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Migrants and Firms: Evidence from China *

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Abstract

This paper estimates the causal effect of rural-urban migration on urban production in China. We use longitudinal data on manufacturing firms between 2001 and 2006 and exploit exogenous variation in rural-urban migration due to agricultural price shocks. Following a migrant inflow, labor costs decline and employment expands. Labor productivity decreases sharply and remains low in the medium run. A quantitative framework suggests that destinations become too labor-abundant and migration mostly benefits low-productivity firms within locations. As migrants select into high-productivity destinations, migration however strongly contributes to the equalization of factor productivity across locations.

JEL codes: D24; J23; J61; O15.

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1 Introduction

Firm productivity in developing countries is low and highly heterogeneous, even within sectors (Hsieh and Klenow, 2009). A number of factors explain this pattern, e.g., the lack of capital (Banerjee and Duflo, 2014) or bad management (Bloom et al., 2013). An important factor could be the abundance of unskilled labor: the process of economic development induces large movements of rural workers from agriculture to manufacturing and services (Lewis, 1954). Despite its relevance (Todaro, 1980), empirical evidence on the role of rural-urban migration in shaping urban production in developing countries is scarce. One challenge is to identify the effect of migration on urban production without confounding it with destination characteristics that attract migrants (e.g., high wages). Another challenge is to document not only aggregate productivity effects, but also heterogeneous effects across firms within locations and sectors.

This paper is the first to estimate the causal effect of rural migrant inflows on urban production along 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 trace rural-urban migration flows. We instrument migrant inflows into Chinese cities using exogenous shocks to agricultural productivity in rural areas, which trigger rural-urban migration. We first identify the effect of migration on labor cost, factor use and value added per worker. We then develop a quantitative framework à la Oberfield and Raval (2014), accounting for complementarities between production factors. The production estimates allow us to estimate the effect of migration on productivity, but also heterogeneous employment effects across firms with different factor productivity. In a final exercise, we use our causal estimates to quantify the impact of migration on wage and productivity dynamics, including their dispersion across locations.

Providing empirical evidence on the causal impact of labor inflows on manufacturing firms requires large, systematic and exogenous migrant flows into 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 across prefectures to identify exogenous variation in agricultural labor productivity at origin. In the second step, we combine predicted changes in migrant outflows with baseline migration incidence between all origins and prefectures of destination to predict immigration to urban areas.[1] Migration predictions are

[1]Prefectures are the second administrative division in China, below the province. There were about 330 prefectures in 2000. Each prefecture contains one or several urban cores surrounded by rural areas.

orthogonal to factor demand in the urban sector, strongly predict migrant inflows, and exhibit substantial variation across years and destinations.

We use these origin-driven shocks to instrument actual migrant inflows and estimate their short-term impact on production. We find that migration exerts a downward pressure on labor costs: the implied wage elasticity with respect to migration is about -0.50. Labor inflows strongly affect relative factor use in the average firm as capital does not adjust to changes in employment. In parallel, value added per worker decreases sharply. These effects appear to hold in the medium-run: Firms remain labor-abundant and production increases, but only moderately so.

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, omitting local migration flows, or leveraging forward shocks in a placebo exercise. We also show that changes in worker composition are unlikely to explain the negative impact on wage and labor productivity, and that firm entry and exit only amplifies these effects.

In order to better understand the impact of labor inflows on factor productivity, we develop a model in which production is characterized by sector-specific elasticities of substitution between factors and between differentiated final goods, and firm-specific factor distortions (Hsieh and Klenow, 2009). We estimate the sector-specific elasticities of substitution between capital and labor following Oberfield and Raval (2014), and using origin-driven migration shocks as an instrument for relative factor costs. The quantitative framework suggests that production becomes too labor-abundant at destination—capital and labor being complements in production—, and the shift in factor use negatively affects labor productivity. This approach also allows us to characterize recruiting firms and distinguish them along their ex-ante factor productivities: Immigrants are primarily recruited by low-productivity firms within a location, thereby contributing to lower aggregate labor productivity.

Finally, we implement a counterfactual experiment in which we keep constant the allocation of labor across locations between 2001 and 2006 to quantify the influence of migration on recent dynamics of the urban economy.[2] We show that the continuous migration flows largely contributed to wage moderation in cities, and that their distributional aspect had consequences on the dynamics of factor productivity (e.g., moderating its secular growth, Brandt et al., 2012) and its dispersion across locations. The systematic migration towards destinations where manufacturing firms

[2]The Chinese manufacturing sector has grown fast in the past decades, fueled by massive migration flows from rural to urban areas. The share of agricultural employment in China dropped from 70% to 30% between 1980 and 2014, a shift that spanned more than 100 years in most industralized countries (Alvarez-Cuadrado and Poschke, 2011).

are capital-abundant, productive and paying high wages reduces the dispersion in relative factor use and factor productivity across locations.

This paper makes significant contributions to two main strands of the literature. First, this research closely relates to the nascent literature studying how labor supply shocks impact the structure of production (Lewis, 2011; Peri, 2012; Accetturo et al., 2012; Olney, 2013; Dustmann and Glitz, 2015; Kerr et al., 2015). Our empirical analysis borrows from these papers but applies it to a different context: a developing economy with massive rural-to-urban migration flows and large labor frictions. The analysis in such context echoes an older literature on migration and unemployment in cities of developing economies (Todaro, 1969; Harris and Todaro, 1970; Cole and Sanders, 1985). The theory developed in Harris and Todaro (1970) is based on the puzzling observation that large migration flows towards cities are observed together with high unemployment and a large informal sector (Fields, 1975).[3] Recent papers indeed provide evidence of large search and information frictions in accessing formal jobs (Franklin, 2018; Abebe et al., 2016; Alfonsi et al., 2017). One main contribution of the research is to document a consequence of these urban labor market frictions, directly observed from the firm side: the heterogeneous allocation of migrants into production units.

There is a vibrant literature on productivity gaps across space and sectors (Gollin et al., 2014; Brandt et al., 2013). In models of labor allocation (Bryan and Morten, 2015; Tombe and Zhu, 2015), mobility frictions are inferred from observed differences in productivity across locations, and rural-urban migration flows adjust in order to reduce these differences. A contribution of our analysis is to propose an empirical counterpart to these analyses. We provide well-identified empirical evidence on the allocation of labor inflows at the firm level. A counterfactual exercise allows to quantify the role of migration in equalizing productivity across locations. Our findings suggest that labor market frictions across *and* within locations are paramount to explaining firm productivity and its dispersion in developing economics.[4]

Second, our empirical investigation sheds light on disparities in productivity and factor allocation across firms of developing economies in general, and China in particular (Hsieh and Klenow, 2009; Song et al., 2011). We show, in particular,

[3]One explanation behind this puzzle is the existence of a subsistence income in cities, or labor market imperfections related to the existence of formal and informal labor markets (Satchi and Temple, 2009; Meghir et al., 2015; Ulyssea, 2018). Another institutional factor which could affect the absorption of migrants into cities is the existence of minimum wage regulations; the impact of minimum wages in Chinese cities is discussed in Mayneris et al. (2014).

[4]Another important source of misallocation 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 public-private sector differences.

that migrants are recruited by low-productivity firms at destination, which tends to widen disparities in factor productivity. A large literature has documented the role of credit market imperfections in generating dispersion in factor returns across firms, even within the same sector and location (Buera et al., 2011; Midrigan and Xu, 2014; Gopinath et al., 2017). The empirical observation that production becomes too labor-intensive after a migrant inflow, in spite of production complementarities between capital and labor, is consistent with large credit market imperfections.

The paper also 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. Among others, Boustan et al. (2010), El Badaoui et al. (2017), Imbert and Papp (2016) and Kleemans and Magruder (2018) study the labor market effects of internal migration in the United States in the 1930s, and in today's Thailand, India and Indonesia, respectively. 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, and our estimates are comparable.

Finally, the research pertains 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., 2013). 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., 2016). However, we find that migration from rural areas is triggered by *negative* shocks to agricultural productivity (as in Gröger and Zylberberg, 2016; Feng et al., 2017; Minale, 2018, for instance). This suggests that worse economic conditions at origin lower the opportunity cost of migrating rather than tightening liquidity constraints on migration (Angelucci, 2015; Bazzi, 2017).[5]

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

[5]In order to identify migration inflows that are exogenous with respect to firms 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).

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 and historical migration patterns. 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) and place of registration and residence at the prefecture level. Second, migrants are asked the main reason for leaving their places of registration and which year they left (up to five years before the date of interview). We combine these two pieces of information to create a matrix of yearly rural-to-urban migration spells "for labor reasons" between all Chinese prefectures from 2000 to 2005.[7]

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 place of registration within the last five years and come back between two census waves. 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]

[6] These data are widely used in the literature (Combes et al., 2015; Facchini et al., 2015; Meng and Zhang, 2010; Tombe and Zhu, 2015, 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-to-urban migration but limit benefits of 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

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 working-age residents (non-migrants) in d at baseline, in 2000, which we denote with N_d, rescaled by the employment rate in manufacturing ($\mu \approx 14.35\%$),

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

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.

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 and potential yield. These data

to using non-adjusted flows (see a sensitivity analysis in Appendix E and Appendix Table E2).

are provided by the Food and Agriculture Organization (FAO) and the International Institute for Applied Systems Analysis (IIASA).[9] The 2000 World Census of Agriculture offers a geo-coded map of harvested area for each crop, which we use to construct total harvested area h_{co} for a given crop c and a given prefecture o. Information on potential yield per hectare, y_{co}, for each crop c and prefecture o comes from the Global Agro-Ecological Zones (GAEZ) Agricultural Suitability and Potential Yields dataset. We compute potential agricultural output for each crop in each prefecture as the product of harvested area and potential yield, $q_{co} = h_{co} \times y_{co}$. By construction, q_{co} is time-invariant and captures cropping patterns at origin. It is measured at the beginning of the study period, and is 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 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 significant pass-through from international prices to domestic prices faced by rural farmers. In Appendix B, we use producer prices, exports and production as reported by the FAO between 1990 and 2010 for China and show that fluctuations in international prices are transmitted to the average Chinese farmer.

[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.

[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.

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 migration outflows.[15]

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:

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

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

[14] As an example, Appendix Figure B2 displays the spatial dispersion in p_{ot} in 2001, when the rice price decreased sharply, and in 2002, after recovery. Appendix Table B1 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 E1) that we find similar results when we use fluctuations in agricultural output due to rainfall shocks, which are not serially correlated.

[16] Incorporating price trends in the analysis does not change the results. We also estimate the

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 (Bazzi, 2017). On the one hand, 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). On the other, 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 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 defined as:

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

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

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 E and Appendix Table E1).

[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.

