Growing without Divergence: The Impact of Innovation on Low- and High-skilled Migration in China*

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Abstract

This paper examines the impact of innovation on migration patterns across skill groups, taking into account labor market, housing market, and amenity responses. Utilizing data from the Chinese Census spanning 2005 to 2015, we find that cities experiencing higher patent growth attract more low-skilled migrants than high-skilled migrants, a pattern that contrasts with findings from other developed countries. These cities also exhibit stronger wage growth for both low- and high-skilled workers, but not faster growth in amenities. To interpret these empirical results, we develop and estimate a spatial equilibrium model. Our analysis indicates that low-skilled workers prioritize wages more highly, whereas high-skilled workers place greater value on amenities. Furthermore, a higher proportion of skilled workers in a city increases the local supply of amenities. As a result, a positive shock to patent activity draws in more low-skilled than high-skilled workers. This then leads to a reduction in amenities, and thereby further discourages high-skilled migration. Counterfactual analysis suggests that technological growth in China has substantially increased wages and welfare for both low-skilled and high-skilled workers. In general, we find that the growth in China in the last decade did not lead to spatial divergence.

Keywords: Patent, Migration, Spatial equilibrium, Wage, Amenity

JEL Codes: J24, J61, R23

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1 Introduction

The impact of economic growth on the geographical distribution of the population has been a prominent area of research for many years. Numerous studies demonstrate a tendency for high-skilled and high socioeconomic-status individuals to cluster in locations with high wages, high rents, and abundant amenities in developed countries (Diamond, 2016; Giannone, 2017; Guerrieri, Hartley, and Hurst, 2013; Moretti, 2012). High-skilled workers are more likely to migrate to large cities with elevated wages due to skill-biased technological change or productivity spillovers, which in turn increase housing rents and amenities. This process often forces low-skilled workers to relocate or exit these areas. This phenomenon is referred to as "the Great Divergence," characterized by a significant increase in the geographic sorting of workers by skill and a rise in inequality (Diamond and Gaubert, 2022; Durlauf, 2004; Fajgelbaum and Gaubert, 2020).

Over the past four decades, China has experienced significant economic growth characterized by rapid increases in Total Factor Productivity (TFP) and technological advancement. This raises an important question: does this substantial technological surge lead to spatial sorting and divergence, primarily benefiting high-skilled workers in China? Our study aims to assess the impact of regional innovation shocks on spatial economic dynamics in China during the period from 2005 to 2015, a timeframe marked by one of the most notable periods of technological growth in recent history.

Regional disparities in economic development are often driven by differences in productivity and innovation levels across regions. China's eastern coastal regions, which have led the country's opening-up policy, benefit from enhanced connectivity to global markets and are more proficient at integrating new technologies from developed countries. As technological advancement accelerates, there are concerns that these eastern regions may further consolidate their advantageous position over inland areas, thereby exacerbating existing regional economic inequalities. This paper examines the impact of local technological innovation, specifically patent shocks, on the spatial sorting of skilled and unskilled labor across prefecture-level cities, as well as the implications for wage and welfare inequality in China. In particular, we analyze how heterogeneous worker preferences based on skill levels influence migration patterns, and how interactions among the labor market, housing market, and amenity market shape these dynamics. We address these issues through a two-step analytical approach.

In the first step, we present descriptive evidence illustrating the causal effects of patent growth on migration inflows, wages, housing prices, and amenities at the prefecture city level from 2005 to 2015. Patent and citation data are sourced from the China National Intellectual Property Administration and Google Patents; innovation is measured by patents weighted by citations to capture both the quantity and quality of inventive activity. Migration flows by skill group between city pairs are calculated using data from the Population Census, with high-skilled workers defined as individuals holding a college degree or higher. Additionally, we collect city-level data on health services, infrastructure, environmental quality, and education services from City Statistical Yearbooks. To synthesize these variables, we employ Principal Component Analysis (PCA) to construct an amenity index, which reflects the provision of public goods by local governments and the overall quality of life in each city. To address potential endogeneity concerns related to citation growth, we use a shift-share Bartik instrument. This instrument is constructed by multiplying national industry-level patent citation growth (the shift component) with the industry employment ratio in each city in the initial period (the share component).

