with low value added per worker by 0.56%, against 0.40% in more productive firms.

Migrant workers are not predominantly recruited by "capital-rich" firms in the same sector and location; they are hired by firms where labor productivity is low. This observation contrasts with empirical regularities of firm growth in developed economies: employment flows are typically directed toward productive firms (see Davis and Haltiwanger, 1998, for evidence in U.S. manufacturing). A possible explanation is that we study large labor supply shocks, which may have different allocative properties from the smaller idiosyncratic labor demand shocks that usually drive employment growth. Our findings are also different from Dustmann and Glitz (2015), who find that more labor-abundant firms expand relative to capital-abundant firms, while we find no heterogeneity in terms of capital-to-labor ratio at baseline.[28] These results may relate to technological differences across manufacturing establishments—a dimension already shown to be a crucial component of the long-term adjustment. In Section 4, we will provide a careful analysis of the allocation of migrants across production units using different technologies.

Aggregation and sample choice The heterogeneity in employment effects suggests that migrant inflows change the allocation of production factors across establishments. To investigate the aggregate consequences of this reallocation, we construct outcomes at the sector $\times$ prefecture level, e.g., by considering total compensation divided by total employment as a measure of aggregate labor cost. We then use specification (5), with a sector $\times$ prefecture as the unit of observation.

Panel A of Table 10 presents the aggregate results, using the same sample as in Table 5, i.e., firms present every year in the NBS firm census between 2001 and 2006. The effects on labor cost, employment, and capital-to-labor ratio are quite similar to the within-firm results from Table 5. The negative effect on value-added per worker is stronger in the aggregate (-0.53 against -0.40). This can be explained by heterogeneous employment effects across establishments: low-productivity establishments hire more, which increases their weight at the aggregate level. Hence, the reallocation of labor across production units within sector amplifies the negative effect of migration on value-added per worker.[29]

[28] In Appendix D, we investigate other firm and industry characteristics (e.g., complementarity between capital and labor, human capital intensity, firm ownership etc.), and do not find strong evidence of heterogeneity along these variables either (see Appendix Table D26).

[29] We present results aggregated at the prefecture level in Appendix Table D27 and find that they are very similar to the results in Table 10. This suggests that the reallocation across sectors is small compared to the reallocation of labor within sectors. This observation is consistent with the literature on developed countries (Lewis, 2011; Dustmann and Glitz, 2015).

Our analysis so far has focused on the balanced sample of firms. However, as discussed in Appendix C, the balanced sample only represents about a third of all firm $\times$ year observations. In order to account for the potential effect of migration on firm entry and exit, we construct outcomes at the sector $\times$ prefecture level using all firms observed at any point in the NBS data between 2001 and 2006. The results are shown in Panel B of Table 10. The wage response to a one percentage point increase in the immigration rate is -0.36%, close to the estimate using the balanced sample (-0.28%). The effects on employment, capital-to-labor ratio and value added per worker are all larger in magnitude—the estimate on employment suggesting that the excess labor supply is entirely absorbed by firms of our sample. Accounting for entry into and exit from our sample amplifies the effect of migration on production, which becomes even more labor-intensive, and on aggregate labor productivity, which declines further.[30]

4 Migration and factor productivity

Assessing the consequences of the labor supply shift on the reorganization of production requires us to account properly for the technological choices of manufacturing establishments and the possible complementarity between production factors. This section develops a quantitative framework, in which there are sector-specific complementarities between capital and labor (Oberfield and Raval, 2014), and individual firms are characterized by (residual) technological choices—different product varieties require different production technologies.[31] Within a sector, some establishments will rely on a labor-intensive technology and be labor-abundant, while others will be capital-abundant. Importantly, technology results from a choice. We use the quantitative model to interpret the impact of labor inflows on factor use and factor productivity in the short run and in the longer run. The model also disciplines the analysis of heterogeneity across establishments.

[30]This resonates with Dustmann and Glitz's (2015) finding that new entrants play an important role in the absorption of labor supply shocks. The censoring of establishments below the RMB 5 million sales threshold makes it harder to measure actual firm entry and exit with the NBS data. We show in Appendix Table D28 that migration has little effect on entry in the sample but seems to reduce exit. The latter observation is consistent with our previous results: cheap labor allows low-profitability firms to survive, or at least to remain large enough to appear in the sample.

[31]This feature allows to capture the wide dispersion in relative factor use within prefecture and industry—See Appendix C and Appendix Figure C10.

4.1 Quantitative framework

We first outline a model of firm production based on Oberfield and Raval (2014) with two factors, sector-specific complementarity between capital and labor, monopolistic competition within sectors, and firm-specific technological differences.

Theoretical framework The economy is composed of D prefectures. In each prefecture d, the economy is divided into sectors within which there is monopolistic competition between a large number of heterogeneous firms. The final good is produced from the combination of sectoral outputs, and each sectoral output is itself a CES aggregate of firm-specific differentiated goods. Firms face iso-elastic demand with σ denoting the elasticity of substitution between the different varieties of the sectoral good. In what follows, we drop prefecture indices for the sake of exposure.

Total sectoral output in a product market (sector $\times$ prefecture) is given by the following CES production function:

$$y = \left[\sum_i x_i y_i^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{7}$$

where x_i captures consumer preferences for product variety i. Each firm i thus faces the following demand for its product variety i:

$$y_i = (p_i/p)^{-\sigma} x_i^{\sigma} y \tag{8}$$

where p_i is the unit price for variety i, and p is the price index at the product market level. We assume that a firm i produces according to a CES production function:

$$y_i = A_i \left[\alpha_i k_i^{\rho} + \beta_i l_i^{\rho}\right]^{\frac{1}{\rho}}, \tag{9}$$

where ρ, governing the elasticity of substitution between capital and labor, is assumed constant over time and within sector, and (α_i, β_i) characterizes the firm-specific technology. We rationalize differences in factor use across production units by technological choices: individual firms produce different varieties—each product variety involving a more or less labor-intensive production line.

For a given technology (α_i, β_i), firm i maximizes the following program,

$$\pi(\alpha_i, \beta_i) = \max_{p_i, y_i, l_i, k_i} \left\{p_i y_i - w l_i - r k_i\right\}, \tag{10}$$

subject to demand for its specific variety (8) and the production function (9).

When firms select their product varieties, they maximize the indirect profit, $\pi(\alpha_i, \beta_i)$, subject to a sector-specific technological frontier,

$$[(\alpha_i/\alpha)^\tau + (\beta_i/\beta)^\tau]^{\frac{1}{\tau}} \leq 1, \tag{11}$$

where τ is the curvature of the technological frontier, and (α, β) is the average industry technology.[32]

Estimation The following fundamentals of the model need to be estimated: the degree of substitution between capital and labor (ρ), the average factor intensities (α, β), the elasticity of substitution between product varieties (σ). The key parameter is the sector-specific elasticity of substitution between factors: once ρ is known for each sector, factor intensities and the elasticity of substitution between product varieties can be imputed from factor shares and the ratio of profits to revenues.

In order to identify ρ, we proceed as Oberfield and Raval (2014). We rely on the relationship between relative factor demand and factor cost, and we exploit the labor supply shock in the short run to shift the labor cost—for a given and constant technology at the firm level.[33] Under given production parameters, optimal factor demand at the firm level verifies:

$$\ln\left(\frac{k_i}{l_i}\right) = \frac{1}{1-\rho}\ln\left(\frac{\alpha}{\beta}\right) - \frac{1}{1-\rho}\ln\left(\frac{r}{w}\right) + \frac{1}{1-\rho}\ln\left(\frac{\alpha_i \beta}{\beta_i \alpha}\right),$$

where we can separately identify three terms: (i) a sector fixed-effect, (ii) the relative factor prices at destination weighted by the elasticity of substitution, and (iii) a measure of firm-specific relative factor intensity. Identifying the elasticity of substitution from this relationship is challenging because omitted variation (e.g., a labor productivity shock) may influence both relative factor prices and relative factor use.

In order to identify the sectoral elasticity of substitution, we exploit exogenous variation in the relative factor cost induced by migrant labor supply shocks. The arrival of migrants shifts the relative price of labor downward, an effect that is orthogonal to omitted variation related to labor demand, at least in the short run. We assume, as in Oberfield and Raval (2014), that firm-specific technological disparities are normally distributed within a sector and a prefecture, and that labor markets

[32] The overall variation in production structure across production units is modeled by sector-specific technologies, (α, β, ρ), and residual variations within each sector: product varieties may be more or less labor-intensive around the average technology and along the technological frontier.

[33] The derivation of optimal factor demand is made explicit in Appendix E. This Appendix also describes the full identification strategy.

are integrated within a prefecture.[34] We do not need to impose that the price of capital, r, is constant across locations—a debatable assumption in the Chinese context (Brandt et al., 2013). Instead, we need time variation in immigration not to affect the price of capital at the prefecture level. A comprehensive description of the empirical strategy can be found in Appendix E.[35]

4.2 Predictions

With the previous production estimates, we can derive two sets of predictions. First, with endogenous technology, optimal factor demand verifies:

$$\ln\left(\frac{k_i}{l_i}\right) = -\frac{\tau}{(\tau-1)(1-\rho)-\rho}\ln\left(\frac{\alpha}{\beta}\right) - \frac{1}{1-\rho-\frac{\rho}{\tau-1}}\ln\left(\frac{r}{w}\right).$$

This equation implies that, if the technological frontier is concave ($\tau > 1$), the elasticity of factor demand is larger in absolute value than with a fixed technology. At heart, following an outward shift in labor supply, firms will not only substitute labor for capital until they adjust marginal product of factors as evaluated at their current technology. They will also eventually adjust their technology toward more labor-intensive product varieties and this effect adds to the direct, short-run, impact. This theoretical prediction echoes the empirical findings presented in Section 3 and Tables 3 and 5. The factor adjustment at destination is larger in the longer run, because establishments redirect their production toward more labor-intensive product varieties along the technological frontier—as shown from the analysis of patents (Table 7) and product varieties (Table 8).

Second, the framework enables us to compute *constructed* factor productivity. We use the term *constructed* because it is evaluated using *sectoral* production parameters at baseline instead of the actual firm-specific technology. The constructed marginal revenue products of factors (MPL_i, MPK_i) and the revenue-based total factor productivity (TFP_i) are defined as,

$$\begin{cases} MPL_i = (1-1/\sigma)\dfrac{\beta l_i^{\rho-1}}{\alpha k_i^{\rho}+\beta l_i^{\rho}}p_i y_i \\ MPK_i = (1-1/\sigma)\dfrac{\alpha k_i^{\rho-1}}{\alpha k_i^{\rho}+\beta l_i^{\rho}}p_i y_i \\ TFP_i = \dfrac{p_i y_i}{[\alpha k_i^{\rho}+\beta l_i^{\rho}]^{\frac{1}{\rho}}} \end{cases} \tag{12}$$

[34] We provide empirical support for this assumption in Appendix D.4, by showing that the shift in labor cost is homogeneous (see Appendix Figure D13).

[35] Due to data limitations, we cannot provide reliable elasticities at the 2-digit industry level. Instead, we aggregate industries in four large clusters (see Appendix E.3 and Appendix Table E30).

Although factor markets are assumed perfect, there is a wedge between the constructed marginal factor productivities and factor costs, because we evaluate these quantities using the average production technology at baseline. More specifically, we have that:

$$\begin{cases} MPL_i = \left(1 + \frac{\left(\frac{\alpha_i}{\beta_i} - \frac{\alpha}{\beta}\right)\left(\frac{k_i}{l_i}\right)^{\rho}}{1+\frac{\alpha}{\beta}\left(\frac{k_i}{l_i}\right)^{\rho}}\right) w \\ MPK_i = \left(1 + \frac{\left(\frac{\beta_i}{\alpha_i} - \frac{\beta}{\alpha}\right)\left(\frac{l_i}{k_i}\right)^{\rho}}{1+\frac{\beta}{\alpha}\left(\frac{l_i}{k_i}\right)^{\rho}}\right) r \end{cases} \tag{13}$$

These expressions provide the following predictions:

Prediction 1: There is within-sector dispersion in constructed factor productivity, which may be higher or lower than factor cost. A firm with a capital-intensive technology (i.e., with $\alpha_i/\beta_i > \alpha/\beta$) would appear to have high labor productivity and thus be too capital-abundant. The dispersion in constructed factor productivity translates into a similar dispersion in wedges between this factor productivity and factor cost (see Equation 13).

Prediction 2: A labor supply shock affects constructed factor productivity in two distinct ways. First, labor cost changes, which triggers an immediate and homogeneous adjustment in factor use. Second, firms moves along the technological frontier by adopting more labor-intensive product varieties. The latter adjustment would be reflected as a decrease in labor productivity, an increase in capital productivity and a negative (resp. positive) drift in the wedge between labor (resp. capital) productivity and its cost.

4.3 Effect of migration on factor productivity

In this section, we use model-based measured of productivity to estimate the impact of immigration on productivity and on the allocation of factors across firms.

Average effect We first study the impact of labor inflows on factor productivity at the firm level, in the short and the longer run. We estimate Equations (4) and (5) using the marginal revenue product of labor, marginal revenue product of capital and total factor productivity in revenue terms as dependent variables (all in logs). The estimates are presented in Table 11. The first column of Table 11 reports how the marginal return to labor responds to migrant inflows. The elasticity with respect to migration is about -0.48 in the short run (Panel A) and reaches -0.64 in the longer run (Panel B). In parallel, the marginal revenue product of capital responds positively to the labor supply shift in the longer run (column 2). There is some evidence of a negative effect on total factor productivity in the short and longer run, but the coefficients are statistically insignificant (column 3).[36]

These findings are inconsistent with optimization under *constant* technology. With fixed production technology, the magnitude of the decline in (log) labor productivity would be similar to the (log) labor cost decline (-0.24, see Table 5), and capital productivity and total factor productivity would remain stable (see Equation 13). Instead, the wedge between the marginal product of labor and its marginal cost decreases with immigrant inflows, and capital productivity slightly increases.[37] This drift, which is particularly apparent in the longer run, is consistent with endogenous and directed technological choice. Firms become more labor-abundant in prefectures experiencing large migrant inflows, specifically so by adopting more labor-intensive production lines. This long-term adjustment affects wedges between constructed factor productivities and factor costs.

Heterogeneity analysis We now investigate the distributional effects of migrant inflows. We classify firms based on (i) their constructed marginal product of labor, (ii) marginal product of capital, and (iii) total factor productivity at baseline (in 2001), and construct a dummy equal to 1 if a firm is above the median of its sector $\times$ prefecture for each productivity measure. We interact migrant inflows with each productivity dummy (see Equation 6) and report estimates of the effect of migration on relative factor use (capital-to-labor ratio) in Table 12.

In the model, firms' elasticity of relative factor demand to factor prices should be independent of their initial factor productivity, because it only depends on the complementarity between factors, a parameter which we assume constant within sectors. The empirical analysis rejects this prediction: immigrants primarily shift factor use in manufacturing firms with high marginal product of labor. The relative capital-intensity of high labor productivity firms decreases by 0.64% following a one percentage point increase in the immigration rate, as against 0.38% in low labor productivity firms (column 1). The opposite and symmetric result holds for

[36] As a robustness check, we construct factor productivity measures using (i) a Cobb-Douglas specification, which corresponds to the limiting case where ρ is zero, and (ii) CES production functions with the sector-level elasticities of substitution estimated by Oberfield and Raval (2014) for the United States in 1987 and 1997. Capital and labor are more complementary than what a Cobb-Douglas production function would imply; the arrival of immigrants without further capitalization affects labor productivity more strongly in our baseline specification (see Appendix Table D29). In contrast, productivity effects are even more pronounced with U.S.-based elasticities.

[37] Our framework assumes that labor is homogeneous, which implies that there is no productivity difference between migrant and resident workers. Any discrepancy between the productivity of urban residents and rural-urban migrants would generate a bias in the estimated effect of migrant inflows on factor productivity. We show in Appendix E.4 that, under reasonable assumptions about the relative efficiency of migrant labor, this bias would however only account for a very small part of the decrease in labor productivity and increase in capital productivity.

capital productivity (column 2): the largest shift in relative factor demand is found among low capital productivity firms. These findings can be rationalized by a simple extension to our baseline framework: introducing a fixed cost to adopting a new product variety. Manufacturing establishments that produce capital-intensive product varieties in 2001—with high MPL and low MPK—will be the most affected by the shift in relative factor cost, since their profit is farther from the optimum. These establishments would be more likely to pay the fixed cost of changing products and adopt a new, labor-intensive variety—a change that would be associated with a larger decline in the capital-to-labor ratio.

The results also suggest that immigrants are primarily recruited by low-TFP establishments (column 3). This observation cannot be rationalized by our framework, but it has non-negligible implications for aggregate total factor productivity at destination. Labor inflows influence aggregate productivity through the difference between the average employer and the marginal employer—the recipient of migrant inflows. Immigrants being hired by unproductive firms, aggregate productivity further decreases through this compositional effect.

Interpretation The interpretation of these findings depends on the nature of the initial productivity differences across firms within a location and sector.