[18] Alternatively, in Appendix E and Appendix Table E3, 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., 2017).

supply-driven migrant inflows that are orthogonal to labor demand at destination. There is spatial auto-correlation due to the geographic determinants of cropping patterns at origin. The shocks however display large cross-sectional and time-varying fluctuations.[19]

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 throughout the sample period: The origin-based variation in the arrival of recent immigrants, z_{dt}, is a strong predictor of observed labor inflows. This relationship constitutes the first stage of 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).[20] The NBS implements every year a census of all state-owned manufacturing enterprises and all non-state manufacturing establishments 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 a large part of the analysis will be performed on the balanced panel (about 80,000 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).

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 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.[21] Third, the RMB 5 million threshold that defines whether a non-publicly

[19] We provide in Appendix B an illustration of this spatial auto-correlation. Appendix Figure B3, shows the geographical distribution of z_{dt} in 2001 (left panel) and 2004 (right panel), after taking out prefecture fixed effects.

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

[21] 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, 88.9% of firms reported a single production plant. In 2007, the share of single-plant firms increased to 96.6% (Brandt et al., 2014).

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.

Our main outcomes include compensation per worker, employment, capital-to-labor ratio and value added per worker. Table 2 provides descriptive statistics of our key outcomes at the firm-level in 2001. There is substantial heterogeneity in firm outcomes, both within and across locations.[22]

2.4 Empirical strategy

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

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

$$y_{idt} = \alpha + \beta m_{dt} + \eta_i + \nu_t + \varepsilon_{idt} \tag{4}$$

where η_i and ν_t are firm and time 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_{id} denote the difference in outcomes between 2001 and 2006, we estimate:

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

where $\overline{m}_d$ is instrumented by $\overline{z}_d$, and ν_j are sector fixed effects. Standard errors are clustered at the level of the prefecture of destination.

[22] We leave the analysis of general trends in China and differences across establishments of the sample to Appendix C, and Appendix Tables C1 and C3 in particular. This analysis shows that manufacturing growth is very unequally shared across prefectures.

In order to identify heterogeneous effects, we estimate:

$$\Delta y_{id} = \alpha + \beta \overline{m}_d + \gamma \overline{m}_d \times X_i + \nu_j + \mu_j \times X_i + \varepsilon_{ijd}, \tag{6}$$

where X_i is a time-invariant characteristic of firm i. The time-invariant characteristics, X_i, will be dummy variables capturing the relative factor-intensity and factor productivity at baseline within a sector $\times$ prefecture. As in the previous specification, ν_j denotes sector fixed effects, and μ_j are characteristic $\times$ sector fixed effects. $\overline{m}_d$ 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

In this section, we quantify the effect of the labor supply shift on labor cost and factor demand, both on impact and in the longer-run. We then analyze heterogeneous responses depending on baseline firm characteristics, most notably a measure of relative labor productivity at destination. We complete this section with a comprehensive sensitivity analysis exploring variations along the baseline specification, a placebo test using future shocks to agricultural livelihoods, and a measure of labor cost cleaned of compositional adjustments.

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). An inflow of rural migrants is negatively associated with labor cost at destination. Since migrants should be attracted to cities that offer numerous employment opportunities and high wages, the OLS estimate should be biased upwards.[23] We indeed find a more negative price elasticity of labor demand in the IV specification, in which the immigration rate is instrumented by the labor supply shock. A one percentage point increase in the immigration rate induces a 0.53% decrease in compensation per employee. This large response of wages to immigration is comparable to other

[23]The association between fluctuations in factor cost and factor use and variation in rural-to-urban migration may result from "pull" factors and "push" shocks. In the IV specification, only push factors contribute to the correlation between migration and the urban economy at destination. In general, we find differences between OLS estimates and IV estimates to be small, except for the price of labor. These findings are not related to an issue of weak instruments; our instrument is a strong predictor of the immigration rate at destination in all baseline specifications.

studies of internal migration in developing economies (Kleemans and Magruder, 2018). Internal migrants in China could be more easily substitutable with "natives" than international migrants in developed countries (see, e.g., Borjas, 2003, for the United States).[24]

Following a positive labor supply shock, manufacturing firms should expand and become more labor-abundant. 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 0.36%. Since we normalize the migration rate by the population working in the manufacturing sector, one would expect the coefficient to be 1 if all newly-arrived immigrants were to be absorbed by the manufacturing sector without altering the share of the balanced sample in that sector. Some migrant workers may be hired by smaller manufacturing firms or work in other sectors (e.g., construction); some of them may also transit through unemployment or self-employment (Giulietti et al., 2012; Zhang and Zhao, 2015).

The labor supply shift affects the relative factor use at destination. As shown in column 3 of Table 3, the capital-to-labor ratio decreases by 0.26% 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 behind this finding. Firms that expand may belong to sectors with relatively high substitutability between capital and labor, in which case a moderate adjustment of capital could be an optimal response. There may also be credit constraints and adjustment costs that prevent firms from reaching their optimal use of production factors in the short run. We shed light on these two interpretations when investigating treatment heterogeneity and longer-run effects.

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 0.50% (column 4 of Table 3). With employment increasing (only) by 0.36%, the labor supply shock thus *negatively* affects 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 to be adjusted before the expansion of production factors translates into higher output. We now provide an estimation of the impact of migration on urban firms in the medium run, when firms can be

[24]Our findings are in line with recent studies arguing that rural-to-urban migration has markedly tempered wage growth in urban China (De Sousa and Poncet, 2011; Ge and Yang, 2014). The high price elasticity of labor demand may also illustrate that labor markets in developing countries are relatively less regulated. For instance, minimum wage regulations in China only came into force towards the end of our observation period (Mayneris et al., 2014).

expected to have overcome some of these short-run adjustments.

Longer-run effects The effect of migrant inflows on impact may sharply differ from the longer-run effect. Labor markets at destination may adjust through worker mobility across prefectures, e.g., prefectures that experienced a wage decrease due to a sudden migrant inflow may 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 for the arrival of new workers. We investigate these long-run effects using specification (5), and we report the impact of the labor supply shift on factor cost, factor demand and value added per worker in Table 4.

The price elasticity of labor demand in the longer run, -0.30, is 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 0.58%. 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 induces a *positive* impact of migration on output at destination. With employment increasing by 0.58%, a labor supply shock of one percentage point in the immigration rate increases value added by about 20%.

Overall, the (few) discrepancies between the short- and longer-run impacts of immigration are consistent with (i) slow labor market adjustments, (ii) either low levels of complementarity between capital and labor or non-negligible frictions in access to capital, and (iii) a disruption of production on impact, explaining why the decrease in average labor productivity at the firm-level is partly tempered in the longer run. While our study cannot provide any direct insight about the consequences of large rural-to-urban migration over a long period, 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 towards a more labor-intensive mode of production and this choice locks them over longer horizons. Such a mechanism would require (already) labor-abundant manufacturing firms to hire the marginal low-skill worker. We now provide some evidence on the heterogeneous absorption of migrants in the urban economy.

3.2 Heterogeneity in factor demand

We study the heterogeneous response in factor demand by interacting migrant inflows with fixed firm characteristics (see Equation 6). We limit our analysis to two characteristics related to labor needs and leave the analysis along additional dimensions to Appendix E and Appendix Table E5.[25] We label as capital-abundant all firms with a capital-to-labor ratio at baseline in the top quartile within their sector and prefecture. We label as labor-productive all firms with a value added per worker at baseline in the top quartile within their sector and prefecture. Under the assumption that firms in the same sector and prefecture use similar technologies, a high capital-to-labor ratio indicates a shortage of labor and we should expect capital-abundant firms to recruit aggressively. Along the same lines, newly arrived immigrants should be hired by the most productive firms.

Table 5 presents the IV estimates for labor cost and labor demand.[26] In columns 1 and 3, we test for the existence of heterogeneous effects of migrant inflows on labor cost, which could occur if firms with different relative factor use or productivity recruited in segmented labor markets. The reduction in labor cost is found to be remarkably homogeneous across firms; more or less capital-abundant or productive firms appear to face similar labor market conditions. 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 0.38% as against 0.20% in productive firms.

These findings are puzzling. Migrant workers are not recruited by more "capital-rich" firms in the same sector and location, and they are predominantly hired by seemingly unproductive firms. This observation sharply contrasts with empirical regularities of firm growth in developed economies: Employment growth at the firm level usually correlates with indicators of productivity; employment flows are typically directed towards productive firms (see Davis and Haltiwanger, 1998, for evidence in the U.S. manufacturing sector). The allocation properties of large inflows of rural migrants appear to differ from the adjustments induced by labor demand shocks. This finding is however consistent with Lewis (2011), who finds that some firms respond to migrant inflows by adopting a more labor-intensive organization of

[25] Appendix Table E5 investigates heterogeneous treatment effects along complementarity between capital and labor, whether an industry predominantly hires high-skill workers, and firm ownership, age and size. We do not find strong evidence of heterogeneity along these variables.

[26] We do not report the estimates for the adjustment of capital-to-labor ratio or value added, as a more systematic heterogeneity analysis will be provided in the next section.

production.

One issue with the present analysis is that it does not account properly for complementarity between factors and uses a crude measure of labor productivity. In order to better characterize recruiting firms and the impact of recruitment on factor productivity, we develop in Section 4 a production function estimation allowing for sector-specific complementarity between factors and residual differences between firms of the same sector. Before developing this more structural approach, we discuss the robustness of our baseline reduced-form approach.

3.3 Sensitivity analysis and compositional effects at destination

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. Changes in the supply of agricultural output may affect specific sectors where agricultural output is used as intermediate input, and the geographical distribution of vulnerable industries may correlate with migration patterns. Omitted spatial variation in the distribution of manufacturing firms may also correlate with migration flows. Moreover, cities and their surroundings may be integrated through final goods markets, so that changes in agricultural income in rural hinterlands affects demand for manufactured products in cities (Bustos et al., 2016; Santangelo, 2016).

To alleviate these concerns, we carry out seven robustness checks, which are presented in Table 6. In Panel A, we report the baseline specification in which we control for the residual agricultural income shock in the receiving prefecture. 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 all migrant flows that occur within a 300-km radius of the prefecture's centroid when constructing the immigration rate and the instrument (Panel C). In Panel D, we exclude industries in which agricultural products are used as intermediate inputs (food processing and beverage manufacturing industries). In Panel E, we add sector $\times$ year fixed effects to control for sector-specific fluctuations. In Panel F, we control for a measure of market access—the sum of population in all rural 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 comparable to the baseline estimates

Finally, we perform a placebo test in which we correlate firm outcomes with future immigration rate, instrumented by the forward supply push. As Panel G of

Table 6 shows, the placebo estimates are all insignificant and much smaller than our main estimates. The sensitivity analysis supports our main interpretation, i.e., that shocks to agricultural productivity affect manufacturing firms through the arrival of new immigrants—as potential workers—into cities.