Our analysis yields three primary findings. First, cities experiencing higher patent citation growth saw greater wage increases for both high- and low-skilled workers, with the magnitude of these increases being similar across skill levels. This indicates that innovation in China over the past decade did not exhibit a strong skill-biased pattern.[1] Second, patent citation growth significantly increases migration flows for both skill groups, but the effect is notably stronger for low-skilled workers, resulting in a decreased skilled-worker ratio in cities with faster innovation-driven growth. Third, while citation growth is associated with rising housing prices, it has a significantly smaller impact on amenities. In summary, we find no evidence of positive spatial sorting driven by innovation shocks in China. Instead, low-skilled workers respond more strongly to these shocks, indicating a different pattern of spatial mobility than what might be expected under traditional sorting models.

To elucidate the mechanisms underlying these findings, the second part of the paper develops a spatial equilibrium model. This model incorporates heterogeneous workers, local innovation shocks, and endogenous wages, housing rents, and amenity provision within a general equilibrium framework, building on Diamond (2016). To capture the unique institutional features of the Chinese economy, we extend the model by introducing two sectors within each prefecture city: agricultural and non-agricultural sectors. We assume that each worker is characterized

[1]Technological progress may enhance productivity for both low- and high-skilled workers. Additionally, advancements can stimulate growth in the low-skilled service sector, increasing demand for low-skilled labor.

by a home city, a *hukou* type, and a skill level (high or low).[2] Workers make sector and location choices based on wages, housing rents, amenities, migration costs, and location-sector preference shocks, and they hold heterogeneous preferences for city attributes. Migration costs depend on the *hukou* policies of the destination city and the relative location of the origin and destination.

For the non-agricultural sector, we assume a Cobb-Douglas production function with capital, high-skilled, and low-skilled labor as inputs. Local production technology in this sector is influenced by patent citations, reflecting innovation activity. In contrast, the agricultural sector employs a simpler production function that depends solely on the total number of workers, with its growth unaffected by patents. Housing supply is determined by local construction activities and land costs, where land costs are affected by overall housing demand in the area. Amenities in each location are endogenously determined by the local technology level and the ratio of high-skilled workers; technological growth directly enhances amenities, while a higher proportion of high-skilled workers improves local education quality and the social environment (Diamond, 2016; Su, 2022; Couture et al., 2024). A spatial general equilibrium is achieved when labor and housing supplies balance with demand in each location. To estimate this model, we log-linearize and transform it into a system of linear equations. We then employ the Bartik IV method to identify key model parameters (Borusyak, Hull, and Jaravel, 2022; Goldsmith-Pinkham, Sorkin, and Swift, 2020). The estimation of the labor supply equation follows the approach of Berry, Levinsohn, and Pakes (2004) using a two-step estimation procedure.

Our estimation underscores the significance of heterogeneous worker preferences, which are influenced by skill levels, in shaping sorting patterns. While workers across different skill levels respond similarly to changes in rent, low-skilled workers are more sensitive to wage fluctuations, whereas high-skilled workers prioritize amenities more heavily. This difference likely stems from the fact that low-skilled workers are predominantly rural-to-urban temporary migrants and thus are less eligible for urban amenities, while high-skilled migrants are more often urban-to-urban movers seeking to settle in the destination city, and permanent migrants have much better access to amenities. Although patent shocks significantly impact wages for both worker types, they tend to attract a larger influx of low-skilled workers, resulting in a decline in the overall skill ratio. This decrease in the skill ratio subsequently reduces amenities, partly offsetting the direct

[2] The household registration policy in China, known as the *hukou* policy, classifies individuals along two dimensions: sector and location. Those with an agricultural *hukou* are tied to farmland in their hometown, while individuals with a non-agricultural *hukou* have access to a broad range of public services—including education, healthcare, and social insurance—in urban areas. Changing the *hukou* sector or location is generally difficult, and policies for granting local *hukou* vary across cities (Fan, 2019).

positive effects of technological innovation on amenities.[3] This dynamic influences migration decisions, particularly deterring high-skilled migrants. As a result, China's economic growth over the past decade has increased wages and benefited both high- and low-skilled workers without leading to significant spatial skill sorting or divergence. Figure 1 illustrates the primary structure of our spatial equilibrium model (to be explained in more detail in Section 5.6).

We further conduct several counterfactual analyses using the estimated quantitative model. First, we examine the impact of eliminating innovation and patent growth in China from 2005 to 2015 by setting patent citation levels to their 2005 values, effectively removing technological progress during this period. Consequently, migration sharply decreases by nearly 30% nationwide, with low-skilled migration dropping even more. Wages in the non-agricultural sector also fall by about 70%, narrowing the urban-rural wage gap and discouraging migration, while housing rents and amenities decline substantially, reflecting reduced income and technological progress. Most regions are significantly affected, except the northeastern region, which experienced population loss due to stagnating patent growth during the studied period.