In the spirit of the model, disparities in factor productivity arise from technological differences across production units. Establishments specializing in labor-intensive product varieties would appear to have low labor productivity, which would translate into a negative wedge with respect to the labor cost. While a negative wedge would be observationally equivalent to a subsidy on labor cost (as in Hsieh and Klenow, 2009), the wedges of our model do not imply that factors are misallocated for a given technology. The dispersion in wedges within sectors would instead indicate the existence of some frictions in *setting* technology. For instance, technological choices may be staggered, so that in a given cross-section firms would differ according to the timing of their last technological adoption. The differential adjustment of factor use across production units may also be rationalized by such frictions: with a fixed cost of resetting technology, labor-intensive establishments would respond less than capital-intensive ones (as observed in Table 12).

This interpretation of our results assumes that our model is a valid representation of production patterns and differences across establishments. Some deviations from this benchmark could also induce initial dispersion in constructed factor productivity and a differential response to the labor supply shift. For example, factor wedges may reflect firm-specific factor complementarities in production or complementarities in production with other unobserved factors (e.g., skilled labor) that are heterogeneously allocated across establishments. We do not however find strong evidence of heterogeneity along these dimensions (see Appendix Table D26).

Alternatively, the initial dispersion in factor productivity may reflect factor market imperfections (as in Hsieh and Klenow, 2009). Firms with a high marginal product of labor may be constrained in hiring labor: the initial misallocation may be due to information asymmetry between job seekers and employers (Abebe et al., 2016; Alfonsi et al., 2017), the intervention of intermediaries, and the prevalence of migrant networks (Munshi, 2003). Capital productivity dispersion may be indicative of capital market distortions: firms within a sector and location may be more or less constrained in their access to capital (Buera et al., 2011; Midrigan and Xu, 2014). In that framework, our finding that the capital-to-labor ratio declines more among firms with high labor productivity and less among firms with high capital productivity points toward a better allocation of factors at destination.

Total factor productivity differences across firms may capture entrepreneur characteristics, management practices (Bloom et al., 2013) or differences in the organization of production (Akcigit et al., 2016; Boehm and Oberfield, 2018). Better entrepreneurs or organizations would be captured by high total factor productivity within a sector. Our finding that employment expands more in firms with low total factor productivity suggests that migration benefits firms whose management is of low quality, and hence worsens the allocation of resources within locations.

5 Conclusion

This paper provides unique evidence on the causal effect of rural-urban migration on manufacturing production in China. The analysis combines information on migration flows with longitudinal data on manufacturing establishments between 2001 and 2006, a period of rapid structural transformation and sustained manufacturing growth. We instrument migrant inflows using predictions based on agricultural commodity price shocks interacted with cropping patterns and pre-existing migration networks between rural areas and cities.

We find that migration decreases labor costs and increases employment in manufacturing. Manufacturing production becomes more labor-intensive, as capital does not adjust, even in the medium run. The shift in relative factor cost affects the whole organization of production toward more labor-intensive production lines, as shown by the systematic analysis of end products and patents.

Another consequence of rural-urban migration is that labor productivity falls sharply. A quantitative framework with complementarity between factors and endogenous technological choice suggests that production becomes more labor-abundant through two effects: a direct substitution between capital and labor for a given technology, and an indirect effect deriving from directed technological change toward labor-intensive product varieties.

The allocative properties of immigrant flows across firms are ambiguous. Resources appear to be directed toward factor-scarce firms: the largest decline in the capital-to-labor ratio is found among capital-rich and labor-scarce establishments. However, recruiting firms tend to have low total factor productivity.

Overall, our results show that the abundance of rural migrant labor induces labor-oriented directed technological change in manufacturing. This mechanism is likely at play in other developing countries that are currently in the process of structural transformation. In China, rural-urban migration slowed down at the end of the 2000s, and in the last decade manufacturing has been experiencing a steep rise in automation (Cheng et al., 2019).

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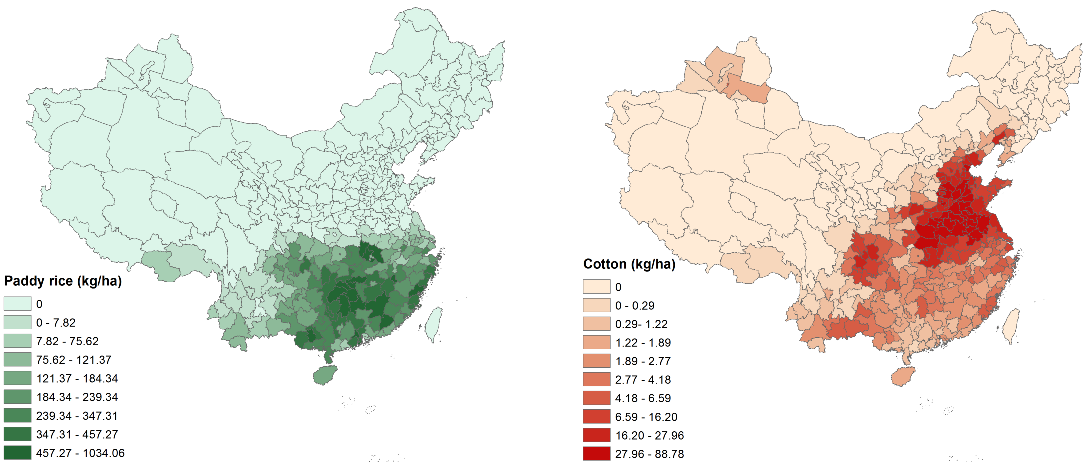
Figures and tables

Figure 1. Potential output in China for rice and cotton (2000).

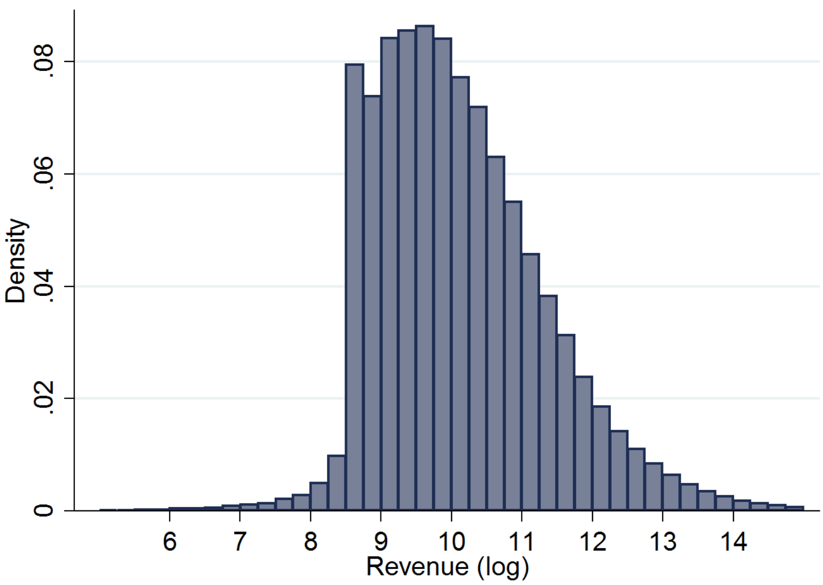


(a) Paddy rice.

(b) Cotton.

Notes: These maps represent the potential output constructed from interacting harvested areas (2000) and potential yield (GAEZ model) for two common crops in China, i.e., paddy rice (left panel) and cotton (right panel).

Figure 2. Distribution of revenue across firms (NBS, 2001–2006).



Sources: Firm-level data from the National Bureau of Statistics (NBS), 2001–2006. The revenue threshold for appearing in the NBS Census of above-scale firms is RMB 5,000,000, corresponding to $ln(5,000) \approx 8.52$ along the logarithmic scale (of revenues expressed in thousands of RMB).

Table 1. Origin-based migration predictions.

	Emigration	
	Inter-prefecture	Outside 300-km radius
Panel A: Predicting emigration		
Price shock	-0.104	-0.088
	(0.018)	(0.017)
Observations	2,028	2,028
Fixed effects	Year; prefecture	Year; prefecture
	Immigration	
	Inter-prefecture	Outside 300-km radius
Panel B: Predicting immigration		
Predicted immigration	2.815	2.738
	(0.845)	(0.917)
Observations	2,052	2,052
Fixed effects	Year; prefecture	Year; prefecture

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. In Panel A, the dependent variable is the number of rural emigrants to urban areas in other prefectures or in prefectures located outside of a 300-km radius around the origin, divided by the number of rural residents at origin. In Panel B, the dependent variable is the number of rural immigrants from other prefectures or prefectures located outside of a 300-km radius around the destination divided by the number of urban residents at destination. See Section 2 and Equations (2) and (3) for a more comprehensive description of the two specifications.

Table 2. Summary statistics of key firm-level outcomes.

	Mean	Standard deviation total	within	between
Panel A: 2001				
Labor cost	2.14	0.68	0.59	0.33
Employment	4.70	1.06	1.01	0.29
K/L ratio	3.56	1.26	1.23	0.27
Y/L ratio	3.50	0.93	0.89	0.25
Panel B: 2006				
Labor cost	2.78	0.55	0.49	0.25
Employment	4.58	1.03	0.99	0.28
K/L ratio	3.81	1.24	1.20	0.31
Y/L ratio	4.16	0.92	0.88	0.29

Sources: NBS firm-level data (2001, 2006). The first and second columns present the mean and standard deviation of the key outcome variables. The third and fourth columns report the standard deviation within and across prefectures. *Labor cost* is the (log) compensation per worker including social security and housing benefits. *Employment* is the (log) number of workers. *K/L ratio* is the (log) ratio of fixed assets to employment. *Y/L ratio* is the (log) ratio of value added to employment.

Table 3. Impact of migration inflows on urban firms—short run.

	Labor cost (1)	Employment (2)	K/L ratio (3)	Y/L ratio (4)
Panel A: OLS estimates				
Migration	-0.164	0.201	-0.239	-0.257
	(0.040)	(0.028)	(0.048)	(0.049)
Observations	303,636	303,636	303,636	303,636
Number Firms	50,606	50,606	50,606	50,606
Panel B: IV estimates				
Migration	-0.499	0.330	-0.278	-0.307
	(0.137)	(0.064)	(0.066)	(0.137)
Observations	303,636	303,636	303,636	303,636
Number Firms	50,606	50,606	50,606	50,606
F-stat. (first stage)	21.58	21.58	21.58	21.58

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. The sample is composed of the firms present every year in the NBS firm census between 2001 and 2006. *Migration* is the immigration rate, i.e., the migration flow divided by destination population at baseline. *Labor cost* is the (log) compensation per worker including social security and housing benefits. *Employment* is the (log) number of workers. *K/L ratio* is the (log) ratio of fixed assets to employment. *Y/L ratio* is the (log) ratio of value added to employment. All specifications include firm and industry $\times$ year fixed effects. See Section 2 and Equation (4) for a description of the IV specification.

Table 4. Impact of migration inflows on urban firms—sensitivity analysis.

	Labor cost (1)	Employment (2)	K/L ratio (3)	Y/L ratio (4)
Panel A: Controlling for local shock				
Migration	-0.529	0.319	-0.308	-0.297
	(0.149)	(0.066)	(0.067)	(0.136)
Observations	303,612	303,612	303,612	303,612
Panel B: Controlling for shocks in neighboring prefectures				
Migration	-0.511	0.310	-0.299	-0.289
	(0.143)	(0.064)	(0.065)	(0.131)
Observations	303,636	303,636	303,636	303,636
Panel C: Excluding migrant flows within 300 km				
Migration	-0.402	0.412	-0.323	-0.279
	(0.108)	(0.081)	(0.082)	(0.155)
Observations	303,636	303,636	303,636	303,636
Panel D: Excluding processing industries				
Migration	-0.474	0.364	-0.285	-0.319
	(0.135)	(0.067)	(0.066)	(0.141)
Observations	275,382	275,382	275,382	275,382
Panel E: Controlling for market access × year fixed effects				
Migration	-0.508	0.356	-0.282	-0.315
	(0.143)	(0.068)	(0.069)	(0.142)
Observations	303,636	303,636	303,636	303,636
Panel F: Forward shocks				
Migration $t+1$	-0.014	0.031	0.124	0.053
	(0.095)	(0.047)	(0.053)	(0.079)
Observations	303,636	303,636	303,636	303,636

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. The sample is composed of the firms present every year in the NBS firm census between 2001 and 2006. All specifications include firm and industry × year fixed effects. See Section 2 and Equation (4) for a description of the IV specification.

Table 5. Impact of migration inflows on urban firms—long run.

	Labor cost (1)	Employment (2)	K/L ratio (3)	Y/L ratio (4)
Migration	-0.221	0.520	-0.542	-0.403
	(0.133)	(0.097)	(0.097)	(0.157)
Observations	50,606	50,606	50,606	50,606
F-stat. (first stage)	30.17	30.17	30.17	30.17

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. The sample is composed of the firms present every year in the NBS firm census between 2001 and 2006. *Migration* is the average yearly immigration rate over the period 2001–2006, i.e., the sum of migration flows between 2001 and 2006 over population in 2000, divided by the number of years. *Labor cost* is the (log) compensation per worker including social security. *Employment* is the (log) number of workers. *K/L ratio* is the (log) ratio of fixed assets to employment. *Y/L ratio* is the (log) ratio of value added to employment. See Section 2 and Equation (5) for a description of the IV specification.

Table 6. Impact of migration inflows on urban firms—profitability and investment.

	Profitability (1)	Any profit (2)	Short-term investment (3)	Long-term investment (4)
Migration	0.017	0.192	0.021	0.032
	(0.011)	(0.058)	(0.011)	(0.036)
Observations	50,606	50,606	50,606	50,606
Outcome Mean	0.030	0.840	0.200	0.050

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. The sample is composed of the firms present every year in the NBS firm census between 2001 and 2006. *Migration* is the immigration rate, i.e., the migration flow divided by destination population at baseline. *Profitability* is the ratio of profits to revenues. The other dependent variables are (differences between 2001 and 2006 in) dummies equal to one if profits, short-term investment, and long-term investment are strictly positive. See Section 2 and Equation (5) for a description of the IV specification.

Table 7. Impact of migration inflows on urban firms—technological innovations.

New patent	Any (1)	Design (2)	Invention (3)	Utility (4)
Panel A: Patent categories				
Migration	-0.040 (0.012)	-0.017 (0.008)	-0.017 (0.010)	-0.021 (0.010)
Observations	50,606	50,606	50,606	50,606
New patent	High ed. (1)	Low ed. (2)	High K/L (3)	Low K/L (4)
Panel B: Patent characteristics				
Migration	-0.033 (0.011)	-0.020 (0.009)	-0.038 (0.011)	-0.008 (0.009)
Observations	50,606	50,606	50,606	50,606

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. The sample is composed of the firms present every year in the NBS firm census between 2001 and 2006. *Migration* is the immigration rate, i.e., the migration flow divided by destination population at baseline. The dependent variable is the difference in the probability to submit a patent application between 2001 and 2006. In Panel A, we distinguish three categories: design, invention and utility. In Panel B, we divide patents into technologies associated with high/low average human capital, and labor-abundant technologies versus capital-abundant ones. See Section 2 and Equation (5) for a description of the IV specification.

Table 8. Impact of migration inflows on urban firms—production restructuring.

New product	Any (1)	High ed. (2)	Low ed. (3)	High K/L (4)	Low K/L (5)
Migration	0.226 (0.135)	0.010 (0.040)	0.217 (0.108)	0.067 (0.052)	0.159 (0.094)
Observations	50,606	50,606	50,606	50,606	50,606

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. The sample is composed of the firms present every year in the NBS firm census between 2001 and 2006. *Migration* is the immigration rate, i.e., the migration flow divided by destination population at baseline. The dependent variables are dummy variables equal to one if there is any change in the main product (1), and if this change goes toward products manufactured by establishments with a more (2) or less (3) educated workforce, and by more (4) or less (5) capital-abundant establishments. See Section 2 and Equation (5) for a description of the IV specification.

Table 9. Impact of migration inflows on urban firms—heterogeneous effects.

	Labor cost (1)	Employment (2)	Labor cost (3)	Employment (4)
Migration	-0.226	0.507	-0.239	0.564
	(0.139)	(0.105)	(0.141)	(0.102)
Migration × *High K/L*	0.024	-0.010		
	(0.074)	(0.084)		
Migration × *High Y/L*			0.072	-0.168
			(0.078)	(0.086)
Observations	50,606	50,606	50,606	50,606

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. The sample is composed of the firms present every year in the NBS firm census between 2001 and 2006. *High K/L* is a dummy equal to 1 if the baseline capital-to-labor ratio is above the median within the industry/prefecture. *High Y/L* is a dummy equal to 1 if the baseline value added-to-labor ratio is above the median within the industry/prefecture. See Section 2 and Equation (6) for a description of the IV specification.

Table 10. Impact of migration inflows on urban firms—sensitivity analysis with aggregate variables at the prefecture × sector level.

	Labor cost (1)	Employment (2)	K/L ratio (3)	Y/L ratio (4)
Panel A: Balanced sample of firms				
Migration	-0.284	0.650	-0.611	-0.527
	(0.125)	(0.114)	(0.128)	(0.141)
Observations	4,538	4,538	4,538	4,538
F-stat (first)	30.01	30.01	30.01	30.01
Panel B: Unbalanced sample of firms				
Migration	-0.363	0.992	-0.714	-1.009
	(0.129)	(0.156)	(0.128)	(0.245)
Observations	5,269	5,269	5,269	5,269
F-stat. (first)	26.37	26.37	26.37	26.37

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. The unit of observation is a prefecture × sector in a given year. In Panel A (resp. Panel B), the sample is composed of the firms present every year in the NBS firm census between 2001 and 2006 (resp. all firms present in the NBS firm census between 2001 and 2006); outcomes are then aggregated at the prefecture × sector level. *Migration* is the immigration rate, i.e., the migration flow divided by destination population at baseline. *Labor cost* is the (log) compensation per worker including social security. *Employment* is the (log) number of workers within the firm. *K/L ratio* is the (log) ratio of fixed assets to employment. *Y/L ratio* is the (log) ratio of value added to employment. All specifications include prefecture × sector and year fixed effects.