Aggregation and sample choice The baseline specification (4) is estimated at the firm-level. An alternative empirical specification would be to aggregate quantities at the sector $\times$ prefecture level, which could limit the influence of outliers. In Panel A of Table 7, we use the sample of firms present every year in the NBS firm census between 2001 and 2006, aggregate outcomes within a cell (prefecture $\times$ sector), estimate a specification similar to Equation (4) where i is a cell instead of an individual firm, and condition the analysis on cell and year fixed effects. The IV estimates are found to be robust to this alternative specification, and standard errors are slightly lower than in the baseline specification.

Our baseline analysis focuses on the balanced sample of firms. However, as shown in Appendix Table C1 and discussed in Appendix C, the balanced sample only represents about a third of all firm $\times$ year observations. In order to account for the possible effect of entry into and exit from the NBS census of above-scale firms, we replicate the previous exercise on the sample of all firm $\times$ year observations between 2001 and 2006 (Panel B of Table 7). The estimated wage response to a one percentage point increase in the migration rate is -0.56%, very close to the estimate on the balanced sample (-0.48%). The effects on employment, capital-to-labor ratio and value added per worker are all larger in magnitude. Including firms that enter our sample over time and aggregating at the sector $\times$ prefecture level strengthens the finding that production becomes more labor-intensive with migration, and labor productivity declines.

Worker heterogeneity and compositional effects at destination We have interpreted so far 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 NBS data do not provide yearly information on the skill composition of the workforce or their migrant status. To clean the price elasticity of labor demand from compositional effects, we exploit yearly cross-sections of the Urban Household Survey (2002–2006)—a representative survey of urban "natives" (see description in Appendix C.2).

The empirical analysis is based on estimating changes in the wage of urban

residents triggered by changes in migrant inflows.[27] 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.[28] More formally, we estimate:

$$y_{jdt} = \alpha + \beta_0 m_{dt} + \beta_1 m_{dt} \times L_{jdt} + \delta s_{dt} + \gamma \mathbf{X}_{jdt} + \eta_d + \theta_d \times L_{jdt} + \nu_t + \mu_t \times L_{jdt} + \varepsilon_{jd}, \quad (7)$$

where η_d and θ_d are destination fixed effects, ν_t and μ_t are year fixed effects, s_{dt} are destination $\times$ year fixed effects, and $\mathbf{X}_{jdt}$ is a vector of individual characteristics, including marital status, gender, education level and age. We estimate Equation (7) 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 8 presents the results. Column 1 reports the OLS and IV estimates of β_0 and β_1, when 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 8, we analyze the possible displacement of urban residents. Rural-to-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.

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 D.4; the compositional effect

[27] 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.

[28] 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).

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.

4 Migration and factor productivity

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 factor market distortions (Hsieh and Klenow, 2009). We use the quantitative model to interpret the impact of labor inflows on factor productivity at the prefecture level and to discipline the analysis of heterogeneity across firms. The last subsection provides a counterfactual analysis that quantifies the contribution of rural-to-urban migration to the recent wage and productivity growth (and dispersion) in the Chinese economy.

4.1 Quantitative framework

We first describe a static 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 wedges in factor prices.

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:

$$y = \left[\sum_i x_i y_i^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{8}$$

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

$$y_i = (p_i/p)^{-\sigma} x_i^{\sigma} y \tag{9}$$

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

$$y_i = A_i \left[\alpha k_i^{\rho} + (1-\alpha) l_i^{\rho}\right]^{\frac{1}{\rho}}, \tag{10}$$

where α, governing the capital share, and ρ, governing the elasticity of substitution between capital and labor, are assumed constant over time and within sector.

As in Hsieh and Klenow (2009), we rationalize differences in factor use across firms by assuming that individual firms face different firm-specific wedges in factor prices. Let τ_i^l denote the labor wedge and τ_i^k denote the capital wedge, respectively impacting the marginal cost of labor and capital. Firm i maximizes the following program, taking as given factor prices and the aggregate demand and price at the product market level,

$$\max_{p_i, y_i, l_i, k_i} \left\{ p_i y_i - (1+\tau_i^l) w l_i - (1+\tau_i^k) r k_i \right\} \tag{11}$$

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

Estimation The following fundamentals of the model need to be estimated: the degree of substitution between capital and labor (ρ), the capital share (α), the elasticity of substitution between product varieties (σ)—all at the sector level—, and firm-specific distortions (τ_i^k, τ_i^l).

The identification of the model derives from estimating the sector-specific elasticity of substitution between factors. Indeed, conditional on knowing the parameter ρ at the sector level, α and σ 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 a labor supply shock to shift the labor cost.[29]

Optimal factor demand at the firm level verifies:

$$\ln\left(\frac{r k_i}{w l_i}\right) = \frac{1}{1-\rho} \ln\left(\frac{\alpha}{1-\alpha}\right) + \frac{\rho}{1-\rho} \ln\left(\frac{w}{r}\right) + \frac{1}{1-\rho} \ln\left(\frac{1+\tau_i^l}{1+\tau_i^k}\right),$$

in which one 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 distortions in access to factor markets. Identifying the elasticity of substitution from this relationship is challenging because omitted

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

variation (e.g., an increase in labor productivity) may influence both relative factor prices and relative factor use.

We identify the sectoral elasticity of substitution ρ by exploiting exogenous variation in the relative factor cost induced by our labor supply shock. The arrival of migrants shifts the relative price of labor downward, an effect that is orthogonal to omitted variation related to labor demand. We assume, as in Oberfield and Raval (2014), that firm-specific relative distortions are normally distributed within a sector and a prefecture, and that labor markets are integrated within a prefecture.[30] 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 D.[31]

We use the sector-specific parameter ρ and the structure of the model to recover (i) the other parameters underlying production at the sector level and (ii) firm-specific measures of factor productivity. The marginal revenue products of factors (MPL_i, MPK_i) and the revenue-based total factor productivity (TFP_i) verify:

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

These factor productivities relate to factor wedges as follows:

$$\begin{cases} \tau_i^k = MPK_i/r - 1 \\ \tau_i^l = MPL_i/w - 1. \end{cases} \tag{13}$$

In the next section, we use these quantities to estimate the impact of migration inflows on factor productivity at the firm level, and to classify recruiting firms along their initial factor productivity.[32]

[30] We provide empirical support for this assumption in Appendix E.3, by showing that the shift in labor cost is homogeneous (see Appendix Figure E3).

[31] 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 D.3 and Appendix Table D1).

[32] As a robustness check, we also construct factor productivity measures assuming a Cobb-Douglas production function, or using the sector-level elasticities of substitution estimated by Oberfield and Raval (2014) for the United States in 1987 and 1997.

4.2 The effect of migration on factor productivity

Average effect We first study the impact of labor inflows on factor productivity at the firm level. We estimate Equation (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 9 for the following production functions: the baseline CES production function with our own sectoral estimates of ρ and the Cobb-Douglas specification, which corresponds to the limiting case where ρ is zero. The first column of Table 9 (Panel A) reports how marginal return to labor responds to migrant inflows. The elasticity with respect to migration is about -0.54. In parallel, the marginal revenue product of capital positively responds to the labor supply shift, as apparent from the second column of Table 9. Finally, we find a small and non-significant negative effect of migration on total factor productivity (see column 3).

These findings are inconsistent with a theoretical framework assuming optimization under *constant* firm-specific distortions (see Equation 13). In this benchmark, the magnitude of the decline in labor productivity would be similar to that of the labor cost (-0.30, see Table 4), and capital productivity and total factor productivity would remain stable. Instead, the gap between the marginal product of labor and its marginal cost slightly decreases with immigrant inflows, and capital productivity slightly increases.[33] Firms become too labor-abundant in prefectures experiencing large migrant inflows, which may hint at difficult access to capital.

The second row of Table 9 shows that a Cobb-Douglas production fails to capture these effects and underestimates the decrease in labor productivity. Capital and labor are more complementary than what a Cobb-Douglas production function would imply; the arrival of immigrants without further capitalization thus strongly affects labor productivity.[34]

Heterogeneity analysis We now investigate the distributional effects of migrant inflows. We classify firms based on (i) their marginal product of labor, (ii) marginal product of capital and (iii) revenue-based total factor productivity at baseline (in

[33] 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-to-urban migrants would generate a bias in the estimated effect of migrant inflows on factor productivity. We show in Appendix D.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.

[34] Appendix Table E6 shows that the productivity effects are similar when we use U.S. estimates for the CES parameters (Oberfield and Raval, 2014). These estimates also point to a higher complementarity between capital and labor than induced by a Cobb-Douglas framework.

2001), and we construct a dummy equal to 1 if a firm is in the top quartile of its sector × prefecture for each productivity measure. We interact migrant inflows with each productivity dummy (see Equation 6), and report estimates of the employment effect in Table 10.

Immigrants are primarily recruited by manufacturing firms with low marginal product of labor: Employment in low-productivity firms increases by 0.60% following a one percentage point increase in the immigration rate, as against 0.32% in high-productivity firms (column 1). The same result holds for capital productivity and total factor productivity (columns 2 and 3): Hiring firms are unproductive firms. This observation has implications for aggregate factor productivity at destination. Labor inflows influence aggregate factor productivity through a direct effect, but also through possible differences between the average employer and the marginal employer—the recipient of migrant inflows. Immigrants being primarily hired by unproductive firms, we should observe a negative compositional effect.

To show how the correlation between baseline factor productivity and employment growth affects aggregate productivity dynamics, we collapse factors and output at the sector × prefecture level and create aggregate measures of factor productivity. We then estimate a specification similar to Equation (4) where each observation is a sector × prefecture in a given year. The aggregate elasticities of factor productivity to migrant inflows are reported in Table 9 (Panel B). Following a one percentage point increase in the immigration rate, changes in factor productivity appear to be consistently more negative with aggregate measures than at the firm level (with differences ranging between -0.05 and -0.12%). The systematic bias between Panels A and B of Table 9 is consistent with the observed productivity differences between the average and marginal employers, and is the most pronounced for capital productivity.