The welfare analysis reveals that eliminating innovation significantly harms all groups, especially low-skilled workers with non-agricultural Hukou. Overall inequality in income decreases, but welfare inequality increases, highlighting differences between income and well-being. The simulation suggests that technological growth in China has helped reduce welfare inequality by enabling low-skilled workers to migrate and access better amenities.

The second counterfactual analysis examines how wages, rents, amenities, and skill ratios influence workers' migration decisions. We identify four channels through which technological growth impacts migration: the wage effect, the rent effect, the direct amenity effect, and the indirect amenity effect mediated by changes in skill ratios. By running simulations that isolate and eliminate each channel individually, we analyze the impact of patent shocks on high- and low-skilled migration in each scenario. For high-skilled workers, the results indicate that amenities are the primary drivers of migration. Specifically, removing the direct amenity effect almost entirely eliminates the positive impact of patents on high-skilled migration, whereas removing the indirect amenity effect strengthens this relationship. Conversely, for low-skilled workers, migration responds strongly to wage changes, with the wage effect playing a dominant role, while amenities exert minimal influence on their migration decisions.

We further analyze how equalizing worker preferences for wages, rents, and amenities

[3] The inflow of both low- and high-skilled migrants also drives up housing rents, but these groups exhibit similar sensitivities to rent.

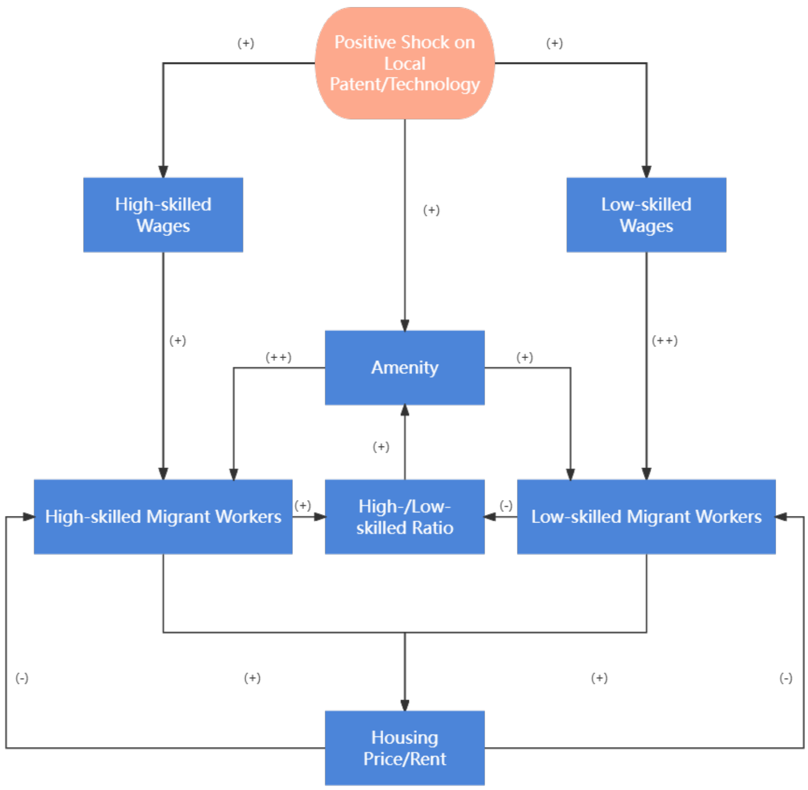
affects migration responses to patent growth. When preferences differ, patent growth impacts low-skilled migration more than high-skilled. However, when preferences are aligned across groups, the differential effect diminishes, highlighting that heterogeneous worker preferences are key to explaining skill sorting patterns in China.

Our study contributes to three strands of the existing literature. First, many studies have examined the effects of local labor demand shocks on wages, employment, rents, and amenities (Topel, 1986; Bartik, 1991; Blanchard et al., 1992; Moretti, 2011; Notowidigdo, 2020). While some other research has focused on the impact of technological change on employment (Autor, Levy, and Murnane, 2003; Acemoglu and Restrepo, 2018, 2020; Battisti, Dustmann, and Schönberg, 2023), our work specifically investigates how technology growth influences spatial migration patterns by analyzing its effects on the labor market, housing market, and amenity supply. By employing a general equilibrium framework, we allow wages, housing rents, and amenities to adjust endogenously to shifts in labor supply, offering a more comprehensive understanding of how technology shocks impact welfare and inequality across regions.