Table 11. Impact of migration inflows on urban firms—long-term effects on factor products.

	Labor pr. (1)	Capital pr. (2)	Total fact. pr. (3)
Panel A: Short-run effects			
Migration	-0.483	0.087	-0.211
	(0.157)	(0.150)	(0.154)
Observations	303,610	303,610	303,610
Panel B: Long-run effects			
Migration	-0.642	0.311	-0.163
	(0.184)	(0.163)	(0.163)
Observations	50,597	50,597	50,597

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. The sample is composed of the firms present every year in the NBS firm census between 2001 and 2006. *Migration* is the immigration rate, i.e., the migration flow divided by destination population at baseline. *Labor pr.* is the (log) marginal revenue product of labor; *Capital pr.* is the (log) marginal revenue product of capital; *Total fact. pr.* is the (log) total factor productivity in revenue terms. See Section 4 for details about the construction of these variables, and see Section 2 and Equations (4) and (5) for a description of the two specifications.

Table 12. Impact of migration inflows on urban firms—long-term heterogeneous effects on relative factor use depending on factor productivity.

	K/L ratio (1)	(2)	(3)
Migration	-0.377	-0.712	-0.665
	(0.109)	(0.116)	(0.110)
Migration × *High MRPL*	-0.259		
	(0.100)		
Migration × *High MRPK*		0.258	
		(0.111)	
Migration × *High TFPR*			0.189
			(0.111)
Observations	50,606	50,606	50,606

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. The sample is composed of the firms present every year in the NBS firm census between 2001 and 2006. *Migration* is the immigration rate, i.e., the migration flow divided by destination population at baseline. *Employment* is the (log) number of workers. *High MPL* (resp. *High MPK*, *High TFPR*) is a dummy equal to 1 if the baseline marginal product of labor (resp. marginal product of capital, total factor productivity) is above the median within a sector × prefecture. See Section 4 for the construction of these variables, and see Section 2 and Equation (6) for a description of the IV specification.

FOR ONLINE PUBLICATION

A Migration flows: construction and description

In this section, we provide elements of context about migration in China, focusing on the *hukou* system and its implementation over time and across provinces. We describe the construction of migration flows from retrospective questions, and the adjustment accounting for return migration. Finally, we discuss key descriptive statistics.

A.1 Elements of context

An important feature of China's society is the division of the population according to its household registration or *hukou* status.[38] Chinese citizens are classified along two dimensions: their *hukou* type (*hukou xingzhi*)—agricultural (*nongye*) or non-agricultural (*fei nongye*)—and *hukou* location (*hukou suozaidi*). *Hukou* characteristics, which are recorded in the household registration booklet, may not correspond to actual occupation and location.

Since the inception of the reforms in the late 1970s, rules regarding migration within China have been relaxed. Labor mobility remains subject to legal requirements—e.g., being lawfully employed at destination—, but the large flows of internal migrants that have characterized China's recent development show that barriers are low in practice, at least for individual (as opposed to family) migration. Migrants however seldom gain local registration status and do not enjoy the same rights as the locally registered population. This is likely to impede mobility, reduce migrant workers' bargaining power, and lock them in a position of "second-class workers" (Demurger et al., 2009). Whereas an agricultural *hukou* grants access to land, non-agricultural-*hukou* holders enjoy public services in their cities of registration. We focus below on the challenges faced by agricultural-*hukou* holders settling in urban areas.

The type and place of registration have far-reaching consequences. Access to welfare benefits and public services (e.g., enrollment in local schools, access to health care, urban pension plans, and subsidized housing) is conditional on being officially recorded as a local urban dweller. Subsequently, migrants face a high cost of living in cities and are supposed to return to their places of registration for basic services such as education and health care or they are charged higher fees (Song, 2014). Labor outcomes are also affected as local governments may issue regulations restricting access to job opportunities or rely on informal guidelines to employers to favor local permanent residents. As it became possible for state-owned enterprises (SOEs) to

[38]This subsection draws partly on Chan and Buckingham (2008).

lay off "permanent workers" in the 1990s, regulations were introduced to bar them from employing migrant labor instead (Demurger et al., 2009).

Despite the rigidity of the *hukou* system and the persistently low rate of *hukou* conversion, reforms have progressively been introduced during the structural transformation of China. Since the 1980s, China has experienced a gradual devolution of power from the central to local governments in terms of *hukou* policy and management. As a consequence, rules and implementation vary substantially across places and over time. Provincial governments typically set general guidelines, and more specific rules are then determined by prefectures, which in practice hold the most power over *hukou* policy (Song, 2014). Two major reforms were introduced in recent years. First, the distinction between agricultural and non-agricultural *hukou* was abolished within local jurisdictions in about one third of Chinese provinces. Albeit an important evolution, this reform does not affect rural-urban migrants who come from other prefectures, let alone different provinces. Second, *hukou* conversion rules have been gradually loosened. The main channels to change one's *hukou* from agricultural to non-agricultural used to include recruitment by an SOE, receiving college education or joining the army. These conditions have been relaxed since 2000, especially in small cities and towns that attract fewer migrants (Zhang and Tao, 2012). In larger cities, however, conditions for eligibility are tough, so that *hukou* conversion reforms primarily benefit the richest and highly educated (Song, 2014).

The identification strategy described in Section 2 allows us to deal with the potential endogeneity of migration policy to local factor demand. The predicted, supply-driven migration flows that are used as an instrument for actual flows in our IV strategy are indeed orthogonal to such dynamics.

A.2 Data sources and construction of migration flows

Data description In order to measure migration flows, we use the 2000 Population Census, the 2005 1% Population Survey, also called "2005 Mini-Census," and the 2010 Population Census.

After the beginning of the reforms and loosening of restrictions on mobility, there was a growing disconnect between census data focusing on *hukou* location and the rising "floating population" of non-locally registered citizens. The 2000 Population Census was the first census to acknowledge this gap and record migrants' places of residence—provided they had been living there for more than 6 months (Ebenstein and Zhao, 2015). In addition to the place of residence (at the prefecture level in our data), *hukou* location (province level) and *hukou* type, the 2000 and 2010 Population

Censuses contain retrospective information on the place of residence 5 years before the survey (province level) and the reason for departure if residence and registration *hukou* do not coincide. The 2000 and 2010 Censuses slightly differ in how they record migration: The 2000 (resp. 2010) Census records the year of arrival (resp. departure), censored if migration happened 5 years or more before the interview, and the 2000 (2010) Census provides information on the last prefecture of residence before the move (the prefecture of *hukou* registration).

The 2005 1% Population Survey constitutes a 1.3% [*sic*] sample of the population selected from 600,000 primary census enumeration districts using a three-stage cluster sampling (Ebenstein and Zhao, 2015). All Chinese counties (the level of administration below prefectures) are covered. The sampling weights provided by the National Bureau of Statistics (NBS) account for the underlying proportional probability sampling scheme based on the 2004 population registry of the Public Security Bureau. The 2005 Mini-Census was used to test new ways of recording migration and uses the same questionnaire and definitions as the 2010 Census.

A few caveats are in order. First, the sampling frame of the 2005 1% Population Survey contains only information on population by registration. High-immigration areas could thus be under-sampled. Comparing the flows for 2005 in the 2005 Mini-Census and 2010 Census, we indeed find a small discrepancy that we attribute to coverage issues. Second, the 2005 Mini-Census offers a set of variables similar to standard censuses, but some discrepancies are worth bearing in mind: (i) All three data sources provide prefecture-level information on the place of residence, but it is defined as "current residence" in 2005 and 2010 and thus also captures migrants who have been established at destination for less than 6 months. (ii) The 2000 Census contains prefecture-level information on the place of residence prior to arrival at destination, while the 1% Survey records *hukou* location at the prefecture level, just like the 2010 Census. These two places are one and the same if there is no step migration, i.e., if rural dwellers move directly to their final destinations. Along the same lines, the 2005 Mini-Census records the timing of *departure* from a migrant's place of registration rather than of *arrival* at destination. (iii) The data do not record the place of residence at high enough resolution to unambiguously infer whether a migrant is residing in a rural or urban area. Nevertheless, rural-rural migration represents a small share of emigration from rural areas, mostly explained by marriage—which usually gives right to local registration (Fan, 2008).[39] (iv) We cannot account for migrants who changed their *hukou* location or type. This

[39]In the 2005 Mini-Census, only 4.7% of agricultural-*hukou* holders who migrated between prefectures reported having left their places of registration to live with their spouses after marriage. See Table A14 for further descriptive statistics on reasons for moving.

assumption is quite innocuous given that *hukou* conversion is marginal.

Migration flow construction The retrospective data on migration spells in the Censuses and Mini-Census allows us to construct yearly migration flows over the period 1996–2010. These flows are directly observed rather than computed as a difference of stocks as common in the migration literature.

We construct annual migration flows between all prefectures of origin and destination by combining information on the current place of residence (the destination), the place of registration (the origin), and the year in which the migrant left the origin. One advantage of working with those data is that they cover—or are representative of—the whole population: All individuals, irrespective of their *hukou* status, were interviewed in 2000, 2005 and 2010. However, not all migration spells are observed. We describe below (i) which migration spells are directly observed and which spells are omitted, and (ii) how we can infer some of the unobserved spells and adjust the raw migration flows.

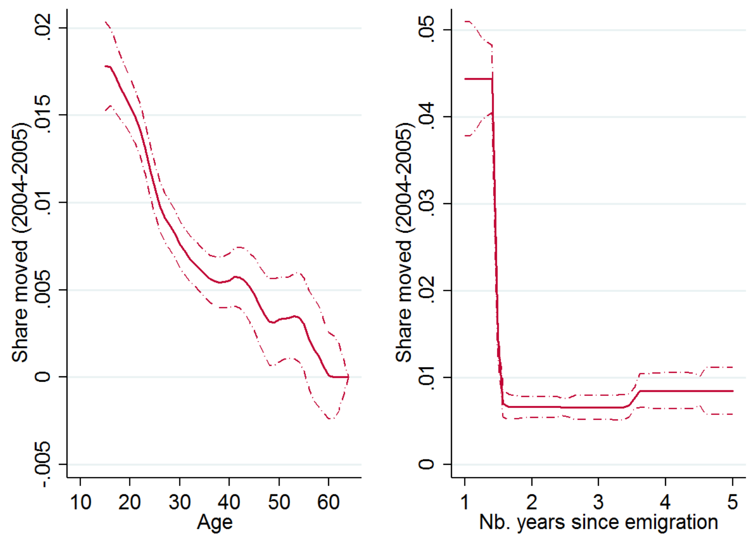
Not all migration spells are observed in the data. We only observe single migration spells, i.e., migration spells in which the interviewed individual is at destination at the time of interview, and whose origin coincides with the *hukou* location. For these individuals, the origin is deduced from their *hukou* location, and the date of their unique relocation is available. All other types of migration histories during the five years preceding the interview are less straightforward to identify.

For instance, if one individual were to leave her *hukou* location to city A in 2002 and then transit to city B in 2005, we would only record the last relocation. In such *step migration* cases, we would correctly attribute arrival dates at destination for the last spell, but we would incorrectly attribute the departure time from origin in the 2000 Census. In the 2005 Mini-Census and 2010 Census, we would incorrectly attribute arrival dates at destination for the last spell, but we would correctly specify the departure time from origin. In both data sets, we would miss arrival in city A. If, instead, one individual were to leave her *hukou* location to city A in 2002 and then return to her *hukou* location by 2005, we would miss her entire migration history. In such *return migration* cases, we would incorrectly omit emigration flows from origins and immigration to destinations.

The incidence of *step migration* and *return migration* spells can, however, be measured. The 2005 Mini-Census records where individuals were living 1 and 5 years before the survey (province level), while the 2000 and 2010 Censuses include a question about the residence 5 years prior to the interview. We can estimate how many migrants report different destinations between 2000 and 2005, which would be a proxy for step migration, and we can observe total return migration between 1995 and 2000, 2000 and 2005, 2004 and 2005, and 2005 and 2010.

We first study the importance of step migration. Among all the migrants who were in their provinces of registration in 2000 and in other provinces in 2005, we compute the fraction that lived in yet another province in 2004. As Figure A3 shows, only a minority of migrants have changed provinces of destination between 2004 and 2005. Step migration is not only low, it is also concentrated in the very first year after the first migration spell. In other words, step migration induces errors in arrival and departure dates that are quite small. As adjusting for step migration would require strong assumptions about the intermediate destination, which is not observed in the data, we do not correct migration flows for step migration.

Figure A3. Share of step migrants as a function of age and time since departure.



Source: 2005 1% Population Survey.
Notes: The sample comprises all working-age (15–64) agricultural-*hukou* holders who were living in a province different from their province of registration in 2004 and left their prefecture of registration less than 6 years prior to the interview.

We then consider the extent of return migration. Among all migrants from rural areas who were living in their provinces of registration in 2000 and in other provinces in 2004, we compute the fraction that had returned to their provinces of registration by 2005. This share is not negligible: In a given year, between 4 and 6% of rural migrants who had left their provinces of registration in the last 6 years go back to their *hukou* locations. Return migration is hence an important phenomenon, which leads us to underestimate true migration flows and the effect of shocks on emigration. Because of the retrospective nature of the data, past flows, for instance in 2000 for an individual interviewed in 2005, are mechanically underestimated. In contrast with step migration, however, it is possible—under reasonable assumptions—to adjust migration flows and account for return migration. We provide below a description of these adjustments.

Adjusting for return migration requires us to observe the destination and duration-specific yearly rate of return. There is a wide disparity in return rates across destinations. Besides, there are non-negligible compositional adjustments along the duration of the migration spell—as in any survival analysis with censoring. Specifically, the probability for a migrant to return home sharply decreases with the length of the migration spell, mostly reflecting heterogeneity across migrants in their propensity to return. Ignoring such heterogeneity would lead us to underestimate return migration for recent flows and overestimate it for longer spells.

To capture variation across destinations and along the length of the migration spell, we make the following assumptions. (i) The "survival" at destination is characterized by a constant Poisson rate f for each migrant. (ii) We suppose that there is a constant distribution of migrant types $H(f)$ *upon arrival.* We allow the distributions to differ across provinces of destination and *hukou* types, i.e., agricultural and non-agricultural. (iii) In order to fit the observed return rates as a function of migration duration, we further assume that:

$$h(f) = \lambda_p^2 f e^{-\lambda_p f}.$$

where λ_p is province- and *hukou* type-specific.

Under the previous assumptions and in a steady-state environment, the evolution of the pool of migrants with duration can easily be computed. In the cross-section (i.e., across all cohorts and not only newly-arrived migrants), the distribution of migrant types is exponential, i.e., $h_c(f) = \lambda_p e^{-\lambda_p f}$, such that the average yearly return rate is $1/\lambda_p$. In all census waves, we observe the *hukou* location, the place of residence five years before the survey, and the place of residence during the survey. This observation allows us to compute the empirical return rate in the cross-section over a period of five years. We calibrate the *hukou*- and province-specific exponential parameter λ_p to match this return rate, and we perform this calibration *in each wave* such that we flexibly allow for long-term fluctuations in these province-specific distributions.

Using the calibrated distribution $H(\cdot)$, we can infer the initial flow of migrants from the number of survivors observed k years later and correct for return migration. More precisely, letting $M_{T,k}$ denote the number of migrants arrived in period $t = T - k$ and recorded in period T, the actual number of newly-arrived migrants in

$t = T - k$ is $\left[(\lambda_p + k)^2/\lambda_p^2\right] M_{T,k}$. We carry out this exercise for the 2000 Census, the 2005 Mini-Census, and the 2010 Census.

One concern with this methodology is that we may not precisely capture the duration-dependence in return rates, and thus over- or underestimate return rates for individuals arriving immediately before the interview. Using the 2005 Survey, we provide an over-identification test by computing the return probability between 2004 and 2005 for recently-arrived migrants (i.e., between 2000 and 2004), and compare it with the empirical moment. We compute this model-based probability under our baseline specification (B) and under an alternative specification (R) where return rates are assumed to be independent of duration.

Figure A4. Over-identification test for the return migration correction.

Source: 2005 1% Population Survey.
Notes: Blue dots correspond to the baseline specification (duration-dependent return rates). Red dots correspond to an alternative specification, where return rates are assumed independent of migration duration.