Interpretation The interpretation of our findings depends on the nature of productivity differences across firms within location and sector. In the spirit of the model, firms in the same sector and location are perfectly identical except for (constant) factor wedges, which capture unequal access to factor markets as in Hsieh and Klenow (2009). Labor productivity dispersion would reflect labor market imperfections: firms with high marginal product of labor are constrained in hiring labor. Our finding that firms with low marginal product of labor expand the most following a migration inflow points towards a growing misallocation of labor at destination. This misallocation may be due to information asymmetry between job seekers and employers (Abebe et al., 2016; Alfonsi et al., 2017), to the intervention

of intermediaries and to the prevalence of migrant networks (Munshi, 2003; Barwick et al., 2018). Similarly, capital productivity dispersion is indicative of capital market distortions: firms with harder credit constraints have higher productivity than the median firm in their sector and location (Buera et al., 2011; Midrigan and Xu, 2014). Our finding that firms become too labor-abundant, given the complementarities between capital and labor, suggests that capital constraints are even more binding following a migrant inflow. Finally, productivity differences may capture inherent 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 would then suggest that migration benefits more to firms whose management is of lower quality. In this case, again, our results would indicate that migration worsens factor allocation within locations.

The previous interpretation of our results relies on the hypothesis that sector-level estimates are a valid representation of production patterns in each firm. Any deviation from this benchmark would be captured by firm-specific factor wedges. For example, factor wedges may reflect technological differences across firms within sectors due to firm-specific complementarities in production, or complementarities in production with unobserved factors (e.g., skilled labor). A convincing normative analysis would require us to estimate production at a more disaggregated level, explicitly model factor market distortions, their interaction with labor supply and their impact on firm dynamics, which is beyond what our data would permit. In the next section, we show the implications of our findings on the allocation of factors *across* locations.

4.3 Counterfactual experiment

As highlighted in the development literature (Lewis, 1954), migration should affect the growth pattern of the manufacturing sector in cities and help bridge the gap in factor productivity between locations. Our causal estimates of the effect of immigration can help us shed light on these questions. We combine (i) the observed (selective) migration flows towards more or less booming locations and (ii) our causal estimates of these flows at destination. This allows us to compare the growth rate and dispersion of key characteristics of the Chinese manufacturing sector in two scenarios: the actual economy, and a counterfactual scenario without any migration.[35]

[35]Firm characteristics in the counterfactual scenario are obtained by subtracting the long-term causal effects of migration, i.e., the coefficients reported in Table 4 multiplied by the migration

Growth Column 1 of Table 11 presents the annual growth rates of labor cost (Panel A), relative factor use (Panel B), and factor productivity (Panels C and D) in the actual economy and the counterfactual "no-migration" economy. Each year, the urban economy becomes 6% more capital-abundant. However, the capital-to-labor ratio would have grown even faster in the absence of migration—about 19% per year. The impact of migrants on relative factor use has implications for the growth in labor cost and factor productivity. In the counterfactual economy without migration, wage and labor productivity growth would have been almost twice as large as in the actual economy (22 and 23%, against 13 and 14%). By contrast, the growth of capital productivity would have been negative. Hence, migration played an important role in the development of the manufacturing sector by slowing down the secular increase in labor cost and rapid capitalization of manufacturing firms.

Dispersion The most interesting consequence of migration however lies in the dispersion of factors and factor productivity across destinations. We report in column 2 of Table 11 the standard deviation of the outcomes in 2006, normalized by the standard deviation in 2001. The dispersion in labor cost across firms decreased by about 14% between 2001 and 2006 (Panel A). Migration markedly contributed to this equalization of labor costs across production units: in the counterfactual economy, the dispersion in labor costs would have *increased* by 14%. Along the same lines, migration contributed to a moderate equalization of relative factor use (Panel B) and factor productivity (Panels C and D) across firms. These modest effects on total dispersion conceal a major impact of migration on dispersion across prefectures (see columns 3 and 4 for the within and between standard deviations). This finding illustrates that migrants do not select destinations at random; there is a selective and systematic migration toward destinations where manufacturing firms are capital-abundant, productive and paying high wages.

The allocative properties of rural-to-urban migration seem vastly different, when studied within a destination or across locations. The absorption of migrant workers by the manufacturing sector tends to worsen the allocation of factors within destinations, thereby indicating significant distortions in capital and labor markets. In this section, we have shown that the large and secular movement of workers across locations significantly reduces productivity gaps between Chinese cities.

rate in each destination over the period.

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 from population censuses with longitudinal data on manufacturing firms between 2001 and 2006, a period of rapid structural transformation and sustained manufacturing growth. We instrument migrant inflows using migration predictions based on shocks at origin, i.e., the interaction of international price shocks for agricultural commodities, cropping patterns and historical migration patterns between rural areas and cities.

We leverage micro data by estimating the effect on factor use and factor cost in the average firm. We find that migration decreases labor costs and increase employment in manufacturing. Manufacturing production expands but becomes more labor-intensive, as capital does not adjust, even in the medium run. Labor productivity falls sharply. A quantitative framework suggests that labor allocation worsens following a migration shock: recruiting firms have lower productivity than other firms in the same sector and location. Productivity differences could also reflect unobserved heterogeneity in capital constraints, product quality or technology: our results suggest that production becomes too labor-abundant and migration favors firms with labor-intensive production. Finally, we perform a counterfactual analysis to quantify the role of migration in productivity growth and dispersion across and within locations. While migration slows down productivity growth, it strongly contributes to the equalization of factor productivity and wages across prefectures.

A limitation of our analysis is that we cannot provide evidence on labor market frictions responsible for the observed factor reallocation due to the arrival of rural migrants. Worker sorting across firms and sectors is likely driven by formal or informal actors (e.g., recruiters or migrant networks), and depends on worker skills, which we do not observe. We leave this for future work.

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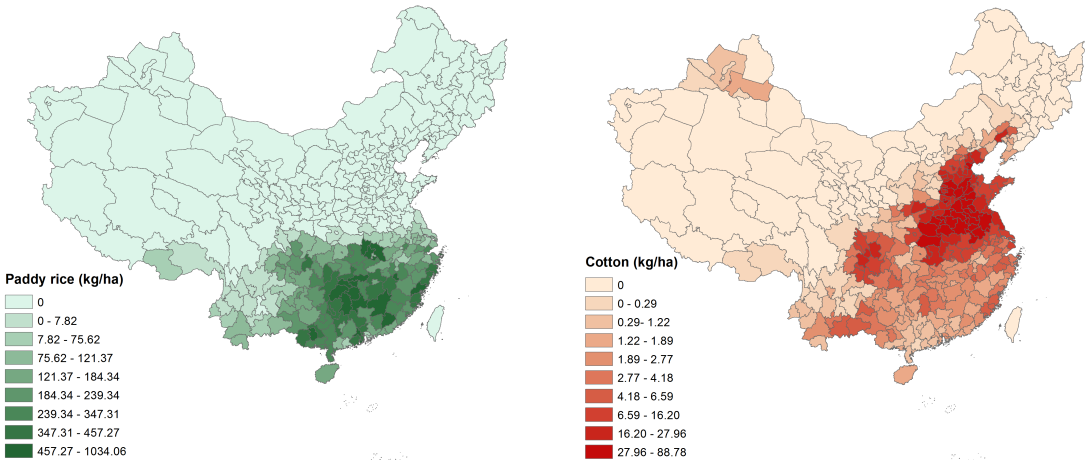
Figures and tables

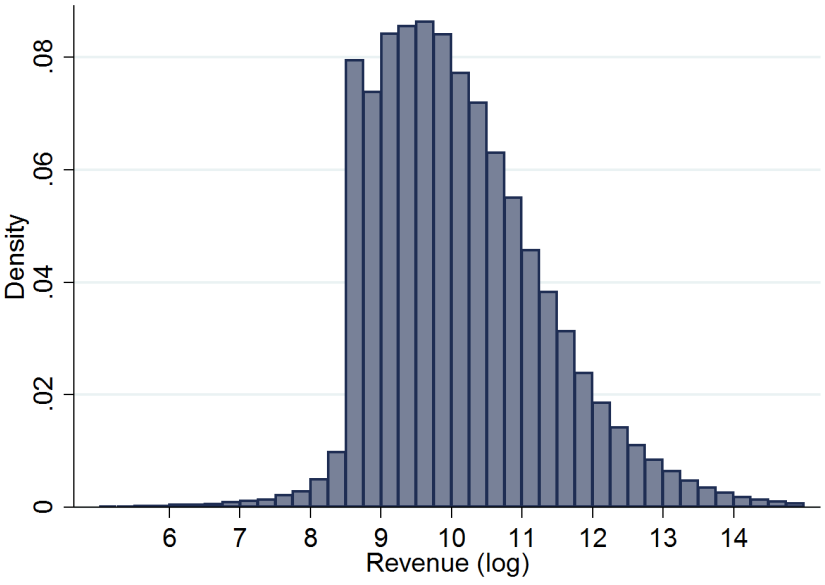
Figure 1. Potential output in China for rice and cotton (2000).



(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.

VARIABLES	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
VARIABLES	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.

		Standard deviation		
	Mean	total	within	between
Labor Cost	2.52	0.64	0.41	0.49
Employment	5.16	1.08	0.34	1.03
K/L Ratio	3.88	1.10	0.43	1.01
Y/L Ratio	3.74	0.95	0.54	0.78

Sources: NBS firm-level data (2001). The sample includes the 77,270 firms used in the baseline specification (4). *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 (in thousand yuan) to employment. *Y/L ratio* is the (log) ratio of value added to employment. 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.

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

VARIABLES	Labor cost	Employment	K/L ratio	Y/L ratio
	(1)	(2)	(3)	(4)
Panel A: OLS estimates				
Migration	-0.195	0.264	-0.195	-0.349
	(0.035)	(0.023)	(0.047)	(0.049)
Observations	463,620	463,620	463,620	463,620
N(Firms)	77,270	77,270	77,270	77,270
Panel B: IV estimates				
Migration	-0.533	0.359	-0.259	-0.499
	(0.114)	(0.058)	(0.056)	(0.142)
Observations	463,620	463,620	463,620	463,620
N(Firms)	77,270	77,270	77,270	77,270
F-stat (first)	24.82	24.82	24.82	24.82

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. *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 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—long run effects.

VARIABLES	Labor cost (1)	Employment (2)	K/L ratio (3)	Y/L ratio (4)
Panel A: OLS estimates				
Migration	-0.217	0.381	-0.317	-0.391
	(0.072)	(0.045)	(0.066)	(0.066)
Observations	77,270	77,270	77,270	77,270
Panel B: IV estimates				
Migration	-0.299	0.577	-0.452	-0.383
	(0.121)	(0.092)	(0.094)	(0.135)
Observations	77,270	77,270	77,270	77,270
F-stat (first)	30.50	30.50	30.50	30.50

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 3 and Equation (5) for a description of the IV specification.

Table 5. Impact of migration inflows on urban firms—heterogeneous effects.

VARIABLES	Labor cost (1)	Employment (2)	Labor cost (3)	Employment (4)
Migration	-0.536	0.360	-0.533	0.381
	(0.119)	(0.060)	(0.115)	(0.060)
Migration × *High K/L*	0.021	-0.050		
	(0.055)	(0.056)		
Migration × *High Y/L*			0.031	-0.182
			(0.057)	(0.061)
Observations	463,620	463,620	463,620	463,620

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 belongs to the top quartile within the industry/prefecture. *High Y/L* is a dummy equal to 1 if the baseline value added-to-labor ratio belongs to the top quartile within the industry/prefecture. All specifications include firm and year fixed effects. See Section 2 and Equation (6) for a description of the IV specification.

Table 6. Impact of migration inflows on urban firms—sensitivity analysis.

VARIABLES	Labor cost (1)	Employment (2)	K/L ratio (3)	Y/L ratio (4)
Panel A: Controlling for local shock				
Migration	-0.556	0.351	-0.280	-0.471
	(0.123)	(0.059)	(0.057)	(0.138)
Observations	463,578	463,578	463,578	463,578
Panel B: Controlling for shocks in neighboring prefectures				
Migration	-0.544	0.341	-0.273	-0.468
	(0.119)	(0.057)	(0.056)	(0.135)
Observations	463,620	463,620	463,620	463,620
Panel C: Excluding migrant flows within 300 km				
Migration	-0.452	0.460	-0.286	-0.465
	(0.096)	(0.076)	(0.067)	(0.158)
Observations	463,620	463,620	463,620	463,620
Panel D: Excluding processing industries				
Migration	-0.514	0.386	-0.259	-0.511
	(0.113)	(0.060)	(0.056)	(0.147)
Observations	418,717	418,717	418,717	418,717
Panel E: Controlling for industry × year fixed effects				
Migration	-0.567	0.347	-0.242	-0.432
	(0.133)	(0.063)	(0.063)	(0.153)
Observations	463,620	463,620	463,620	463,620
Panel F: Controlling for market access × year fixed effects				
Migration	-0.535	0.367	-0.258	-0.503
	(0.114)	(0.058)	(0.056)	(0.143)
Observations	463,620	463,620	463,620	463,620
Panel G: Forward shocks				
Migration $t+1$	-0.035	0.008	0.088	-0.119
	(0.080)	(0.036)	(0.044)	(0.081)
Observations	463,620	463,620	463,620	463,620

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 year fixed effects. See Section 2 and Equation (4) for a description of the IV specification.

Table 7. Impact of migration inflows on urban firms—sensitivity analysis with aggregate variables at the prefecture × sector level.

VARIABLES	Labor cost	Employment	K/L ratio	Y/L ratio
	(1)	(2)	(3)	(4)
Panel A: Balanced sample of firms				
Migration	-0.479	0.339	-0.314	-0.482
	(0.088)	(0.060)	(0.067)	(0.107)
Observations	33,798	33,798	33,798	33,798
F-stat (first)	26.24	26.24	26.24	26.24
Panel B: Unbalanced sample of firms				
Migration	-0.556	0.456	-0.394	-0.653
	(0.102)	(0.123)	(0.070)	(0.170)
Observations	36,276	36,276	36,276	36,276
F-stat (first)	23.72	23.72	23.72	23.72

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 8. Impact of migration inflows on urban residents.

VARIABLES	Wage	Employee	Unemployed	Self-employed
	(1)	(2)	(3)	(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)†	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%).

Table 9. Impact of migration inflows on urban firms—long term effects on product of factors.

VARIABLES	Labor pr. (1)	Capital pr. (2)	Total fact. pr. (3)
Panel A: Micro-estimates			
CES (sectoral ρ, China)	-0.536	0.230	-0.161
	(0.146)	(0.160)	(0.143)
Cobb-Douglas	-0.432	0.158	0.043
	(0.139)	(0.148)	(0.155)
Observations	77,270	77,270	77,270
F-Stat (first)	30.50	30.50	30.50
Panel B: Aggregate variables			
CES (sectoral ρ, China)	-0.603	0.122	-0.214
	(0.131)	(0.121)	(0.143)
Cobb-Douglas	-0.484	0.029	0.012
	(0.116)	(0.109)	(0.108)
Observations	5,633	5,633	5,633
F-Stat (first)	32.28	32.28	32.28

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. *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. In Panel A, the unit of observation is a firm. In Panel B, a unit of observation is a prefecture $\times$ sector. *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. See Section 4 for details about the construction of these variables, and see Section 3 and Equation (5) for a description of the IV specification.

Table 10. Impact of migration inflows on urban firms—long-term heterogeneous effects on employment depending on factor productivity.

VARIABLES	Employment		
	(1)	(2)	(3)
Migration	0.607	0.648	0.631
	(0.095)	(0.091)	(0.091)
Migration × *High MRPL*	-0.282		
	(0.087)		
Migration × *High MRPK*		-0.350	
		(0.081)	
Migration × *High TFPR*			-0.324
			(0.087)
Observations	77,270	77,270	77,270

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. *Employment* is the (log) number of workers. *K/L ratio* is the (log) ratio of fixed assets to employment. *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. In Panel A, the unit of observation is a firm. *High MPL* is a dummy equal to 1 if the baseline marginal product of labor is in the top quartile within a sector × prefecture. *High MPK* is a dummy equal to 1 if the baseline marginal product of capital is in the top quartile within a sector × prefecture. *High TFP* is a dummy equal to 1 if the baseline total factor productivity is in the top quartile within a sector × prefecture. See Section 4 for details about the construction of these variables, and see Section 3 and Equation (5) for a description of the IV specification.

Table 11. Counterfactual experiment—effects of migration on wages, factor use and factor productivity (growth and dispersion).

	Annual growth (2001–2006)	Standard deviation (2006/2001)		
		all	within pref.	betw. pref.
Panel A: Labor cost				
Actual	0.13	0.86	0.87	0.83
No migration	0.22	1.14	0.86	1.72
Panel B: K/L Ratio				
Actual	0.06	0.92	0.92	0.92
No migration	0.19	1.00	0.90	2.01
Panel C: Labor productivity				
Actual	0.14	0.95	0.96	0.87
No migration	0.23	0.99	0.95	1.36
Panel D: Capital productivity				
Actual	0.04	0.94	0.93	1.01
No migration	-0.06	1.00	0.92	1.83

Notes: In the counterfactual scenario (*No migration*), we set the immigration rates equal to 0 in every prefecture and every year between 2001 and 2006. Column 1 reports the average annual growth rate between 2001 and 2006 under the different scenarios. Column 2 reports the standard deviation of the variable of interest in 2006 normalized by its standard deviation in 2001; columns 3 and 4 replicates this exercise with the separate between- and within-components.

ONLINE APPENDIX

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.[36] Chinese citizens are classified along two dimensions: their *hukou* type (*hukou xingzhi*)—agricultural (*nongye*) or non-agricultural (*fei nongye*)—and *hukou* location (*hukou suozaidi*). Both characteristics, recorded in the household registration booklet, may not correspond to the 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, to reduce migrant workers' bargaining power and to lock migrants 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

[36] 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-to-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' place 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 thanks to 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.

A few caveats are in order. First, the sampling frame contained 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) Both data sources provide prefecture-level information on the place of residence, but it is defined as "current residence" in 2005 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-to-rural migration represents a small share of emigration from rural areas, mostly explained by marriage—which usually gives right to local registration (Fan, 2008).[37] (iv) We cannot account for migrants who changed their *hukou* location or type. This assumption is quite innocuous given that *hukou* conversion is marginal.

[37]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 A2 for further descriptive statistics on reasons for moving.

Migration flow construction The retrospective data on migration spells in the two 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.

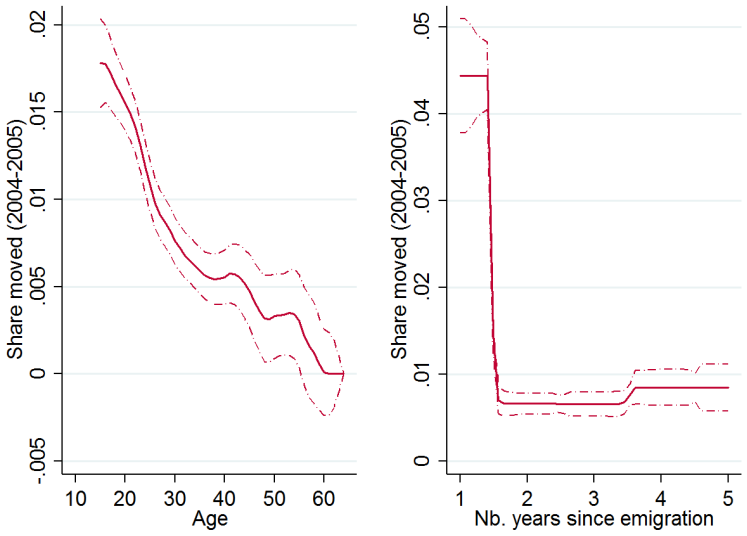
Not all migration spells are observed in the three censuses. We only observe single migration spells, i.e., migration spells in which the interviewed individual is at destination at the time of interview, and whose origin coincides with the *hukou* location. For these individuals, the origin is deduced 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. Indeed, 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 A1 shows, only a minority of migrants have changed provinces of destination between 2003 and 2004. Step migration is not only small but 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 also 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 A1. Share of step migrants as a function of age and time since departure.



Sources: 2005 1% Population Survey.

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 A2. Over-identification test for the return migration correction.

Sources: 2005 1% Population Survey.

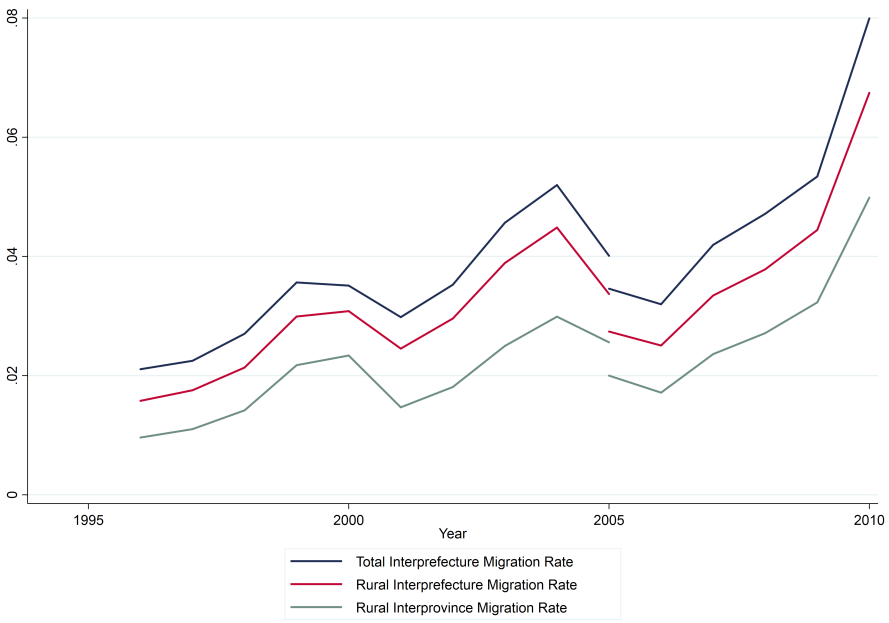
Figure A2 displays the model-based return probabilities for recently-arrived migrants against the actual observed return rate. The baseline specification (B, blue dots) matches well the prefecture-level variation in annual return rate for recently-arrived migrants, while the alternative specification (R, red dots) systematically underestimates 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 A3 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 A3 provides some information about the nature of these migration spells. Migration is mostly rural-to-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 ruralto–urban migrations involve the crossing of a provincial border.