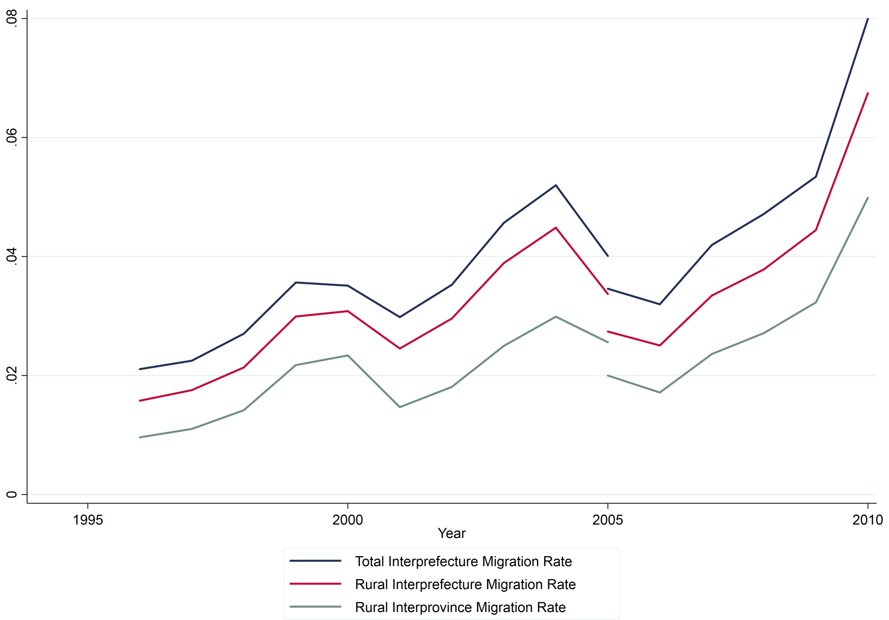
Figure A4 displays the model-based return probabilities for recently-arrived migrants against the actual observed return rate. The baseline specification (B, blue dots) matches well the prefecture-level variation in annual return rate for recently-arrived migrants, while the alternative specification (R, red dots) systematically underestimates the incidence of return. Under the alternative specification (R), the return rate after one year is about half the observed rate—a difference due to the fact that the calibration then ignores the difference between the (high) return rate conditional on a short migration spell and the (low) return rate conditional on longer spells. Note that, even under specification (B), there is noise, and some model-based estimates are quite far from the actual return rates. This difference could be due to fluctuations in return rates across years: While the calibration uses the 2000–2005 period, the validation check focuses on 2004–2005 only.

A.3 Description

In this section, we provide descriptive statistics about migration flows and the selection of migrants.

Migration patterns over time and across regions Migration patterns vary both over time and across origins and destinations. First, there is a general increase in migrant inflows during the period 1996–2010, probably related to the decline in mobility costs and the attractiveness of new buoyant cities. We report in Figure A5 the ratio of annual inter-prefecture migrant flows to the population registered in urban areas. The average annual inflow of migrants from other prefectures is around 3% of the destination population. Figure A5 provides some information about the nature of these migration spells. Migration is mostly rural-urban and long-distance. Over the period 1996–2010, about 80% of the yearly migrant inflows consist of agricultural-*hukou* holders ("rural" migrants), the remainder being urban dwellers originating from other prefectures. About 80% of inter-prefectural rural-urban migrations involve the crossing of a provincial border.

Figure A5. Evolution of migration rates between 1996 and 2010.



Sources: 2000 and 2010 Censuses, and 2005 Mini-Census.

There is a large variation in the spatial distribution of migration inflows and outflows. Some regions (e.g., East and South Central) are net recipients and attract a large share of local migrants, while other regions (e.g., North-West) are net senders. As shown in Table A13, there is significant variation in terms of immigration rates across regions; no region is left aside from the migration phenomenon. Moreover, there is a lot of dispersion of migration spells across destinations. The bottom panel of Table A13 displays the prefecture-level Herfindahl-Hirschmann Index of destination concentration by region of *origin*. Regions differ in terms of destination concentration, but in none of the six main regions do migrants all flock to a single destination.

Table A13. Descriptive statistics of migration flows by region.

	North	North-East	East	South Central	North-West	West
Immigration rate (%), 2000						
In prov., out of pref.	0.37	0.32	0.99	1.47	1.37	0.65
In region, out of prov.	0.61	0.19	1.97	2.89	0.64	0.49
Out of region	1.65	0.37	1.55	2.26	0.38	1.75
Immigration rate (%), 2005						
In prov., out of pref.	0.97	0.77	2.97	3.67	2.92	1.54
In region, out of prov.	1.25	0.80	4.09	7.17	1.15	0.85
Out of region	4.11	0.73	6.71	4.98	0.90	2.42
Destination concentration						
HHI, 2000	0.42	0.30	0.22	0.20	0.22	0.27
HHI, 2005	0.35	0.35	0.21	0.18	0.21	0.36

Notes: Migration flows are corrected for return migration and adjusted for coverage issues in the 2005 1% Population Survey. The top and middle panels display yearly migration rates in 2000 and 2005, respectively, by region of destination. Rates are expressed as a share of the total urban population in the region in 2000. The bottom panel provides standardized Herfindahl-Hirschmann Indices (HHI) of destination concentration by region of origin. Prefecture-level HHIs are averaged by region. The index ranges between 0 and 1: an index of 1 indicates that all migrants from a prefecture of origin move to a single prefecture of destination; 0 indicates perfect dispersion.

Selection of migrants We now provide some descriptive statistics on the profile of internal migrants in China—in terms of education, demographics, and labor market situation. In order to understand the effects of our shocks on emigration and the impact of rural-urban migrants on the urban labor market and firms, it is useful to know the motives behind migration spells and describe the profile of rural migrant workers relative to non-migrants both in rural and urban areas.

Table A14 sheds some light on the motives behind migration. We define migrants as agricultural-*hukou* holders who crossed a prefecture boundary and belong to working-age cohorts (15–64). A vast majority of these migrants (82%) moved away in order to seek work.[40]

Table A14. Descriptive statistics from the 2005 Mini-Census.

Reason for moving	Count	Share of migrants
Work or business	100,670	82.01
Follow relatives	6,474	5.27
Marriage	5,783	4.71
Support from relatives/friends	4,461	3.63
Education and training	1,367	1.11
Other	3,879	3.17

Notes: *Rural migrants* are defined as inter-prefectural migrants with an agricultural *hukou* and aged 15–64. *Urban population* is defined as the population in the prefecture that is either locally registered and holds a non-agricultural *hukou* or resides in the prefecture but holds an agricultural *hukou* from another prefecture. The sample is restricted to inter-prefectural rural migrants.

Rural-urban migrants are a selected sample of the origin population. We provide some elements of comparison between migrants and stayers in Table A15. Migrants tend to be younger, more educated, and more often single than the non-migrant rural population. They are also more likely to be self-employed or employees and to work in the private sector. The rural-urban productivity gap appears to be massive as the migrants' monthly income is more than twice as large as the stayers', which may reflect both selection and different returns to skills in urban and rural areas.

Rural-urban migrants are however also different from urban residents. As is usual with studies of internal migration, we consider in our baseline specification that migrants and locally registered non-agricultural-*hukou* holders are highly substitutable. Table A15 provides summary statistics on key characteristics of inter-prefectural migrants and compares them with the locally registered urban population. Migrants and natives are significantly different on most accounts, the former being on average younger (and thus less experienced), less educated, more likely to be illiterate, and more often employed without a labor contract. Rural-urban migrants are also over-represented in privately owned enterprises and in manufacturing and construction industries: 91% of them are employed in the private sector as against 42% of locally registered non-agricultural-*hukou* holders; and the share of rural-urban migrants working in manufacturing and construction is 51% and 9%, as against 20% and 4% for urban residents, respectively. Finally, migrants' monthly income is 17% lower than urban residents'.

[40]The only other reasons that display shares in excess of 1% are "Education and training," "Other," "Live with/Seek refuge from relatives or friends," which Fan (2008) identifies as "Migration to seek the support of relatives or friends," or "Following relatives," which should be understood as "Family members following the job transfer of cadres and workers", and "Marriage."

To summarize, (i) migrants are selected at origin, (ii) they choose their destination, and (iii) they differ from urban workers along observable characteristics and in wages conditional on these characteristics. Our empirical strategy, based on exogenous variation in agricultural prices at origin, is affected by the previous issues as follows. First, shocks on agricultural livelihoods push migrants out of their prefectures of residence. The compliers are however selected, and our estimates are a local average treatment effect. In counterfactual experiments, we assume that the characteristics of the marginal migrant do not change with the size of the initial push, or with time. Second, our empirical strategy, based on exogenous bilateral migration incidence, fully accounts for selection of destination. Third, Chinese rural-urban migrants may not compete with urban residents for the exact same jobs. We cannot fully account for imperfect substitutability. Instead, we provide supporting evidence that labor markets are partially integrated: The wages of residents respond to the arrival of immigrants. We further quantify the bias induced by the hypothesis of homogeneous labor in Appendix E.4.

Table A15. Migrant selection (2005 mini-census).

	Rural-urban migrants	Local urban *hukou*	Non-migrant rural *hukou*
Age	30.22	38.54	37.43
Female	0.49	0.49	0.51
Married	0.64	0.76	0.75
Education:			
Primary education	0.20	0.08	0.34
Lower secondary	0.60	0.33	0.47
Higher secondary	0.14	0.33	0.09
Tertiary education	0.02	0.24	0.01
Unemployed	0.00	0.00	0.00
Self-employed/Firm owners	0.15	0.08	0.07
Employees	0.66	0.46	0.11
...of which:			
Public sector	0.11	0.72	0.21
Private sector	0.89	0.28	0.79
Out of the labor force	0.15	0.43	0.23
Monthly income (RMB)	961.8	1157.1	408.6
Hours worked per week	55.19	45.88	45.41
Industry:			
Agriculture	0.05	0.06	0.78
Manufacturing	0.51	0.20	0.08
Construction	0.09	0.04	0.03
Wholesale and retail trade	0.15	0.14	0.04
Other tertiary	0.20	0.51	0.06
Observations	122,756	509,817	1,176,791

Notes: All variables except *Age*, *Monthly income*, and *Hours worked per week* are dummy-coded. The sample is restricted to individuals aged 15–64. Descriptive statistics for *Monthly income (RMB)*, *Hours worked per week*, and industrial sectors are restricted to individuals who reported positive working hours in the past week.

B Shocks to rural livelihoods

Our identification strategy relies on exogenous variation in agricultural livelihoods. The baseline specification uses international prices, weighted by fixed prefecture-specific cropping patterns, to predict outflows of migrants from rural areas. The methodology is detailed in Section 2.

In this Appendix, we first illustrate the source of cross-sectional variation, i.e., the disparity in cropping patterns across Chinese prefectures. We then analyze our time-varying shocks, and we show that international prices vary substantially from one year to the next, as well as across crops, and that they translate into large fluctuations in domestic returns to agriculture. Finally, we generate similar shocks to rural livelihoods based on rainfall and crop-specific growing cycles.

B.1 Crop suitability and use across Chinese prefectures

In order to assign crop-specific international price shocks to prefectures, we weight prices by the expected crop share in agricultural revenue. We estimate agricultural revenue using potential yields and harvested areas in 2000. Harvested areas come from the 2000 World Census of Agriculture, which provides a geo-coded map of harvested areas for each crop at a 30 arc-second resolution (approximately 10 km). We overlay this map with a map of prefectures and construct total harvested area h_{co} for a given crop c and a given prefecture o. Yields come from the Global Agro-Ecological Zones (GAEZ) Agricultural Suitability and Potential Yields dataset. The GAEZ dataset uses information on crop requirements (i.e., the length of the yield formation period and stage-specific crop water requirements) and soil characteristics (i.e., the ability of the soil to retain and supply nutrients) to generate the potential yield for each crop and soil type, under different levels of input and both for rain-fed and irrigated agriculture. We use the high-input scenarios and weight the rain-fed and irrigated yields by the share of rain-fed and irrigated land in harvested areas in 2000 to construct potential yield q_{co} for each crop c and prefecture o.

Table B16 shows the variation in harvested areas across prefectures, by crop and region. We focus on the four most important crops—rice, wheat, maize, and soy—and on the high-input scenarios. As expected, some crops are more spatially concentrated than others, both within and across regions. Rice, for instance, is absent from the colder and drier northern regions. Table B16 however shows that there is substantial regional variation, and no crop is cultivated in a single region, or a region specializing in a single crop. A large part of the cross-sectional variation that we exploit does not come from regional differences, but from more local and granular disparities across prefectures.[41] The table shows that there is also substantial variation within regions. Wheat, for instance, is widely grown in the North but displays a large variation in terms of harvested areas across the prefectures of this region.

Table B16. Variation in price shocks and harvested areas by region.

	North	North-East	East	South Central	North-West	West
Harvested area						
Rice, rain-fed	0.000	0.001	0.026	0.041	0.023	0.000
Rice, irrigated	0.119	0.432	0.935	0.715	0.474	0.083
Wheat, rain-fed	0.066	0.016	0.173	0.139	0.141	0.081
Wheat, irrigated	0.706	0.038	0.696	0.789	0.257	0.332
Maize, rain-fed	0.126	0.375	0.208	0.180	0.287	0.094
Maize, irrigated	0.428	0.215	0.317	0.281	0.062	0.160
Soy, rain-fed	0.045	0.094	0.113	0.061	0.086	0.035
Soy, irrigated	0.071	0.028	0.064	0.038	0.015	0.025
Price shock						
Within variation	0.494	0.167	0.248	0.140	0.268	0.690
Between variation	0.283	0.465	0.420	0.481	0.409	0.173

Notes: This table displays the variation in harvested area and prices. The top panel shows between-prefecture variation (measured by the standard deviation and averaged by region over the period 1998–2007) in harvested area for the main crops under irrigated and rain-fed agriculture. Harvested area refers to the normalized area under cultivation. The bottom panel shows the within- and between-prefecture variation (estimated by ANOVA and averaged by region over the period 1998–2007) in the price shock variable.

B.2 International price variation and domestic prices

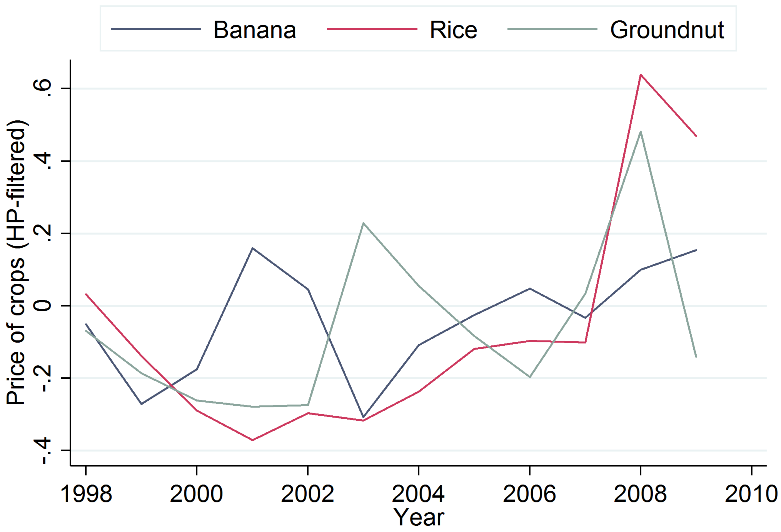
The construction of our shocks to rural livelihoods relies on time variation in international commodity prices. This strategy hinges on two assumptions.

A first assumption is that short-term fluctuations in international crop prices are quantitatively relevant. Figure B6 plots the evolution of international prices for a selection of crops and shows that there are large swings followed by a gradual return to the mean—similarly to AR(1) processes with jumps. Importantly, many different crops display such (uncoordinated) fluctuations over time. We interpret these short-term fluctuations as random shocks on the international market due to fluctuations in world supply and demand for each crop.

The second assumption is that local prices are not insulated from world market fluctuations. Table B17 confirms that international price variations do translate into price fluctuations on the Chinese domestic market. The first column provides the

[41] An illustration of these regional differences is also provided in Figure 1 of the paper.

Figure B6. Price deviations from trends on international commodity markets, 1998–2010.



Source: authors' calculations using the World Bank Commodities Price Data ("The Pink Sheet"). Notes: These series represent the Hodrick-Prescott residual applied to the logarithm of international commodity prices for three commodities: banana, rice, and groundnut. For instance, the price of rice can be interpreted as being 35% below its long-term value in 2001.

correlation between Chinese domestic prices and international prices for different crops in different years. A 10% increase in international prices yields a 4% hike in domestic prices, which constitutes a substantial pass-through from the international to domestic markets. The second column looks at the logarithm of output as the dependent variable and explains it by international and domestic prices. We can see that both prices are positively associated to crop production over the period of interest. While output and local prices are both determined by local demand and supply, international prices better explain the variation in local output than local prices. One explanation could be that local demand and local supply have opposite effects on the co-movement of output and prices, while international price shocks are pure demand shocks from the viewpoint of Chinese producers.