Figure A3. 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 (see Table A1). Some regions (e.g., East, South Central) are net recipients, and attract a large share of local migrants, while some other regions (e.g., North-West)

are net senders. However, even if there is significant variation in terms of both emigration and immigration rates across regions, no region is left aside from the migration phenomenon. Moreover, conditional on originating from the same prefecture, there is dispersion of migration spells across destinations. The bottom panel of Table A1 displays the prefecture-level Herfindahl-Hirschmann Index of destination concentration. Regions differ in terms of destination concentration but migrants from any of the six main regions do not all flock to a single destination.

Table A1. 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 panel displays yearly migration rates in 2000 and 2005 by region of destination. Rates are expressed as a share of the total urban population in the region in 2000. The bottom panel (Destination concentration) provides standardized Herfindahl-Hirschmann Indices (HHI) for destination concentration. 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 profiles 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-to-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 A2 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.[38]

[38]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."

Table A2. 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-to-urban migrants are a selected sample of the origin population. We provide some elements of comparison between migrants and stayers in Table A3. 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-to-urban productivity gap appears to be massive as the migrants' monthly income is more than twice as large as the stayers'.

Rural-to-urban migrants are however also different from urban residents. As is usual with studies of internal migration, we consider in our main specifications that migrants and locally registered non-agricultural *hukou* holders are highly substitutable. Table A3 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-to-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-to-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', a gap that is even higher when accounting for the fact that migrants are attracted to buoyant cities.[39]

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 pre-

[39]Results available upon request.

fectures of residence. The compliers are however selected, and our estimates are a local average treatment effect. In counterfactual experiments, we incorrectly 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-to-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 D.4.

Table A3. Migrant selection (2005 mini-census).

	Rural-to-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* and *Monthly income* are dummy-coded. Only the income of individuals who reported having a job is considered. 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 in a 30 arc-second resolution (approximately 10km). 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. It is a time-invariant, model-based measure that 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 a potential yield for a given crop and a given soil under different levels of input 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 harvested and irrigated areas in 2000 to construct potential yield y_{co} for each crop c and prefecture o.

Table B1 shows the variation in potential yields and harvested areas 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 concentrated in particular regions. Rice, for instance, is absent from the colder and drier northern regions. Nonetheless, there is substantial regional variation, and no crop is cultivated in a single region, or a region characterized by 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.[40]

Table B1. Variation in price shocks, potential yields 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 potential yields, 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 potential yields and harvested area for the main crops under irrigated and rain-fed agriculture. The bottom panel shows the shares (estimated by ANOVA and averaged by region over the period 1998–2007) of within- and between-prefecture variation in total variation in the price shock variable. Harvested area refers to the normalized area under cultivation.

B.2 International price variations and domestic prices

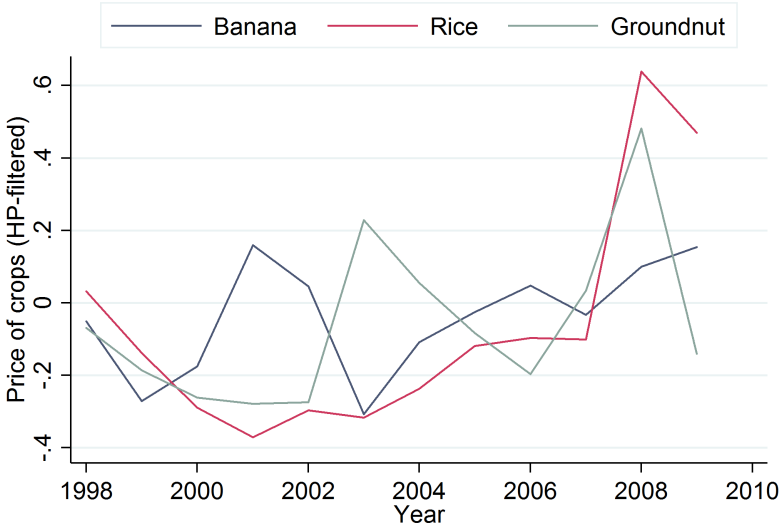
The construction of our shocks to rural livelihoods relies on time variation in international commodity prices. This strategy hinges on two assumptions.

A first assumption is that short-term fluctuations in international crop prices are quantitatively relevant. Figure B1 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 B2 confirms that international price variations do translate into price fluctuations in the Chinese domestic market. The first column provides the 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

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

Figure B1. Price deviations from trends on International Commodity Markets 1998–2010.



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.

to the domestic market. 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 livelihoods exhibit variation both across space and over time. The bottom panel of Table B1 provides between- and within-region variation in the price shock for China's 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. No region stands out as being particularly subject to such shocks or immune to them. Figure B2 displays the price shocks in 2001 (left panel) and 2002 (right panel).

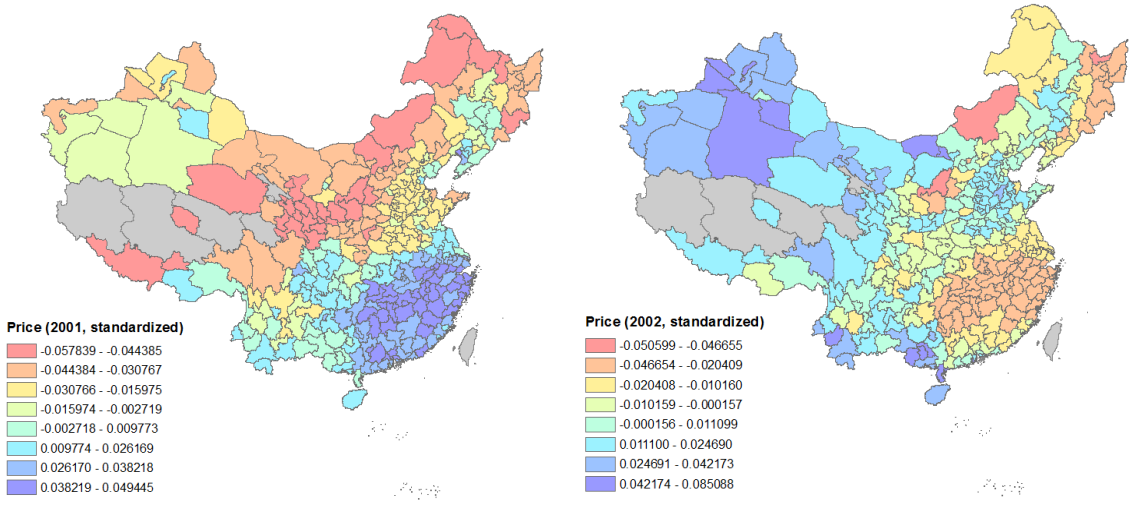
These cross-sectional and time variations carry over from the price shocks to the supply-push instrument, i.e., the predicted flows of immigrants. Figure B3

Table B2. Correlation between crop international prices and local Chinese prices/production.

VARIABLES	Price (1)	Output (2)
Price (International)	.402	.201
	(.086)	(.062)
Price (China)		.082
		(.043)
Observations	210	210
R-squared	.579	.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.

Figure B2. Shocks to rural livelihoods across Chinese prefectures in 2001 and 2002.



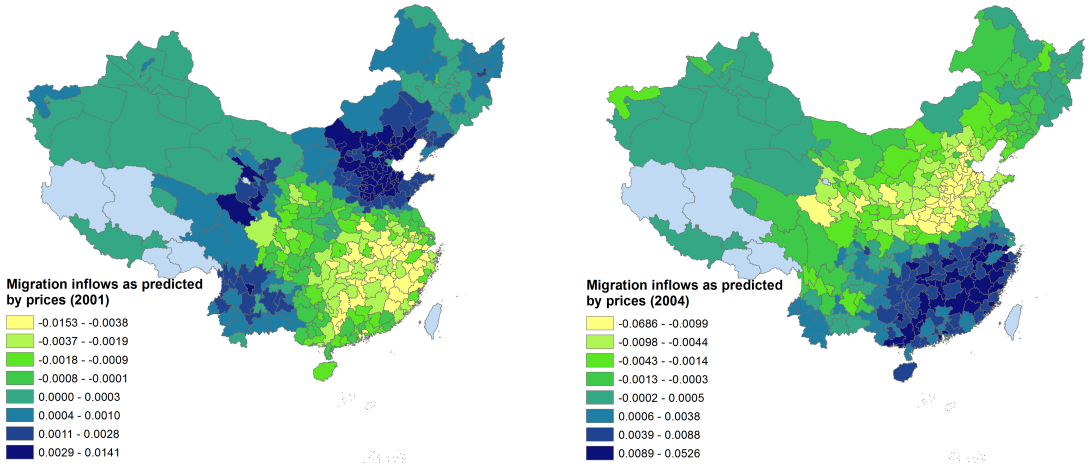
(a) 2001 (b) 2002

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.

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 underlying cropping patterns induce non-negligible spatial correlation. We quantify this spatial auto-correlation in Figure B4, where we report an "Incremental Spatial Autocorrelation" analysis, which shows that spatial auto-correlation fades away

Figure B3. Predicted migrant inflows into cities in 2001 and 2004.

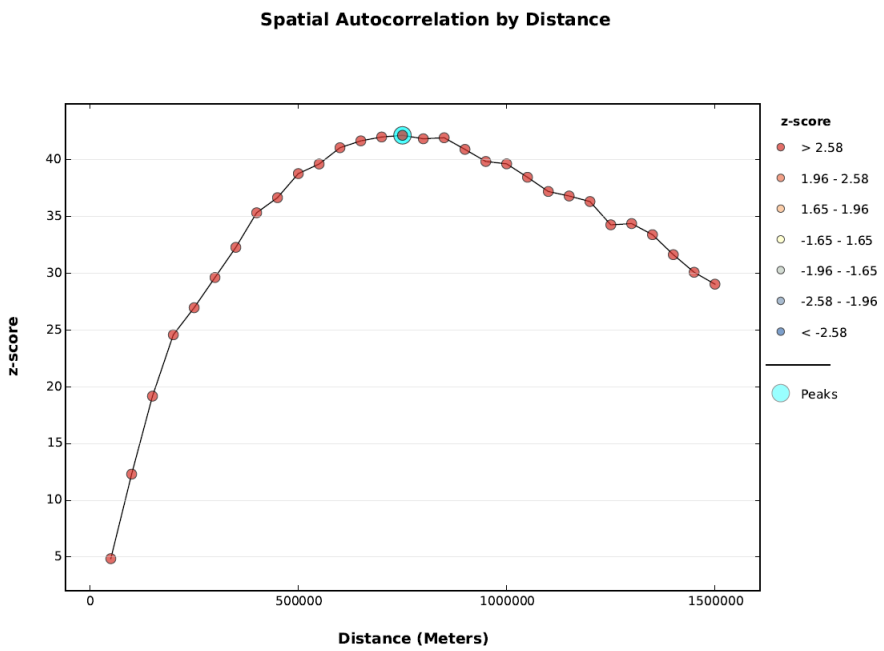


(a) 2001 (b) 2004

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 distance between origin and destination.

beyond 500–600km.

Figure B4. 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.

B.4 An additional source of variation: rainfall shocks

As a robustness check (see Table E1), we construct a second type of shocks to agricultural income based on rainfall deficit during the growing period of each crop.

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.[41] 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) the crop-specific rainfall requirements. For a given year, there are several sources of variation across Chinese prefectures in actual yields 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, (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.[42] We then generate

$$r_{ot} = \left(\sum_c \left(\frac{\max\{\sum_{m \in M_c} wr_c - ra_{omt}, 0\}}{wr_c} \right)^{\alpha} h_{co} y_{co} \bar{P}_c \right) / \left(\sum_c h_{co} y_{co} \bar{P}_c \right). \quad \text{(B1)}$$

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 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.[43] Finally, we weight rainfall deficits by potential output for each crop in each prefecture to obtain a measure of rainfall deficits for each prefecture × 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.

[41] 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/.

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

[43] 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 UHS, used to capture the wage of urban residents. We then provide additional descriptive statistics about the 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.[44]

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. However, data for 1992, 1993, 1995, 1997 and 2008–2009 sometimes offer a different set of variables and cannot easily be used to create a panel of firms. For that reason, we restrict ourselves to the balanced panel of firms over a restricted period 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 or phone number. 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 of observation may be unfamiliar to readers accustomed to U.S. or European data,

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

"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 C1 displays descriptive statistics for the sample of all firm $\times$ year observations over the period 2001–2006, for the balanced panel and for 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.[45] The difference between the balanced panel and whole sample comes from inflows (new entrants) and outflows (exiters). The third and fourth columns of Table C1 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 sharply but 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.[46] Figure 2 however shows that this is unlikely to be a serious issue and the threshold is quite sharp. Firms that are below the threshold represent but a small share of the total sample and dropping them does not affect the results.

[45] Ownership type is defined based on official registration (*qiye dengji zhuce leixing*). Out of 23 exhaustive categories, Table C1 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.

[46] 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 C1. 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	463,620	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 2001, 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.

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 and 70% of the industrial workforce.

Third, firms may have an incentive to under-report the number of workers as the report 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 thanks to the 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 UHS data

In order to study the impact of immigration on local labor markets, we use the national 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.[47]

[47]While all households living in urban areas are eligible, sampling still ignores urban dwellers living in townships and in suburban districts (Park, 2008). Rural-to-urban migrants, who are more

Table C2. 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.

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—and 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).[48]

likely to live in peripheral areas of cities, are therefore under-represented.

[48]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 dependent variable in our analysis.

Table C2 provides some descriptive statistics of key variables over the period 2002–2008 and shows that the sample is not so different from the exhaustive sample of locally registered urban *hukou* holders (Census data, see Table A3).

C.3 Descriptive statistics

In this section, we provide additional descriptive statistics to inform two crucial aspects of the quantitative analysis: (i) the heterogeneity 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, 2015). We provide some evidence of these patterns in Table C3, where we report the dispersion in aggregate factor use and factor productivity across prefectures and 2-digit industries in 2001 and 2006.

Table C3. General trends in China (2001–2006).

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

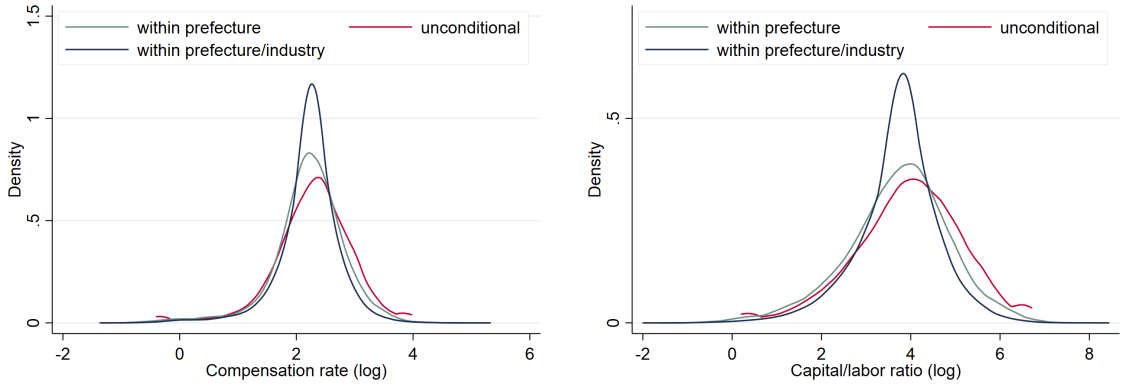
Notes: NBS firm-level data (2001–2006). Standard deviations are displayed in parentheses. This table displays descriptive statistics from the unbalanced firm-level data aggregated at the prefecture × 2-digit industry × year level. *25th (75th)* stands for the 25th (75th) percentile. The growth rate is 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. *Log Y/L* (resp. *Log Y/K*) is the logarithm of the ratio of value added to employment (resp. capital).

Table C3 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 factor use increased across prefectures/industries (as captured by the difference in variance between 2001 and 2006), the dispersion of factor returns decreased. This observation is consistent with the improved factor reallocation already documented in Brandt et al. (2013) and Tombe and Zhu (2015). Third, consistent with the previous insight, there is a slight decrease in the dispersion of wages.

Table C3 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 C1, 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/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 C1. Dispersion in labor cost and capital/labor ratio across firms.



(a) Labor cost.

(b) Capital/labor ratio.

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

D 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 the estimation of the main parameters of the model, i.e., the industry-specific elasticity of substitution between capital and labor, the industry-specific capital share 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. Finally, we discuss the bias induced by the hypothesis of homogeneous labor (i.e., ignoring productivity differences between migrants and established workers).

D.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,

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

firm i in a certain product market thus maximizes the following program,

$$\max_{p_i, y_i, l_i, k_i} \left\{ p_i y_i - (1+\tau_i^l) w l_i - (1+\tau_i^k) r k_i \right\},$$

subject to the production technology,

$$y_i = A_i \left[\alpha k_i^\rho + (1-\alpha) l_i^\rho \right]^{\frac{1}{\rho}},$$

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

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

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

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

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

D.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 and derive the firm-specific relative factor demand:

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

where ε_i depends on the distortions $\left(\tau_i^l, \tau_i^k\right)$. We identify the parameter ρ using the variation in relative factor prices across prefectures and across years induced by counterfactual 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:

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

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.

D.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 × 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:

$$\ln\left(k_{sdt}/l_{sdt}\right) = \frac{1}{1-\rho}\ln\left(\frac{\alpha}{1-\alpha}\right) + \frac{1}{1-\rho}\left(w_{dt}/r_t\right) + \varepsilon_{sdt}. \tag{D1}$$

where s denotes the industrial sector, 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 (D1) 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.[49] Second, the residual, ε_{sdt}, which captures the firm-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.

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

$$\ln\left(k_{sdt}/l_{sdt}\right) = a + b\ln\left(w_{dt}\right) + \mathbf{X_{sdt}}\beta_{\mathbf{2}} + \varepsilon_{sdt}, \tag{D2}$$

where the vector $\mathbf{X_{sdt}}$ contains prefecture × broad industry, year and year × broad industry fixed effects. The standard errors are clustered at the level of the prefecture.

[49] 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.

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.[50] 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:

$$\ln(w_{dt}) = \gamma z_{dt} + \mathbf{X_{sdt}}\beta_{\mathbf{1}} + u_{dt},$$

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 × industry cell.

Table D1. Elasticities of relative factor cost to relative factor prices across sectors.

Panel A: first stage				
Labor cost	(1)	(2)	(3)	(4)
Predicted immigration rate	-3.37	-2.79	-3.18	-4.87
	(0.59)	(0.49)	(0.50)	(0.70)
Panel B: second stage				
Relative factor cost	(1)	(2)	(3)	(4)
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.	33.48	33.41	41.52	48.26
Broad sector	Agro.	Petroleum	Metal	Misc.

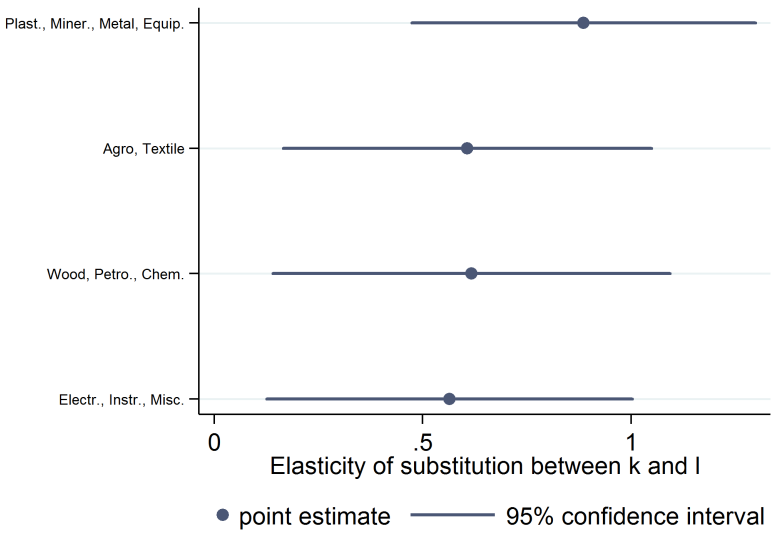
Notes: Standard errors are clustered at the prefecture level and reported between parentheses. An observation is a prefecture × broad industrial sector × year. *Labor cost* is the average compensation rate in the prefecture—$\ln(w_{dt})$ in Equation (D2),—and *Relative factor cost* is $\ln(k_{sdt}/l_{sdt})$. 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 prefecture × sector, year and year × sector fixed effects.