B.3 Shocks over time and across regions

The shocks to rural livelihood exhibit variation both across space and over time. The bottom panel of Table B16 provides between- and within-region variation in the price shock for six major regions (between-variation is measured in 2000). Reassuringly for our identification strategy, all regions experience significant fluctuations in the price shocks, both across prefectures and over time. Figure B7 displays the price

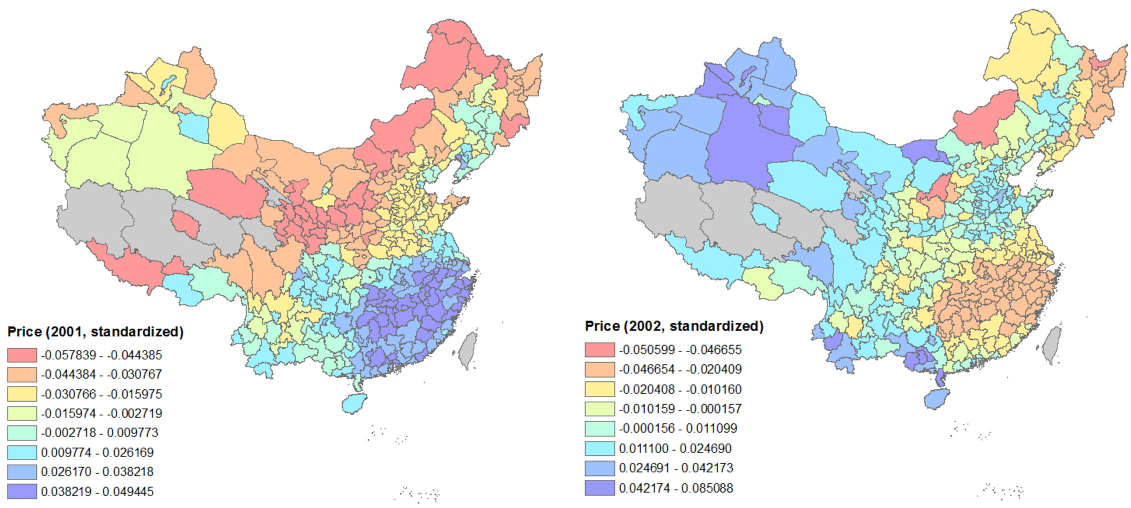
Table B17. Correlation between crop international prices and local Chinese prices/production.

	Price (1)	Output (2)
Price (International)	0.402	0.201
	(0.086)	(0.062)
Price (China)		0.082
		(0.043)
Observations	210	210
R-squared	0.579	0.337

Notes: Standard errors are reported between parentheses and clustered at the crop level. The unit of observation is a crop × year. Both regressions include a time trend and crop fixed effects and are weighted by the average crop production (in tons) over the period 1995–2010. All variables are in logs.

shocks in 2001 (left panel) and 2002 (right panel).

Figure B7. Shocks to rural livelihoods across Chinese prefectures in 2001 and 2002.



(a) 2001

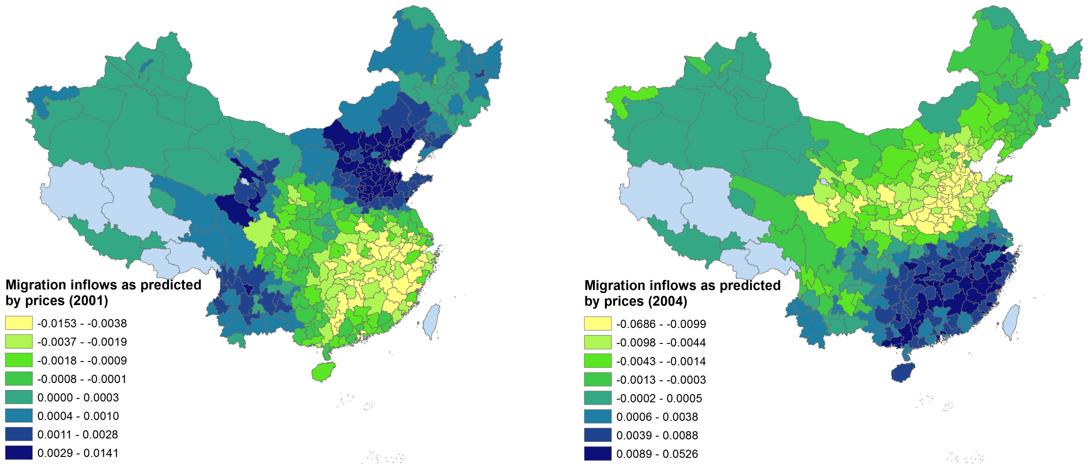
(b) 2002

Notes: These two maps represent the standardized price shock, p_{ot}, in 2001 (left panel) and 2002 (right panel). Note that, in 2001, the price of rice decreased, which generated a very negative shock across China concentrated in rice-producing prefectures.

These cross-sectional and time variations carry over from the price shocks to the "push" instrument, i.e., the predicted flows of immigrants. Figure B8 represents the supply-push instrument at the prefecture level in 2001 (left panel) and 2004 (right panel), as predicted by agricultural price shocks in prefectures of origin.

While there is substantial variation across prefectures in migration inflows, the

Figure B8. Predicted migrant flows to cities in 2001 and 2004.



(a) 2001 (b) 2004

Notes: These two maps present $\widehat{m_{d,2001}}$ and $\widehat{m_{d,2004}}$ after partialling out prefecture fixed effects. $\widehat{m_{dt}}$ is a prediction of migrant inflows based on agricultural price variations at origin and migration patterns between origin and destination.

underlying cropping patterns induce non-negligible spatial correlation. We quantify this spatial auto-correlation in Figure B9, where we report an "Incremental Spatial Autocorrelation" analysis. This analysis shows that spatial auto-correlation fades away beyond 500–600 km and is similar at 300 km and at the maximum distance to a destination's centroid.

B.4 An additional source of variation: rainfall shocks

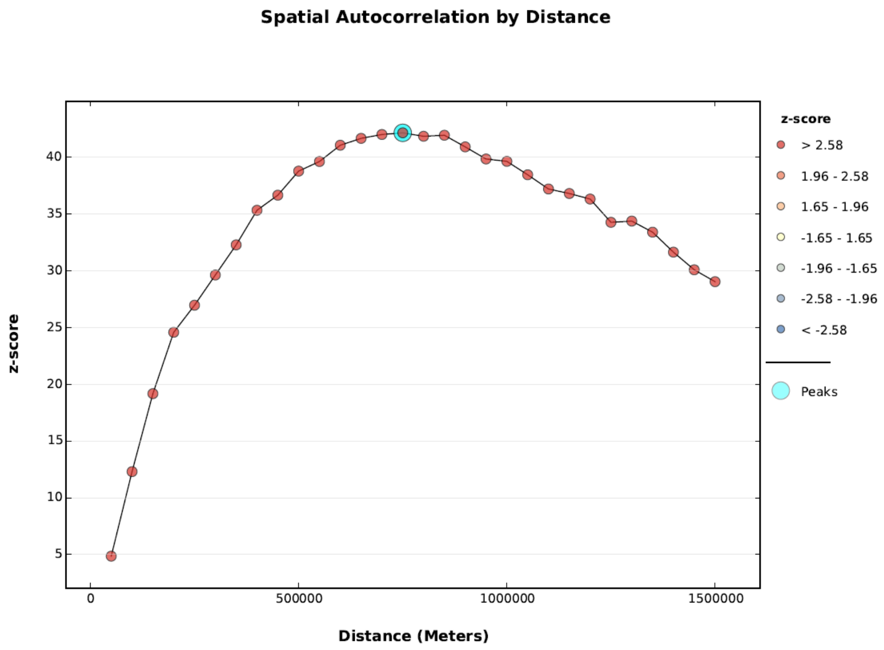
As a robustness check, we construct a second type of shocks to agricultural income based on rainfall deficit during the growing period of each crop. This Appendix describes how we construct these alternative shocks; the results of the robustness checks are displayed in Table D20.

The monthly precipitation measure (0.5 degree latitude × 0.5 degree longitude precision) covers the period 1901–2011 and relies on the Global Historical Climatology Network.[42] Once collapsed at the prefecture level, this provides us with a measure ra_{omt} of rainfall for prefecture o in month m and year t.

We refine this rainfall measure to account for the growing cycle of each crop, i.e., (i) the harvest season and (ii) crop-specific rainfall requirements. For a given year, there are several sources of variation across Chinese prefectures in actual yields

[42]UDel_AirT_Precip data was provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their website at http://www.esrl.noaa.gov/psd/.

Figure B9. Spatial auto-correlation in migration inflows (2001).



Notes: This figure represents the outcome of the Incremental Spatial Autocorrelation tool in ArcGIS (migration inflows in 2001). The x-axis is a certain distance band, and the y-axis reports the p-value associated with the Global Moran's I.

due to rainfall. First, different locations receive different levels of rainfall. Second, exposure to rainfall depends on the growing cycle of the different harvested crops (winter, spring or summer/fall crops). In addition, some crops are resistant to large water deficits, while others immediately perish with low rainfall. The large cross-sectional variation in each year may come from (i) a direct effect of local rainfall and (ii) an indirect effect coming from the interaction with the crop-specific growing cycle and the variety of crops grown across China.

We rely on the measure ra_{omt} of rainfall for prefecture o in month m and year t, and we construct for each crop a measure wr_c of the minimum crop-specific water requirement during the growing season M_c as predicted by the yield response to water.[43] We then generate

$$r_{ot} = \left(\sum_c \left(\frac{\max\{\sum_{m \in M_c} wr_c - ra_{omt}, 0\}}{wr_c} \right)^{\alpha} h_{co} y_{co} \bar{P}_c \right) / \left(\sum_c h_{co} y_{co} \bar{P}_c \right). \quad (14)$$

This measure has a very intuitive interpretation. The ratio $\frac{\max\{\sum_{m \in M_c} wr_c - ra_{omt}, 0\}}{wr_c}$ is the deficit between actual rainfall and the minimum crop water requirement wr_c

[43] http://www.fao.org/nr/water/cropinfo.html.

during the growing season. We penalize this deficit with a factor α capturing potential non-linearities in the impact of rainfall deficit. In our baseline specification, this penalization parameter α is set equal to 3.[44] Finally, we weight rainfall deficits by potential output for each crop in each prefecture to obtain a measure of rainfall deficits for each prefecture $\times$ year. Rainfall deficits exhibit large year-to-year variation, and because of geographical variation in cropping patterns, the spatial auto-correlation of rainfall shocks is much lower than that of rainfall itself.

[44] The results are robust to more conservative values for α, e.g., $\alpha = 1$ or $\alpha = 2$.

C Data sources and descriptive statistics

In this section, we describe the establishment-level data and the Urban Household Survey, used to capture the wage of urban residents. We then provide additional descriptive statistics about general trends of the Chinese economy that are also captured in our data.

C.1 Firm-level data

We present here in greater detail the firm-level data. We first summarize the main characteristics of the data and present some descriptive statistics. We then discuss some possible issues and how we tackle them.[45]

Description The firm data come from the National Bureau of Statistics (NBS). The NBS implements every year a census of all state-owned manufacturing enterprises and all non-state manufacturing firms with sales exceeding RMB 5 million, or about $600,000 over that period. This threshold gives the data their common name of "above-scale" manufacturing firm surveys (*"xian'e"* or *"guimo yishang" gongye qiye diaocha*), despite the fact that the data constitute a census of state-owned enterprises irrespective of their size.

The data cover the manufacturing sector—Chinese Industrial Classification (CIC) codes 1311–4392—over the period 1992–2009. The set of variables changes across years: to ensure consistent outcome measures, we restrict ourselves to 2001–2006. We focus on the balanced panel of firms in most of our analysis. In contrast with firm-level data in developed countries, matching firms over time in the NBS is difficult because of frequent changes in identifiers. In order to match "identifier-switchers," we use the fuzzy algorithm developed by Brandt et al. (2014), which uses slowly-changing firm characteristics such as its name, address, and phone number, and extend it to 1992–2009. While total sample size ranges between 150,000 and 300,000 per year, we end up with 80,000 firms when we limit the sample to the balanced panel.

Although we use the term "firm" in the paper, the NBS data cover "legal units" (*faren danwei*). This implies that different subsidiaries of the same enterprise may be surveyed, provided they meet a number of criteria, including having their own names, being able to sign contracts, possessing and using assets independently, assuming their liabilities, and being financially independent. While this definition of units

[45] Please refer to Brandt et al. (2014) for an exhaustive treatment. This section partly summarizes the challenges that they highlight.

of observation may be unfamiliar to readers accustomed to U.S. or European data, "legal units" almost perfectly overlap with plants in practice, which is also true of establishments in the U.S. In 2007, almost 97% of the units in our data corresponded to single-plant firms.

The data contain a wealth of information on manufacturing firms. Besides the location, industry, ownership type, exporting activity, and number of employees, they offer a wide range of accounting variables (e.g., output, input, value added, wage bill, fixed assets, financial assets, etc.). We use these variables to construct the firm-level measures of factor choices, costs, and productivity.

Table C18 displays descriptive statistics for the sample of all firm $\times$ year observations over the period 2001–2006, the balanced panel, and the sub-samples of new entrants and exiters. Firms of the balanced panel are larger and more capitalized than the average firm (see Panel A). By construction, they are also more likely to be publicly owned.[46] The difference between the balanced panel and whole sample comes from inflows (new entrants) and outflows (exiters). The third and fourth columns of Table C18 better characterize these two categories of firms. Firms on the brink of exit are small, under-capitalized, unproductive, and less likely to be located in an industrial cluster. New entrants are equally small and under-capitalized, but they are comparatively productive.

The period of interest is a period of public sector downsizing. While private firms still accounted for a relatively small share of the economic activity in the 1990s, they represented over 80% of total value added by the end of the 2000s. We see part of these trends in our sample with new entrants being disproportionately privately owned.

Possible issues The NBS data raise a number of challenges. We now discuss these issues and explain how we take them into account.

First, the RMB 5 million threshold that defines whether a non-publicly owned firm belongs to the NBS census was not perfectly implemented. Surveyors do not know the exact level of sales before implementing the survey, and some firms only entered the database several years after having reached the sales cut-off.[47] Figure 2 however shows that this is unlikely to be a serious issue, as the threshold is quite sharp. Firms that are below the threshold represent but a small share of the total

[46] Ownership type is defined based on official registration (*qiye dengji zhuce leixing*). Out of 23 exhaustive categories, Table C18 uses three categories: (i) state-owned, hybrid or collective, (ii) domestic private, and (iii) foreign private firms, including those from Hong Kong, Macau, and Taiwan.

[47] Conversely, about 5% of private and collectively owned firms, which are subject to the threshold, continue to participate in the survey even if their annual sales fall short of the threshold.

Table C18. Firm characteristics (2001–2006).

	All firms	Balanced 2001–2006	Exiters	Entrants
Panel A: Outcome variables				
Labor cost	2.53	2.52	2.32	2.56
	(0.66)	(0.66)	(0.76)	(0.64)
Employment	4.71	5.14	4.21	4.47
	(1.10)	(1.09)	(1.09)	(1.03)
K/L ratio	3.70	3.89	3.61	3.51
	(1.23)	(1.13)	(1.34)	(1.29)
Value added	8.51	8.88	7.72	8.30
	(1.41)	(1.44)	(1.42)	(1.33)
Panel B: Characteristics				
Public	0.14	0.20	0.13	0.06
	(0.34)	(0.40)	(0.33)	(0.24)
Export	0.22	0.32	0.17	0.20
	(0.41)	(0.47)	(0.38)	(0.40)
Large	0.17	0.26	0.05	0.12
	(0.37)	(0.44)	(0.22)	(0.32)
High-skill	0.51	0.52	0.52	0.51
	(0.50)	(0.50)	(0.50)	(0.50)
Old	0.16	0.18	0.20	0.17
	(0.36)	(0.38)	(0.40)	(0.37)
Unionized	0.08	0.12	0.05	0.06
	(0.27)	(0.32)	(0.23)	(0.24)
Ind. park	0.11	0.11	0.04	0.12
	(0.32)	(0.31)	(0.19)	(0.32)
Observations	1,707,231	303,636	374,374	723,093

Notes: NBS firm-level data (2001–2006). Standard deviations are reported in parentheses. All variables in Panel A are in logarithms. All variables in Panel B are dummy-coded and defined for the first year in the sample. *Public* is equal to 1 if the firm is state- or collective-owned in 2001. A similar definition applies to *Export*, *Unionized*, and *Ind. park*, which are equal to 1 if the firm exported, had a trade union, and operated in an industrial park in the first year, respectively. *Large*, *Old*, and *High Benefits* are defined as equal to 1 if the firm belonged to the top 25% of the distribution in terms of size, age, and share of benefits (e.g., housing and pensions) in total compensation. *High-skill* is equal to 1 if the firm belongs to an industry with an above-median share of tertiary-educated employees.

sample and dropping them does not affect the results.

Second, the truncation due to sample restrictions on private and collective firms potentially introduces a selection bias. While the NBS data offer a *census* of state-owned enterprises, the sample tends to over-represent productive private firms that report high sales given their number of employees. This concern about representativeness should however be alleviated by the fact that our firms account for 90% of total gross output in the manufacturing sector.

Third, firms may have an incentive to under-report the number of workers as firm size serves as basis for taxation by the local labor department. This could be of particular concern with migrants, who represent a large share of the workforce and may be easier to under-report. Along the same lines, workers hired through a "labor dispatching" (*laodong paiqian*) company are not included in the employment variable. Migrant workers might thus be under-counted in the firm data. Wage bill may also be slightly under-estimated as some components of worker compensation are not recorded in all years, e.g., pension contributions and housing subsidies, which are reported only since 2003 and 2004, respectively, but accounted for only 3.5% of total worker compensation in 2007.

Fourth, some variables are not documented in the same way as in standard firm-level data. Fixed assets are reported in each data wave by summing nominal values at the time of purchase. We use the procedure developed in Brandt et al. (2014) to account for depreciation: (i) We calculate the nominal rate of growth in the capital stock (using a 2-digit industry by province average between 1993 and 1998) to compute nominal capital stock in the start-up year. (ii) Real capital in the start-up year is obtained using a chain-linked investment deflator (based on separate price indices for equipment-machinery and buildings-structures, and weighted by fixed investment shares provided by the NBS). (iii) We move forward to the first year in the database, assuming a rate of depreciation of 9% per year and using annual deflators. (iv) Once a firm enters the database, we use the nominal figures provided in the data to compute the change in nominal capital stock in a given year, and deflate it. If past investments and depreciation are not available in the data, we use information on the age of the firm and estimates of the average growth rate of nominal capital stock at the 2–digit industry level between 1993 and the year of entry in the database.

C.2 Descriptive statistics

In this section, we provide additional descriptive statistics to inform two crucial aspects of the quantitative analysis: (i) the heterogeneity in factor use across manufacturing firms, 2-digit industries and prefectures, and (ii) general trends in manufacturing between 2001 and 2006, in particular wage and productivity growth.

A large literature has documented the heterogeneity in returns to factors across space (Bryan and Morten, 2015), including in China (Brandt et al., 2013). Our period of interest coincides with lower restrictions to labor mobility and large migration flows, which may increase dispersion in economic activity (thus more concentrated in productive areas) and reduce dispersion in returns to factors (Tombe and Zhu, 2019). We provide some evidence of these patterns in Table C19, where we report the dispersion in aggregate factor use and factor productivity across prefectures and 2-digit industries in 2001 and 2006.

Table C19. General trends in China (2001–2006).

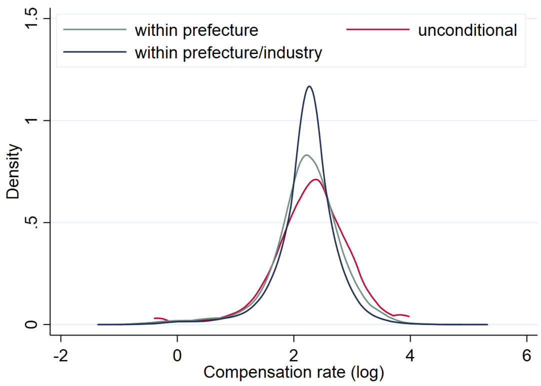
	2001			2006			
	Mean	25^{th}	75^{th}	Mean	25^{th}	75^{th}	Growth
Labor cost	2.01 (0.52)	1.70	2.35	2.77 (0.46)	2.44	3.04	13%
Employment	7.31 (1.74)	6.15	8.58	8.08 (1.82)	6.82	9.39	13%
Capital	11.38 (2.19)	9.94	12.92	12.35 (2.28)	10.85	13.94	17%
Y/L ratio	3.00 (1.07)	2.40	3.68	4.22 (0.85)	3.69	4.28	22%
Y/K ratio	-1.09 (1.00)	-1.66	-0.43	-0.06 (0.83)	-0.56	0.46	18%

Notes: NBS firm-level data (2001–2006). Standard deviations are displayed in parentheses. This table displays descriptive statistics from the unbalanced firm-level data aggregated at the prefecture × 2-digit industry × year level. *25^{th} (75^{th})* stands for the 25^{th} (75^{th}) percentile. The growth rate is the annualized 5-year growth between 2001 and 2006. *Capital* is the logarithm of real capital, constructed thanks to the procedure developed in Brandt et al. (2014) and described in Appendix C. *Y/L ratio* (resp. *Y/K ratio*) is the logarithm of the ratio of value added to employment (resp. capital).

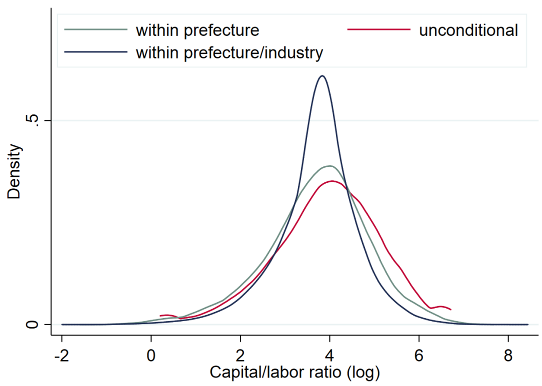
Table C19 provides the following insights. First, aggregate factor use and factor productivity markedly increased over the period. This pattern reflects the rise in productivity in Chinese cities and the associated reallocation of factors. Second, while the dispersion of employment across prefectures/industries remained more or less stable (as captured by coefficients of variation in 2001 and 2006), the dispersion of labor returns decreased. This observation is consistent with the improved factor reallocation already documented in Brandt et al. (2013) and Tombe and Zhu (2019). Third, consistent with the previous insight, there is a marked decrease in the dispersion of wages.

Table C19 however misses an important aspect of heterogeneity across production units in China: A large share of this heterogeneity is driven by differences *within* the same prefecture × industry. Our quantitative analysis points to this heterogeneity as instrumental in understanding the impact of labor inflows on the urban economy. In Panel (a) of Figure C10, we quantify its relative importance. More precisely, we compute (i) the unconditional distribution of labor costs (as a measure of factor return) and the capital-to-labor ratio (as a measure of factor use), (ii) the same distribution cleaned of prefecture differences, and (iii) the same distribution cleaned of prefecture × industry differences. Controlling for disparity across prefecture × industry only reduces overall dispersion by 54%, thereby showing that the granular allocation of factors within a prefecture × industry is not trivial at the aggregate level.

Figure C10. Dispersion in labor cost and capital-to-labor ratio across firms.



(a) Labor cost.



(b) Capital-to-labor ratio.

Notes: These two figures represent the dispersion in labor cost (left panel) and capital-to-labor ratio (right panel) across firms at baseline, in 2001. The red line shows unconditional dispersion; the green line cleans for prefecture fixed effects; and the blue line cleans for prefecture × industry fixed effects. Prefecture × industry fixed effects capture 46% of dispersion both in labor cost and capital-to-labor ratio across firms.

D Robustness checks and sensitivity analysis

In this Appendix, we investigate the robustness of our results to variations along the different steps of the empirical method. We first assess the sensitivity of the emigration effect to various definitions of the agricultural shock (first step of the empirical analysis). We then provide alternative ways to distribute migrants across destinations (second step of the empirical analysis) and vary the definition of migrant flows. Third, we provide complements to the empirical analyses of Sections 3 and 4.

D.1 Emigration and agricultural shocks

Placebo The exclusion restriction may be violated if price fluctuations could be foreseen. The construction of our shock variable is designed to alleviate this concern. We nevertheless check that rural dwellers do not anticipate adverse changes in their revenues by emigrating before the realization of a price shock. Table D20 shows that the forward shock, i.e., the average residual agricultural income at the end of period t, has little impact on emigration (columns 1 and 2). The coefficient is small and not statistically different from 0 in column 2, when we control for the lagged shock.

Table D20. Origin-based migration predictions—forward price shocks and rainfall shocks

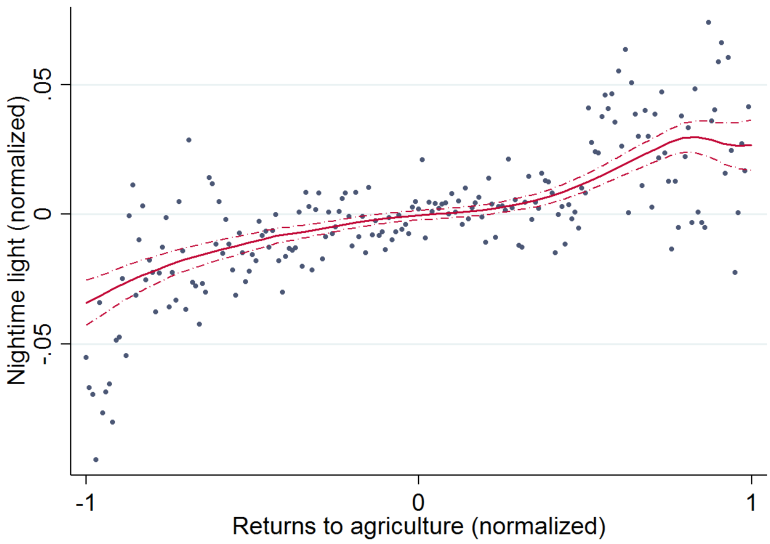
Outmigration	(1)	(2)	(3)	(4)
Price shock (forward)	0.023	-0.004		
	(0.008)	(0.006)		
	[0.035]	[-0.006]		
Rainfall			0.005	0.005
			(0.001)	(0.001)
			[0.095]	[0.094]
Price shock (lag)		-0.107		-0.110
		(0.017)		(0.018)
		[-0.107]		[-0.110]
Observations	2,028	2,028	2,028	2,028
R-squared	0.864	0.868	0.867	0.873
Year FE	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the prefecture level and are reported between parentheses. Standardized effects are reported between square brackets. The outcome variable is the number of rural emigrants to urban areas in year t divided by the number of rural residents.

Alternative shock to rural livelihoods We investigate whether rural emigration reacts to a similar type of agricultural shocks. We compare the effect of commodity prices to that of rainfall, measured using precipitation along the cycle of agricultural crops (see Appendix B.4). The results presented in the third and fourth columns of Table D20 show that rainfall shocks are strong predictors of rural emigration. As expected, a severe rainfall *deficit* reduces the expected output and leads to more emigration. This effect is consistent with that of price shocks: Negative shocks to rural livelihoods lead to more emigration. The fourth column of Table D20 further shows that prices and rainfall constitute two independent sources of variation in rural emigration.

Night lights data We use additional data to show the impact of our shocks on rural livelihoods at a more disaggregated level. We collect night-time lights satellite data between 1996 and 2010, we nest our measure of shocks to agricultural labor productivity at the county level, and we relate changes in average yearly luminosity to the price shock controlling for county- and year-fixed effects (as in Equation 2). We represent the relationship between the price shock and county luminosity in Figure D11.

Figure D11. Push Shocks—evidence from luminosity data.



Notes: This figure illustrates the relationship between the standardized value of the county-specific agricultural portfolio as predicted by international prices (x-axis) and luminosity (y-axis). We consider the residuals of both measures once cleaned by county- and year-fixed effects. For the sake of exposure, we group county × year observations, create bins of observations with similar price shocks, and represent the average night-time luminosity within a bin. The solid line is the output of a locally weighted regression on all observations, and the dotted lines delineate the 95% confidence interval.

D.2 Emigration and immigration flows

Definition of immigration flows In the baseline specification, we use migrant flows of workers between 15 and 64 years old and who crossed a prefecture boundary to construct the emigration rate and the actual and predicted immigration rates. We further rely on migration flows corrected for return migration. In this section, we depart from this baseline and allow for various definitions of a migration spell.

In the first column of Table D21, we show the relationship between the actual and predicted immigration rates when we use the unadjusted measure of migration flows, i.e., raw flows not corrected for return migration (see Appendix A.2). In the second column, we drop intra-provincial flows at all stages of the analysis. In the third column, we use male migrants only, and we consider migrant flows of workers between 18 and 64 in the fourth column. The relationship between predicted and actual migration rates is found to be robust and stable across all specifications (Panel B). The emigration prediction is also unaffected (see standardized effects in Panel A).

Table D21. Origin-based migration predictions—alternative definitions of migration spells

	Emigration			
	(1)	(2)	(3)	(4)
Panel A: Predicting emigration				
Price shock	-0.107	-0.084	-0.049	-0.083
	(0.016)	(0.017)	(0.009)	(0.015)
	[-0.117]	[-0.099]	[-0.089]	[-0.088]
Observations	2,028	2,028	2,028	2,028
R-squared	0.841	0.857	0.864	0.867
	Immigration			
	(1)	(2)	(3)	(4)
Panel B: Predicting immigration				
Supply push	2.607	2.453	2.774	2.698
	(0.807)	(0.917)	(0.889)	(0.862)
Observations	2,052	2,052	2,052	2,052
R-squared	0.801	0.859	0.879	0.870
Migrants	Unadjusted	Out-of-province	Males	18–64

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. Standardized effects are reported between square brackets. The sample is all prefectures every year. The outcome variable in Panel A (B) is the number of emigrants (immigrants) to urban areas in year t divided by the number of rural (urban) residents. All specifications include year- and origin-fixed effects.

Bilateral migration flows In the baseline specification, we use migration patterns from earlier cohorts to construct exogenous probabilities to migrate from each origin to each destination. In this Appendix, we show that an alternative is to estimate a gravity model to predict previous migration (as in Boustan et al., 2010) and use this prediction to redistribute emigration flows across various destinations. We create a measure of travel distance t_{od} between origin o and destination d using the road and railway networks at baseline.[48] We then predict the migration patterns from earlier cohorts λ_{od} using this distance (and the distance as the crow flies) together with a measure of population at destination. This procedure gives us a prediction $\tilde{\lambda}_{od}$ that we can combine with emigration predictions to generate predicted migration flows as in Equation (3).

Table D22. Origin-based migration predictions—gravity equations

		Bilateral flows	
	(1)	(2)	(3)
Panel A: Gravity equation			
Population at destination	0.051	0.048	0.050
	(0.003)	(0.003)	(0.003)
Distance (inverse)	9.454		4.957
	(0.576)		(1.540)
Travel distance (inverse)		6.672	3.366
		(0.371)	(0.935)
Observations	115,599	115,599	115,599
R-squared	0.223	0.223	0.227
		Immigration	
	(1)	(2)	(3)
Panel B: Predicting immigration			
Supply push	0.626	0.704	0.652
	(0.175)	(0.197)	(0.182)
Observations	2,052	2,052	2,052
R-squared	0.860	0.861	0.860

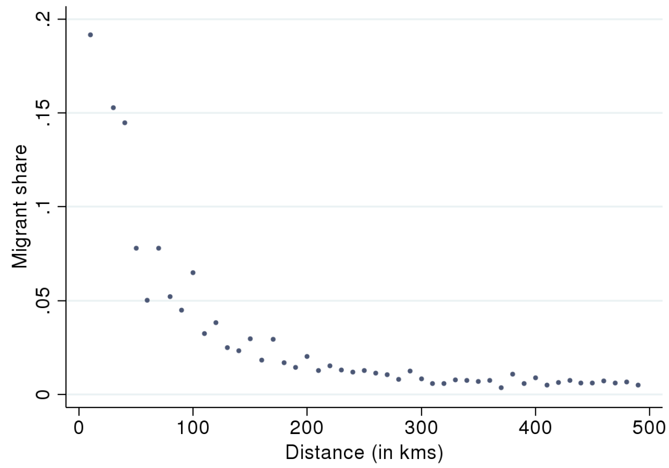
Notes: Standard errors are clustered at the prefecture level and are reported between parentheses. In Panel A, the sample is composed of all couples origin × destination, and the dependent variable is the share of outflows originating from d and going to destination d. In Panel B, the sample is all prefectures every year, and the outcome variable is the number of immigrants to urban areas in year t divided by the number of urban residents. All specifications include year- and origin-fixed effects.

We report the estimated gravity equations in Panel A of Table D22, and the relationship between the constructed and the actual immigration rates is shown in

[48] We also use as-the-crow-flies distance as a robustness check.

Panel B. As apparent in Panel A, both population and bilateral distance (using the as-the-crow-flies or travel distance) are very good predictors of previous migration patterns.[49] Importantly, the immigration prediction is robust to these alternative specifications (see Panel B).

Figure D12. Origin-destination migration predictions—the role of distance.



Notes: Migration flows constructed with the 2000 Census and 2005 Mini-Census. Observations are origin × destination couples and grouped by bins of distance (10 km).

D.3 Worker heterogeneity and compositional effects at destination

UHS data In order to study the impact of immigration on local labor markets and isolate equilibrium effects on wages from compositional effects, we use the Urban Household Survey (UHS) collected by the National Bureau of Statistics. The UHS is a survey of urban China, with a consistent questionnaire since 1986 but considered representative from 2002 onward, and our description will correspond to this latter period. The survey is based on a three-stage stratified random sampling. Its design is similar to that of the Current Population Survey in the United States (Ge and Yang, 2014; Feng et al., 2017) and includes 18 provinces and 207 prefectures. The data are annual cross-sections, with a sample size that ranges from about 68,000 in 2002 to 95,000 individuals in 2008. Our analysis will be restricted to the locally registered urban population.[50]

[49]Figure D12 offers visual evidence of the distance gradient in preferred migration routes. There is a strong and significant inverse relationship between the share of migrants from origin o to destination d (among all migrants from o) and distance between o and d.

[50]While all households living in urban areas are eligible, sampling still ignores urban dwellers living in townships and in suburban districts (Park, 2008). Rural-urban migrants, who are more likely to live in peripheral areas of cities, are therefore underrepresented.

The UHS is a very rich dataset with detailed information on individual employment, income—including monthly wages, bonuses, allowances, housing and medical subsidies, overtime, and other income from the work unit—as well as household-level characteristics—see Feng et al. (2017) for a comprehensive description of the survey. Our measure of real wages relies on monthly wages divided by a prefecture- and year-specific consumer price index, which we compute using the detailed household-level consumption data. We also construct three employment outcomes: wage employment, unemployment, and self-employment (which also includes firm owners).[51] Table D23 provides some descriptive statistics of key variables over the period 2002–2008 and shows that the sample is similar to the locally registered urban *hukou* holders in the Mini-Census data (see Table A15) in terms of demographics and sector of activity, although they tend to be more educated, have a higher probability of being employed, and earn a higher monthly income.

Worker heterogeneity and compositional effects at destination In our baseline analysis, we interpret the decrease in labor cost as a decline in the equilibrium wage. However, compensation per worker may fall due to changes in the composition of the workforce, as less skilled workers enter the manufacturing sector and potentially displace skilled resident workers (Card, 2001; Monras, 2015).