[50] 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.

Results We estimate Equation (D2) separately for **four** broad clusters of industry (Agro-industry and Textile; Wood, Petroleum and Chemicals; Plastics, Minerals, Metal and Equipment; Miscellaneous). We report the first stage in Panel A of Table D1 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 (D2), 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 D1. Moreover, the IV estimates, shown in Table D1, are not significantly different than the (unreported) OLS estimates.

Figure D1. 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 (D1) and are given by the IV coefficients displayed in Table D1. Standard errors are clustered at the prefecture level.

D.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, and 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 $h = l_r + \beta l_m$ denote efficient labor units, where $\beta < 1$ and $l = l_r + l_m$ is observed employment. The production technology is,

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

The first-order conditions give us:

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

where $w = w_r = w_m/\beta$ 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,

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

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

and revenue-based Total Factor Productivity,

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

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:

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

for the labor cost,

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

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

for the returns to factors and

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

for the revenue-based Total Factor Productivity. Under the hypothesis that $l_m << l_r$ (upper bound for the bias) and following a small increase of $\Delta l_m = 1\% l_r$, we have:

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

Quantification of the bias Before we quantify the bias for the different elasticities, we need to calibrate some parameters. First, the value of $\beta < 1$ 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 $\beta = 0.80$. Second, the ratio $(1-\alpha)l^\rho/(\alpha k^\rho + (1-\alpha)l^\rho)$ 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, -0.04.

E 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.

E.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 E1 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 E1. 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.

Another shock to rural livelihoods We investigate whether rural emigration reacts to a similar type of agricultural shocks to rural livelihoods. We compare the effect of commodity prices to a rainfall effect, measured using precipitation along the

cycle of agricultural crops (see Appendix B.4). The results presented in the third and fourth columns of Table E1 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 E1 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 nighttime 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 E1.

Figure E1. 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 all 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 emigration rate 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.

E.2 Emigration and immigration flows

Definition of immigration flows In the baseline specification, we use all migrant flows of workers between 25 and 64 years old to construct the emigration rate and the actual and predicted immigration rates, and we depart from this baseline only in Table E2. In this section, we relax this restriction and allow for various definitions of a migration spell.

Table E2. Origin-based migration predictions—alternative definitions of migration spells

Panel A: Predicting emigration				
Outmigration	(1)	(2)	(3)	(4)
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
Year FE	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes
Panel B: Predicting immigration				
Immigration	(1)	(2)	(3)	(4)
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
Year FE	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes
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.

In the first column of Table E2, 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 all intra-provincial flows at all stages of the analysis. In the third column, we use males 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).

Bilateral migration flows In the baseline specification, we use migration patterns from earlier cohorts in construct exogenous probabilities to migrate from each origin to each destination. In this Appendix, we show that an alternative is to use a gravity model of migration flows to predict previous migration (as in Boustan et al., 2010) and rather 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. 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 E3. Origin-based migration predictions—gravity equations

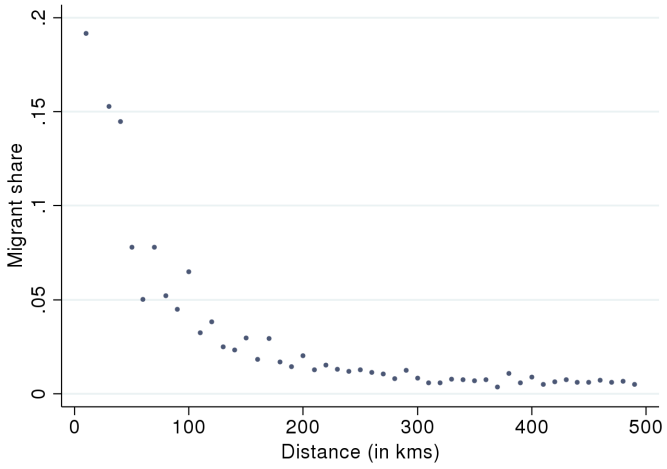
Panel A: Gravity equation			
Bilateral flows	(1)	(2)	(3)
Population at destination	0.051	0.048	0.050
	(0.003)	(0.003)	(0.003)
Distance (inverse)	9.454		4.957
	(0.576)		(1.540)
Travel distance (inverse)		6.672	3.366
		(0.371)	(0.935)
Observations	115,599	115,599	115,599
R-squared	0.223	0.223	0.227
Year FE	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes
Panel B: Predicting immigration			
Immigration	(1)	(2)	(3)
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
Year FE	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes

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.

We report the estimated gravity equations in Panel A of Table E3, and the relationship between the constructed and the actual immigration rates is shown in Panel B. As apparent in Panel A, both population and bilateral travel distance are

very good predictors of previous migration patterns.[51] Importantly, the immigration prediction is robust to these alternative specifications (see Panel B).

Figure E2. Origin-destination migration predictions—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 kilometers).

E.3 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 E4 presents the (unweighted) effect of rural-to-urban migration on labor cost, employment, relative factor use and value added per worker in the short (Panel A) and in the long run (Panel B). The estimates are extremely similar to the baseline estimates (see Tables 3 and 4).

Heterogeneous responses across establishments In this section, we derive additional heterogeneity results (see Section 3 and Table 5 for the baseline analysis).

We explore in Table E5 whether sectoral characteristics matter, notably through the structure of production (elasticity of substitution between labor and capital, and 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, and (ii) a dummy for above-median sectoral educational requirement, as calculated from the

[51]Figure E2 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.

Table E4. Impact of migration inflows on urban firms—sensitivity analysis without regression weights.

VARIABLES	Labor cost	Employment	K/L ratio	Y/L ratio
	(1)	(2)	(3)	(4)
Panel A: baseline specification				
Migration	-0.513	0.333	-0.229	-0.453
	(0.124)	(0.055)	(0.062)	(0.149)
Observations	463,620	463,620	463,620	463,620
N(Prefecture × industry)	77,270	77,270	77,270	77,270
F stat. (first)	21.42	21.42	21.42	21.42
VARIABLES	Labor cost	Employment	K/L ratio	Y/L ratio
	(1)	(2)	(3)	(4)
Panel B: long-term specification				
Migration	-0.251	0.526	-0.402	-0.400
	(0.116)	(0.088)	(0.104)	(0.145)
Observations	77,270	77,270	77,270	77,270
F stat. (first)	29.76	29.76	29.76	29.76

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 prefecture × industry and year fixed effects. The table presents the output of the IV estimation. In Panel A, 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.

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 not statistically significant in either case.

We also interact the immigration rate with a dummy for public firms (column 3), older firms (column 4) and larger firms (column 5). We find that migrants are less likely to be hired in older establishments and in public establishments, where insiders are likely to receive substantial benefits. None of the interactions 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 E3. This finding is consistent with fairly integrated labor markets at destination: A similar decrease in wages is observed across 1-digit industries.

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 on elasticities of substitution as estimated by Oberfield

Table E5. Impact of migration inflows on urban firms—additional heterogeneous treatment effects across firms.

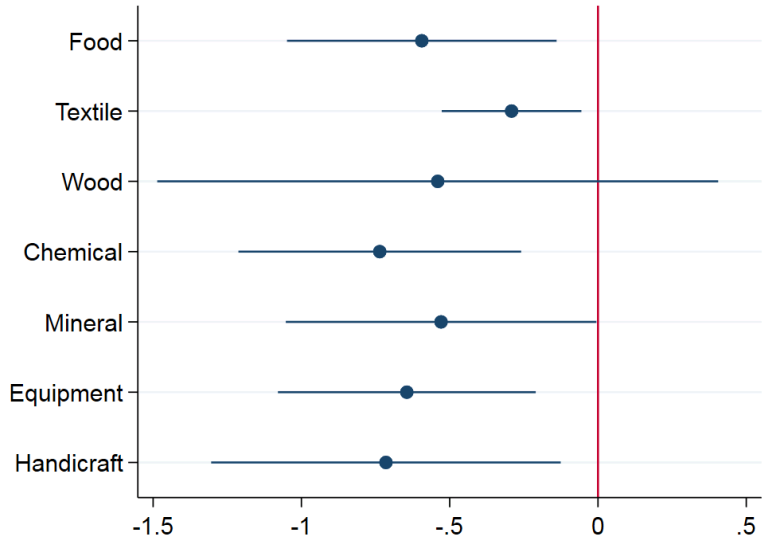
Employment	(1)	(2)	(3)	(4)	(5)
Migration	0.373	0.350	0.282	0.370	0.404
	(0.067)	(0.052)	(0.049)	(0.066)	(0.065)
Migration × *Complementarity*	-0.039				
	(0.060)				
Migration × *High-skill*		0.027			
		(0.065)			
Migration × *Public*			-0.141		
			(0.141)		
Migration × *Older firms*				-0.021	
				(0.058)	
Migration × *Larger firms*					-0.119
					(0.070)
Observations	463,620	463,620	463,620	463,620	463,620

Notes: Standard errors are clustered at the prefecture level and reported between parentheses. See Section 2 and Equation (6) for a description of the IV specification. The sample is composed of firms present every year in the NBS firm census between 2001 and 2006. All specifications include firm and year fixed effects. *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 if the firm belongs to an industry primarily employing workers with higher than high-school attainment. *Older firms* (resp. *Larger firms*) is a dummy equal to 1 for firms whose age (resp. size) is above its industry/prefecture third quartile.

and Raval (2014) on U.S. establishments in 1987 and in 1997.

Table E6 reports the estimates from the long-term specification (5) at the firm-level (77,270 observations). The main insights from Table 9 are robust to the new calibration: There is a sharp decrease in returns to labor and an increase in the returns to capital.

Figure E3. 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.

Table E6. Impact of migration inflows on product of factors—using U.S. estimates for industry-specific factor complementarity.

VARIABLES	Return to labor (1)	Return to capital (2)	Total fact. pr. (3)
CES (sectoral ρ, US 1987)	-0.691	0.412	-0.250
	(0.148)	(0.181)	(0.144)
CES (sectoral ρ, US 1997)	-0.840	0.481	-0.236
	(0.184)	(0.189)	(0.149)
Observations	77,270	77,270	77,270
F-Stat (first)	30.5	30.5	30.5

Notes: Each cell is the outcome of one regression, based on the long-term specification (5) estimated at the firm level. Standard errors are clustered at the prefecture level and reported between parentheses. *Return to labor* is the (log) marginal revenue product of labor; *Return to capital* 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 estimates of Oberfield and Raval (2014). See Section 4 for details.