The empirical analysis is based on estimating changes in the wage of urban residents triggered by changes in migrant inflows.[52] The labor market outcome, y_{jdt}, of individual j surveyed in prefecture d and year t is regressed on the immigration rate m_{dt} and its interaction with a dummy L_{jdt}, equal to 1 if individual j has secondary education or below.[53] More formally, we estimate:

$$y_{jdt} = \alpha + \beta_0 m_{dt} + \beta_1 m_{dt} \times L_{jdt} + \delta s_{dt} + \mathbf{X}_{jdt}\gamma + \eta_d + \theta_d \times L_{jdt} + \nu_t + \mu_t \times L_{jdt} + \varepsilon_{jd}, \quad (15)$$

where η_d and θ_d are destination fixed effects, ν_t and μ_t are year fixed effects, s_{dt} are

[51] Working hours in the month preceding the survey were also recorded in UHS 2002–2006. However, as pointed out by Ge and Yang (2014), they vary within a very narrow range, which means that the UHS measure might understate actual variations in working hours. For this reason, we do not use hours of work as a dependent variable in our analysis.

[52] A recent study uses the Urban Household Survey in 2007 to evaluate the wage effect of migrant inflows across Chinese prefectures and finds a *positive* effect (Combes et al., 2015). The present exercise however differs from their analysis along several dimensions. We exploit the quasi-panel structure of the data and fluctuations over time in the arrival of rural workers; our analysis thus estimates a short-run impact. Moreover, we use a time-varying instrument isolating variation in labor supply.

[53] Unskilled urban residents (58% of the sample) are most likely the ones competing for jobs with migrant workers, and hence their response to migration inflows should be different from the rest (Card, 2001; Borjas, 2003).

Table D23. Descriptive statistics from the UHS data (2002–2008).

	Mean	Standard deviation
Age	40.65	9.47
Female	0.45	0.50
Married	0.88	0.33
Born in prefecture of residence	0.61	0.49
Education:		
Primary education	0.02	0.15
Lower secondary	0.23	0.42
Higher secondary	0.27	0.44
Tertiary education	0.48	0.50
Unemployed	0.02	0.15
Self-employed/Firm owner	0.07	0.25
Employee	0.91	0.29
Public sector	0.64	0.48
Private sector	0.36	0.48
Total monthly income (RMB)	1,510	1,394
Hours worked per week	44.45	9.20
Industry:		
Agriculture	0.01	0.10
Mining	0.02	0.14
Manufacturing	0.22	0.42
Utilities	0.03	0.18
Construction	0.03	0.17
Wholesale and retail trade	0.12	0.33
Other tertiary	0.55	0.50
Observations	483,806	

Notes: All variables except *Age*, *Income*, and *Hours worked per week* are dummy-coded. The table displays averages over the period 2002–2008. The sample is restricted to locally registered urban *hukou* holders aged 15–64.

destination × year fixed effects, and $\mathbf{X}_{jdt}$ is a vector of individual characteristics, including marital status, gender, education level and age. We estimate Equation (15) by OLS and in an IV specification where we instrument the immigration rate m_{dt} and the interaction $m_{dt} \times L_{jdt}$ by the supply shock z_{dt} and its interaction with the low-skill dummy, $z_{dt} \times L_{jdt}$.

Table D24 presents the results. Column 1 reports the OLS and IV estimates of β_0 and β_1; the dependent variable is a measure of hourly wages adjusted by the provincial Consumer Price Index. We find no effect of migration on high-skilled wages (workers with tertiary education), but the wage of less skilled workers falls by 0.30% when the migration rate increases by one percentage point. In columns 2 to 4 of Table D24, we analyze the possible displacement of urban residents. Rural-urban migration has no significant effect on the allocation of urban residents between wage employment, unemployment, and self-employment, which implies that the urban residents mostly adjust to an immigration shock by accepting lower wages.

Table D24. Impact of migration inflows on urban residents.

	Wage (1)	Employee (2)	Unemployed (3)	Self-employed (4)
Panel A: OLS estimates				
Migration	-0.023	-0.029	0.010	0.019
	(0.068)	(0.014)	(0.013)	(0.010)
Migration × *Low Skill*	-0.264	0.017	-0.014	-0.003
	(0.039)	(0.014)	(0.010)	(0.015)
Observations	241,039	338,217	338,217	338,217
Panel B: IV estimates				
Migration	0.001	0.090	-0.011	-0.079
	(0.197)	(0.066)	(0.057)	(0.051)
Migration × *Low Skill*	-0.300	0.018	-0.038	0.019
	(0.139)	(0.054)	(0.040)	(0.050)
Observations	241,039	338,217	338,217	338,217
F-stat. (first stage)†	6.44	7.08	7.08	7.08

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. *Low Skill* is defined as a dummy equal to 1 for workers with no education, primary education or lower secondary education. *Wage* is the (log) hourly wage in real terms. *Employee* is a dummy for receiving a wage, while *Self-employed* is a dummy equal to 1 for individuals who are self-employed or employers. All specifications include year and prefecture fixed effects. † The IV specification uses two endogenous variables and two instruments; the critical value for weak instruments is then 7.03 (at 10%).

The decrease in wages of low-skill residents accounts for about 60% of the labor cost response estimated using firm-level data (see Table 3). The discrepancy between the effect on labor cost and the impact on the wage of residents may be due to various reasons. The labor markets of residents and migrants may be partly segmented, and not many residents may be employed in the manufacturing firms of our main sample. Incumbent worker wages may be more rigid than hiring wages. Finally, migrants may be less productive than residents, and the recruitment of lower-productivity workers could account for part of the decline in average labor cost. We provide a higher bound for this compositional effect in Appendix E.4; the compositional effect can, at most, explain a decrease in the labor cost of -0.08% when the migration rate increases by one percentage point. Overall, the analysis of worker data confirms that rural migrant inflows have a strong negative effect on the equilibrium wage in cities, but limited displacement effects.

D.4 Additional robustness checks

Regression weights We provide a sensitivity analysis of our baseline results to alternative weights. More precisely, we show that weights can be omitted from the baseline specification. Table D25 presents the (unweighted) effect of rural-urban migration on labor cost, employment, relative factor use, and value added per worker in the short (Panel A) and in the longer run (Panel B). The estimates are extremely similar to the baseline estimates (see Tables 3 and 5).

Table D25. Impact of migration inflows on urban firms—sensitivity analysis without regression weights.

	Labor cost (1)	Employment (2)	K/L ratio (3)	Y/L ratio (4)
Panel A: Short-run effects				
Migration	-0.436 (0.125)	0.283 (0.053)	-0.233 (0.067)	-0.328 (0.132)
Observations	303,636	303,636	303,636	303,636
Number Firms	50,606	50,606	50,606	50,606
F stat. (first)	21.20	21.20	21.20	21.20
	Labor cost (1)	Employment (2)	K/L ratio (3)	Y/L ratio (4)
Panel B: Long-run effects				
Migration	-0.165 (0.125)	0.468 (0.092)	-0.448 (0.108)	-0.384 (0.162)
Observations	50,606	50,606	50,606	50,606
F-stat. (first stage)	34.40	34.40	34.40	34.40

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. The sample is composed of all firms present every year in the NBS firm census between 2001 and 2006. In Panel A, all specifications include year × industry and firm fixed effects. The instrument is migration predicted using price shocks at origin and previous migration incidence between origins and destinations. In Panel B, the instrument is the average yearly migration rate between 2001 and 2006 predicted using price shocks at origin and previous migration incidence between origins and destinations.

Heterogeneous responses across establishments In this section, we derive additional heterogeneity results (see Section 3 and Table 9 for the baseline analysis).

We explore in Table D26 whether sectoral characteristics matter, notably through the structure of production (elasticity of substitution between labor and capital, and

Table D26. Impact of migration inflows on urban firms—additional heterogeneous treatment effects across firms.

Employment	(1)	(2)	(3)
Migration	0.548	0.470	0.438
	(0.091)	(0.105)	(0.089)
Migration × *Complementarity*	-0.095		
	(0.064)		
Migration × *High-skill*		0.066	
		(0.077)	
Migration × *Public*			-0.046
			(0.166)
Observations	50,606	50,606	50,606

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. The sample is composed of firms present every year in the NBS firm census between 2001 and 2006. *Complementarity* is a dummy equal to 1 if the elasticity of substitution between capital and labor, as measured in Section 4, is larger than its median value across industries. *High-skill* is a dummy equal to 1 for an above-median share of workers with high-school attainment. See Section 2 and Equation (6) for a description of the IV specification.

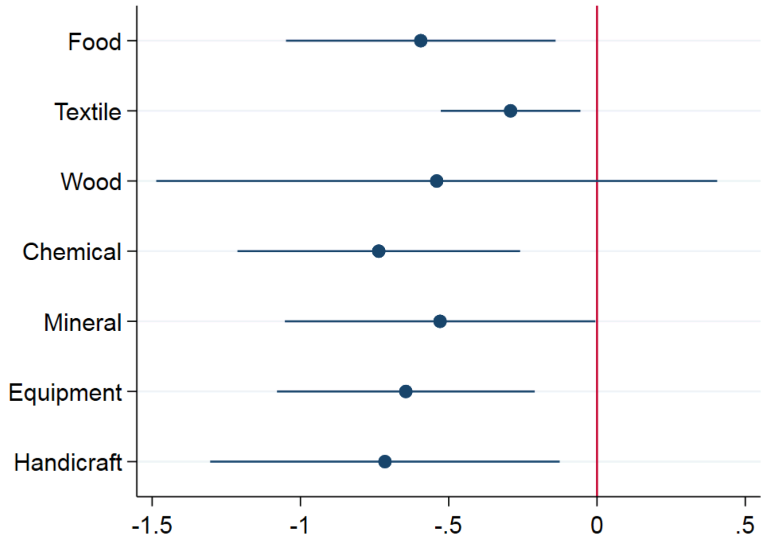
skill requirements). We divide sectors along these two dimensions, and interact the treatment with (i) a dummy equal to 1 if the sectoral elasticity of substitution between capital and labor (as estimated in Section 4) is below the median across industries, and (ii) a dummy for above-median sectoral educational requirement, as calculated from the proportion of workers with high-school attainment or less in 2004 (column 2). We do not find that migrant workers sort themselves into sectors with high elasticity of substitution between capital and labor, or with low education requirements. The interaction coefficient is small and statistically insignificant in both cases.

We also interact the immigration rate with a dummy for public firms (column 3). We find that migrants are less likely to be hired in public establishments, where insiders are likely to receive substantial benefits. The interaction is however statistically significant.

Finally, in spite of power issues, we provide some visual evidence of heterogeneity (or the lack thereof) in the treatment effect on wages across industries in Figure D13. This finding is consistent with fairly integrated labor markets at destination: A similar decrease in wages is observed across 1-digit industries.

Aggregation at the prefecture level In Section 3, we explore the aggregate effects of factor reallocation across firms by aggregating outcomes at the prefecture × sector level. Conceptually, this neutralizes the effect of a possible reallocation of

Figure D13. Impact of migration inflows on wages—heterogeneous treatment effects across industries.



Notes: See Section 2 and Equation (6) for a description of the IV specification (each observation is a prefecture × year). The sample is composed of firms present every year in the NBS firm census between 2001 and 2006.

factors *across sectors*. We now report estimates from our long-term specification (5) with outcomes aggregated at the prefecture level. Table D27 presents the results, which are similar in magnitude to the prefecture × sector level presented in Table 10. The effect of a reallocation of factors across industries on aggregate labor productivity is negligible, as most of the reallocation occurs within sectors. This finding is consistent with the literature in developed countries (Lewis, 2011; Dustmann and Glitz, 2015).

Entry/Exit In Section 3, we present the effect of immigrant flows on aggregate outcomes including all firms in our sample, and we find that allowing for firm entry and exit magnifies the negative effect of migration on relative factor use and labor productivity. Since we only observe firms above a given sales threshold (see Appendix Section C and Figure 2), we only measure entry and exit into and from our sample, which is a combination of actual entry and exit, and of firms growing into and shrinking out of the sample. We use an additional piece of information, i.e., the year the firm was founded, and check whether the year in which establishments enter the sample corresponds to their first year of operation. We label such a case as "real entry". Appendix Table D28 presents results from specification (5), using dummies for entry, real entry, and exit as dependent variables. The sample includes all firms present in 2001, 2006, or both.

Table D27. Impact of migration inflows on urban firms—sensitivity analysis with aggregate variables at the prefecture level.

	Labor cost (1)	Employment (2)	K/L ratio (3)	Y/L ratio (4)
Panel A: Balanced sample of firms				
Migration	-0.285	0.537	-0.570	-0.581
	(0.109)	(0.089)	(0.110)	(0.129)
Observations	304	304	304	304
F-stat. (first stage)	35.85	35.85	35.85	35.85
Panel B: Unbalanced sample of firms				
Migration	-0.413	0.801	-0.886	-1.042
	(0.119)	(0.120)	(0.131)	(0.215)
Observations	309	309	309	309
F-stat. (first stage)	28.99	28.99	28.99	28.99

Notes: Robust standard errors are reported between parentheses. The unit of observation is a prefecture. In Panel A (resp. Panel B), the sample is composed of the firms present every year in the NBS firm census between 2001 and 2006 (resp. all firms present in the NBS firm census between 2001 and 2006); outcomes are then aggregated at the prefecture level. *Migration* is the immigration rate, i.e., the migration flow divided by destination population at baseline. *Labor cost* is the (log) compensation per worker including social security. *Employment* is the (log) number of workers within the firm. *K/L ratio* is the (log) ratio of fixed assets to employment. *Y/L ratio* is the (log) ratio of value added to employment.

We find that migration has no effect on entry into the sample. It has however a negative effect on the probability that a firm is created and appears in the sample. There is a negative and significant effect on the probability that a firm exits the sample. This finding is consistent with one of our main results: migration benefits low-profitability firms and increases the probability to declare some positive profits. This profitability effect allows such establishments to survive, or to remain large enough and appear in our sample of above-scale firms.

Sensitivity to elasticities of substitution In Section 4, we estimate the impact of migration inflows on the product of factors built using our estimation of the industry-specific production function on Chinese firms. We provide in this section a sensitivity analysis relying a Cobb-Douglas production function and on elasticities of substitution as estimated by Oberfield and Raval (2014) on U.S. establishments in 1987 and in 1997.

Table D29 reports the estimates from the long-term specification (5) at the firm-

Table D28. Impact of migration inflows on urban firms—sample entry and exit.

	Entry (1)	Real Entry (2)	Exit (3)
Migration	-0.011	-0.104	-0.102
	(0.065)	(0.081)	(0.040)
Observations	275,663	275,663	275,663
F-stat (first)	36.09	36.09	36.09

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. The unit of observation is an establishment. The sample is composed of all the firms present in 2001, 2006, or both. *Migration* is the immigration rate, i.e., the migration flow divided by destination population at baseline. *Entry* is a dummy variable equal to one if the firm was not present in 2001 but present in 2006. *Real Entry* is a dummy variable equal to one if the firm appeared in the sample between 2001 and 2006 and was founded between these two dates. *Exit* is a dummy variable equal to one if the firm was present in 2001 but had disappeared from the sample in 2006.

level. The main insights from Table 11 are robust to the new calibration: There is a sharp decrease in returns to labor and an increase in the returns to capital. Both features are however attenuated by the Cobb-Douglas specification, which underestimates the complementarity between capital and labor.

Table D29. Impact of migration inflows on product of factors—sensitivity analysis.

	Labor pr. (1)	Capital pr. (2)	Total fact. pr. (3)
Cobb-Douglas	-0.475	0.218	0.089
	(0.168)	(0.152)	(0.165)
CES (sectoral ρ, US 1987)	-0.893	0.510	-0.247
	(0.196)	(0.183)	(0.165)
CES (sectoral ρ, US 1997)	-1.060	0.585	-0.207
	(0.240)	(0.192)	(0.166)
Observations	50,597	50,597	50,597

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. Each cell is the outcome of a separate regression. The sample is composed of the firms present every year in the NBS firm census between 2001 and 2006. *Labor pr.* is the (log) marginal revenue product of labor; *Capital pr.* is the (log) marginal revenue product of capital; *Total fact. prod.* is the (log) total factor productivity in revenue terms. These quantities are computed using a Cobb-Douglas specification (first row), or a CES production function with the elasticities of substitution of Oberfield and Raval (2014) (second and third rows). See Section 4 for details.

E Complements on estimation

This section is organized as follows. We first derive important equations characterizing the optimization program of individual firms. Second, we describe the steps for estimating the main parameters of the model, i.e., the industry-specific elasticity of substitution between capital and labor, the industry-specific factor shares, and the industry-specific elasticity of substitution between product varieties. Third, we provide additional details about the identification of the industry-specific elasticity of substitution between capital and labor (in the short run, i.e., for a given technology). Finally, we discuss the bias induced by the hypothesis of homogeneous labor (i.e., ignoring productivity differences between migrants and established workers).

E.1 Firm optimization

In what follows, we drop sector and prefecture subscripts for the sake of exposure. Letting Y and P denote the aggregate output and prices within a product market (sector $\times$ prefecture), demand for the product variety i is given by,

$$\frac{y_i}{Y} = \left(\frac{p_i}{P}\right)^{-\sigma}.$$

An establishment i in a certain product market maximizes the following program,

$$\max_{p_i, y_i, l_i, k_i} \left\{ p_i y_i - w l_i - r k_i \right\},$$

subject to the production technology,

$$y_i = A_i \left[\alpha_i k_i^\rho + \beta_i l_i^\rho\right]^{\frac{1}{\rho}},$$

and demand for the product variety i. The first-order conditions give:

$$\begin{cases} (1 - 1/\sigma) \dfrac{\alpha_i k_i^\rho}{\alpha_i k_i^\rho + \beta_i l_i^\rho} p_i y_i = r k_i \\ (1 - 1/\sigma) \dfrac{\beta_i l_i^\rho}{\alpha_i k_i^\rho + \beta_i l_i^\rho} p_i y_i = w l_i, \end{cases}$$

Aggregating at the sector level and at first-order, we have:

$$\begin{cases} (1 - 1/\sigma) \dfrac{\alpha \overline{K}^\rho}{\alpha \overline{K}^\rho + \beta \overline{L}^\rho} \overline{PY} = \overline{rK} \\ (1 - 1/\sigma) \dfrac{\beta \overline{L}^\rho}{\alpha \overline{K}^\rho + \beta \overline{L}^\rho} \overline{PY} = \overline{wL}, \end{cases}$$

which characterize factor demand at the sector level. Finally, aggregate profits at the sector level are a fixed proportion of revenues $\overline{\Pi} = \overline{PY}/\sigma$.

E.2 Estimation strategy

The previous equations relate aggregate industry outcomes—which are observed in the data—to the underlying parameters of production α and ρ, and the within-product competition σ.

In order to identify these sector-specific parameters, we proceed in three steps. In a first step, we infer within-product competition σ from the observation of aggregate profits and aggregate revenues:

$$1/\sigma = \overline{\Pi}/\overline{PY}.$$

In a second step, we combine the two first-order conditions, for a given technology, and derive the firm-specific relative factor demand:

$$\ln\left(k_i/l_i\right) = \frac{1}{1-\rho}\ln\left(\frac{\alpha}{\beta}\right) + \frac{1}{1-\rho}\ln\left(w/r\right) + \varepsilon_i,$$

where ε_i depends on the firm-specific technology (α_i, β_i). We identify the parameter ρ using the short-run variation in relative factor prices across prefectures and across years induced by predicted immigration shocks, following the procedure detailed in Section 2. The estimation is described in the next section. In a third step, we use the aggregate first-order condition relating labor costs to revenues in order to identify the last parameter of the model, i.e., the market-specific capital share α:[54]

$$\alpha = \frac{(1-X)\overline{L}^{\rho}}{(1-X)\overline{L}^{\rho} + X\overline{K}^{\rho}},$$

where $X = \overline{wL}/\left[(1-1/\sigma)\overline{PY}\right]$. One important restriction of this empirical strategy is that production parameters cannot be estimated at the product market level (sector $\times$ prefecture). More specifically, the identification of capital-labor complementarity, ρ, will rely on cross-prefecture variation and can only be inferred, at best, at the sectoral level. Thus, given a sector-specific value ρ, both parameters α and σ can only be imputed using aggregate outcomes at the sector level.

[54]We can assume, without loss of generality, that $\beta = 1-\alpha$, as we authorize for the existence of a total factor productivity coefficient outside the CES structure.

E.3 Identification of the elasticity of substitution

A key parameter in the theoretical framework of Section 4 is the elasticity of substitution between labor and capital, η, or equivalently $\rho \equiv \frac{\eta-1}{\eta}$. Following Oberfield and Raval (2014), we use firm data to estimate average elasticities of substitution. We moreover mobilize exogenous variation in relative factor prices from immigration shocks to obtain unbiased estimates. One point of departure with their approach is that we aggregate firm data at the level of prefecture $\times$ broad industrial cluster cells and use the panel dimension of the resulting data set. We now present the specification and discuss the resulting sector-specific estimates.

Specification The strategy for estimating the elasticity of substitution relies on the relative factor demand equation, for a given technology, i.e.,

$$\ln\left(k_{sdt}/l_{sdt}\right) = \frac{1}{1-\rho}\ln\left(\frac{\alpha}{\beta}\right) + \frac{1}{1-\rho}\left(w_{dt}/r_t\right) + \varepsilon_{sdt}, \tag{16}$$

where s denotes a broad industrial cluster, d the prefecture and t the year, and w_{dt} is the average compensation rate in prefecture d at time t. The identification of Equation (16) hinges on variation across prefectures and over time in relative factor prices and requires the following assumptions. First, we assume that ρ and α are constant over time and across all firms in the same sector, in line with Oberfield and Raval (2014). Contrary to their setting, however, we need to aggregate industrial sectors by broader sectoral clusters to obtain consistent estimates.[55] Second, the residual, ε_{sdt}, which captures the sector-specific relative distortions, is assumed to be normally distributed. Third, the rental cost of capital is not observed and is assumed, as in Oberfield and Raval (2014), constant across prefectures. This simplifying assumption—imposed by data limitations—may derive from the incorrect assumption that capital is perfectly mobile within China. The IV strategy will however allow us to use a weaker assumption, i.e., that time variation in the instrument is orthogonal to possible differences in access to capital across prefectures. Fourth, we assume that technological choices are constant in the short run.

We thus estimate, for each broad industrial cluster, the following equation:

$$\ln\left(k_{sdt}/l_{sdt}\right) = a + b\ln\left(w_{dt}\right) + \mathbf{X_{sdt}}\zeta + \varepsilon_{sdt}, \tag{17}$$

where the vector $\mathbf{X_{sdt}}$ contains year $\times$ industry fixed effects. The standard errors

[55] Note that our argument does not hinge on differences across sectors in terms of substitutability between capital and labor, while such differences are central to Oberfield and Raval's (2014) work.

are clustered at the level of the prefecture.

Identification Regressing the relative factor demand on wages poses an identification challenge. For instance, local policies or changes in technologies could affect simultaneously relative factor demand and factor prices.

To purge our estimate of such endogeneity, we adopt the same identification strategy as for the main results presented in this paper.[56] We instrument average prefecture-level wages by local labor supply shocks. The instrument, which affects the relative factor price from the supply side, allows us to identify the elasticity of factor demand to factor prices. Its construction is detailed in Section 2.

The first stage thus writes:

$$\ln\left(w_{dt}\right) = \beta z_{dt} + \mathbf{X_{sdt}}\xi + u_{dt},$$

where z_{dt} stands for the predicted migrant inflow to prefecture d at time t. Our strategy for estimating ρ relies on the same datasets as the rest of the firm analysis (see Section 2). It corresponds to the reduced form of our aggregated results, except that the regression is run separately for different industrial sectors and our dependent variable is the logarithm of mean wages in the prefecture, which is the relevant labor market, rather than in a prefecture $\times$ industry cell.

Results We estimate Equation (17) separately for **four** broad clusters of industry (Agro-industry and Textile; Wood, Petroleum, and Chemicals; Plastics, Minerals, Metal, and Equipment; and Miscellaneous). We report the first stage in Panel A of Table E30 and the second stage in Panel B.

First, instrumenting wages by z_{dt} provides a strong and consistent first stage in the four subsamples of firms defined by the broad industry categories. Second, the elasticities of relative factor demand to relative factor prices, b in Equation (17), differ slightly across sectors and span a similar range as in the U.S. context (Oberfield and Raval, 2014). The values for the elasticities of relative factor demand to relative factor prices imply that the average sector-level elasticities of substitution range between 0.6 and 0.9. The elasticities for the four broad industrial clusters are displayed graphically in Figure E14. Moreover, the IV estimates, shown in Table E30, are not significantly different than the (unreported) OLS estimates.

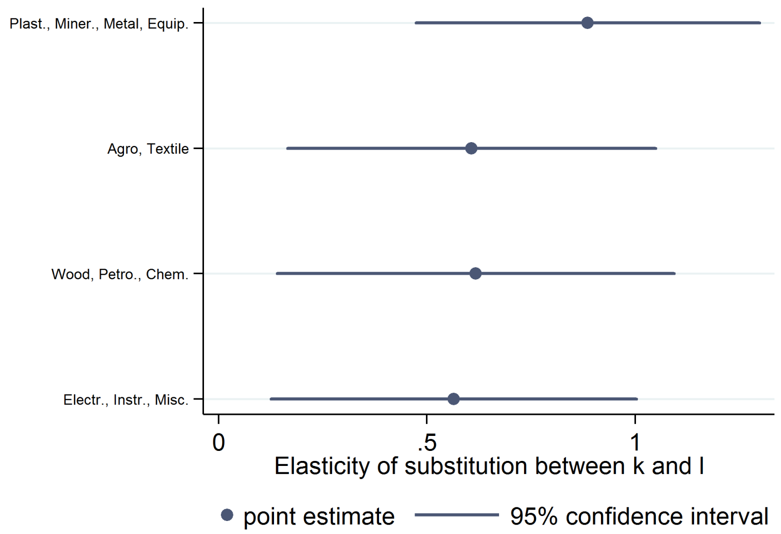
[56] Oberfield and Raval (2014) use a Bartik-style instrument for labor demand, based on the interaction of local industrial composition with the nationwide change in employment in non-manufacturing industries.

Table E30. Elasticities of relative factor cost to relative factor prices across sectors.

	Labor cost			
	(1)	(2)	(3)	(4)
Panel A: First stage				
Predicted immigration rate	-3.37	-2.79	-3.18	-4.87
	(0.59)	(0.49)	(0.50)	(0.70)
	Relative factor cost			
	(1)	**(2)**	**(3)**	**(4)**
Panel B: Second stage				
Labor cost	0.61	0.62	0.89	0.57
	(0.23)	(0.24)	(0.21)	(0.22)
Observations	9,345	11,850	13,499	2,717
F-stat. (first stage)	33.48	33.41	41.52	48.26
Broad sector	Agro.	Petroleum	Metal	Misc.

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. An observation is a prefecture × broad industrial sector × year. *Labor cost* is the average compensation rate in the prefecture—$\ln(w_{dt})$ in Equation (17),—and *Relative factor cost* is $\ln(k_{sdt}/l_{sdt})$. The instrument (*Predicted immigration rate*) is the immigration shock predicted by agricultural price gaps in prefectures of origin, as described in Section 2. The broad clusters are: Agro-industry and Textile; Petroleum, Chemicals, and Wood; Metal, Plastics, Minerals, and Equipment; and Miscellaneous. All four regressions include year and year × sector fixed effects.

Figure E14. Estimates of firm-level elasticities of substitution by broad sector (η).



Notes: This figure represents the average sector-level elasticities of substitution between capital and labor (x-axis), along with 95% confidence intervals, by broad clusters of industry (y-axis). The broad clusters are: Agro-industry and Textile; Wood, Petroleum, and Chemicals; Plastics, Minerals, Metal, and Equipment; and Miscellaneous. The elasticities correspond to $\eta \equiv \frac{1}{1-\rho}$ in Equation (16) and are given by the IV coefficients displayed in Table E30. Standard errors are clustered at the prefecture level.

E.4 Heterogeneous labor and the impact of migration

In the theoretical framework, labor and wage rates are measured in efficient units. In the data, however, the corresponding variables (*employment* and *labor cost*) do not allow us to distinguish between worker types, and we cannot compute efficient units. This limitation may bias our estimates. More specifically, we may attribute part of the decrease in the observed labor cost to labor market adjustments, when it reflects low productivity of the marginal migrant. This bias could also affect the response of measured returns to factors.

Heterogeneous labor In this section, we allow workers to differ in productivity and assume that these differences are observable to the manufacturing firm. Consider two worker types, residents indexed by r and migrants indexed by m, and let $h = l_r + \gamma l_m$ denote efficient labor units, where $\gamma < 1$ and $l = l_r + l_m$ is observed employment. For the sake of exposure, we consider the average production technology,

$$y = A\left[\alpha k^{\rho} + \beta h^{\rho}\right]^{\frac{1}{\rho}}.$$

The first-order conditions give us:

$$\begin{cases} MPL = (1 - 1/\sigma)\dfrac{\alpha k^{\rho-1}}{\alpha k^{\rho} + \beta h^{\rho}} py = r \\ \\ MPK = (1 - 1/\sigma)\dfrac{\beta h^{\rho-1}}{\alpha k^{\rho} + \beta h^{\rho}} py = w, \end{cases}$$

where $w = w_r = w_m/\gamma$ is the wage rate.

A theoretical upper bound for the bias In the empirical exercise, we use the observed revenues py, the total employment cost wh, the observed capital k, and the observed units of labor l in order to compute the labor cost,

$$\widehat{w} = w\left(\frac{h}{l}\right),$$

returns to factors,

$$\widehat{MPL} = (1 - 1/\sigma)\frac{\alpha k^{\rho-1}}{\alpha k^{\rho} + \beta l^{\rho}} py = MPL\left(\frac{l}{h}\right)^{\rho-1}\frac{\alpha k^{\rho} + \beta h^{\rho}}{\alpha k^{\rho} + \beta l^{\rho}}$$

$$\widehat{MPK} = (1 - 1/\sigma)\frac{\beta l^{\rho-1}}{\alpha k^{\rho} + \beta l^{\rho}} py = MPK\frac{\alpha k^{\rho} + \beta h^{\rho}}{\alpha k^{\rho} + \beta l^{\rho}},$$

and revenue-based total factor productivity,

$$\widehat{pA} = pA\left(\frac{\alpha k^\rho + \beta h^\rho}{\alpha k^\rho + \beta l^\rho}\right)^{1/\rho},$$

which all differ from their actual values.

In what follows, we quantify the bias induced by differences in the estimation of the elasticities of these quantities to a marginal increase of the number of migrant workers l_m. For simplicity, we will keep the other factors k and l_r constant. These elasticities are:

$$\frac{\partial \ln(\widehat{w})}{\partial l_m} = \frac{\partial \ln(w)}{\partial l_m} - \frac{(1-\gamma)l_r}{(l_r+\gamma l_m)(l_r+l_m)}$$

for the labor cost,

$$\frac{\partial \ln(\widehat{MPL})}{\partial l_m} = \frac{\partial \ln(MPL)}{\partial l_m} + \frac{\partial}{\partial l_m}\ln\left[\frac{\alpha k^\rho + \beta h^\rho}{\alpha k^\rho + \beta l^\rho}\right] + (\rho-1)\frac{(1-\gamma)l_r}{(l_r+\gamma l_m)(l_r+l_m)}$$

$$\frac{\partial \ln(\widehat{MPK})}{\partial l_m} = \frac{\partial \ln(MPK)}{\partial l_m} + \frac{\partial}{\partial l_m}\ln\left[\frac{\alpha k^\rho + \beta h^\rho}{\alpha k^\rho + \beta l^\rho}\right]$$

for the returns to factors, and

$$\frac{\partial \ln(\widehat{pA})}{\partial l_m} = \frac{\partial \ln(pA)}{\partial l_m} + \frac{1}{\rho}\frac{\partial}{\partial l_m}\ln\left[\frac{\alpha k^\rho + \beta h^\rho}{\alpha k^\rho + \beta l^\rho}\right]$$

for the revenue-based total factor productivity. Under the hypothesis that $l_m << l_r$, which induces that our estimate will be an upper bound for the bias, and following a small increase of $\Delta l_m = 1\% l_r$, we have:

$$\begin{cases} \Delta \ln(\widehat{w}) = \Delta \ln(w) - (1-\gamma)\% \\ \Delta \ln \widehat{MPL} = \Delta \ln(MPL) - (1-\gamma)\rho\dfrac{\beta l^\rho}{\alpha k^\rho + \beta l^\rho}\% + (\rho-1)(1-\gamma)\% \\ \Delta \ln \widehat{MPK} = \Delta \ln(MPK) - (1-\gamma)\rho\dfrac{\beta l^\rho}{\alpha k^\rho + \beta l^\rho}\% \\ \Delta \ln \widehat{pA} = \Delta \ln(pA) - (1-\gamma)\dfrac{\beta l^\rho}{\alpha k^\rho + \beta l^\rho}\%. \end{cases}$$

Quantification of the bias Before we quantify the bias for the different elasticities, we need to calibrate some parameters. First, the value of $\gamma < 1$ can be retrieved by regressing the (log) wages of all individuals present in the 2005 Mini-Census on a dummy for newly-arrived migrants and a large set of controls, including occupation fixed effects, destination fixed effects, age, education, and gender. This exercise yields $\gamma = 0.80$. Second, the ratio $\beta l^\rho/(\alpha k^\rho + \beta l^\rho)$ is approximately equal to the share of total labor costs over total factor costs, which in China is around 60%. Third, the value of ρ depends on the industry, but for most industries this value ranges between -0.1 and -0.7, and we will use an estimate of -0.4. These calibrated values lead to the following order of magnitude for the (maximum) biases:

$$\begin{cases} \Delta \ln(\widehat{w}) \approx \Delta \ln(w) - 0.20\% \\ \Delta \ln \widehat{MPL} \approx \Delta \ln(MPL) - 0.23\% \\ \Delta \ln \widehat{MPK} \approx \Delta \ln(MPK) + 0.05\% \\ \Delta \ln \widehat{pA} \approx \Delta \ln(pA) - 0.12\%. \end{cases}$$

For an employment effect between 0.3 and 0.4, the elasticities of the labor cost, the returns to labor and capital, and the total factor productivity would need to be corrected at most by -0.07, -0.08, +0.02, and -0.04.