Secondly, our study contributes to the literature on workers' migration. Previous research has examined how workers sort into various local labor markets and the resulting issues of segregation and divergence in developed countries (Bayer, McMillan, and Rueben, 2004; Bayer, Ferreira, and McMillan, 2007; Card, Mas, and Rothstein, 2008; Guerrieri, Hartley, and Hurst, 2013; Giannone, 2017; Fajgelbaum and Gaubert, 2020; Bilal and Rossi-Hansberg, 2021). Our work is particularly relevant to Diamond (2016), who observed that local demand shocks drive skill sorting across locations, influence local amenities, and exacerbate welfare inequalities among skill groups in the United States. However, our model diverges from hers in several key aspects. First, we explicitly incorporate patents, one of the most significant labor demand shifters, into our model. Second, we extend the framework by introducing a two-sector model that captures sector and location choices in China. Our findings suggest that rapid technological growth in China does not lead to skill sorting; instead, it benefits both high- and low-skilled workers, which contrasts with the findings in Diamond (2016). The primary reason for these contrasting outcomes is that high-skilled workers are less sensitive to wages, whereas low-skilled migrants are less responsive to amenities compared to their counterparts in the US. This difference is primarily driven by the *hukou* system in China, which significantly limits low-skilled migrants' chances of obtaining an urban *hukou*, thereby restricting their access to local amenities.

Thirdly, our study contributes to the literature on spatial economic issues in China. Many existing studies have explored various aspects of China's spatial economic patterns using spatial general equilibrium models (Tombe and Zhu, 2019; Fan et al., 2018; Fan, 2019; Fang et al., 2022; Zi, 2022; Fang and Huang, 2022; Ma and Tang, 2024). Our research advances this body of work by focusing on the impact of technological growth on migration patterns among different skill groups within China. To the best of our knowledge, this is the first study to integrate a general equilibrium framework with micro-level data to examine the spatial economic implications of China's technological progress.

Figure 1: Mechanism of the Model



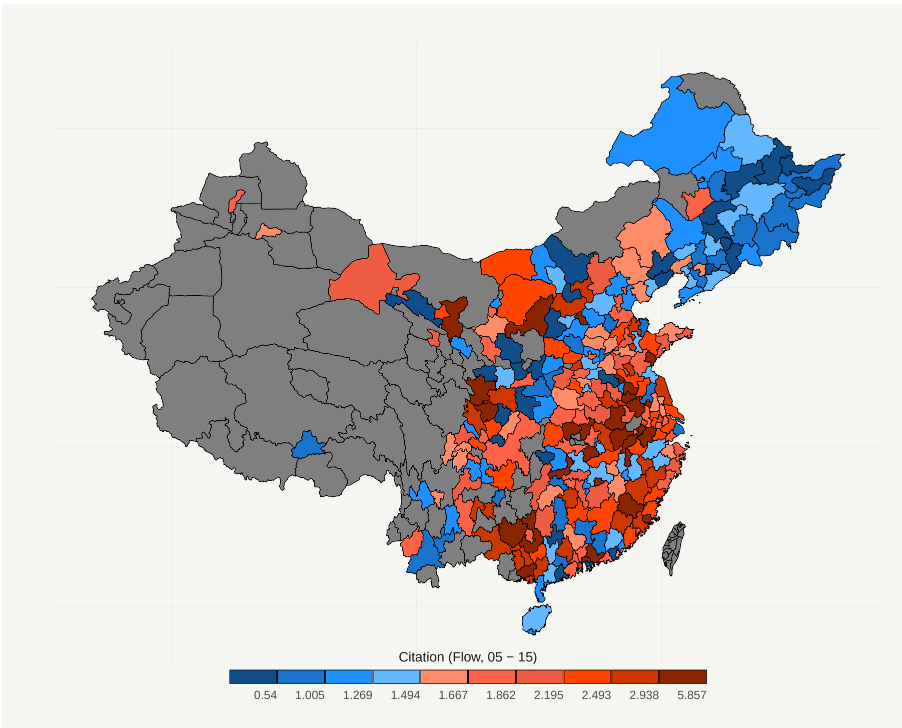
Notes: This is an illustration of the main mechanism of the model proposed in this study. "(+)" indicates positive causal impacts along the direction of arrows. "(−)" indicates negative causal impacts along the direction of arrows. "(++)" means a larger effect than "(+)". The box in peach indicates exogenous variables. Boxes in blue indicate endogenous variables.

2 Data and Summary Statistics

The data used in this study are sourced from various providers. To measure technological development, we utilize data on all granted patents from the China National Intellectual Property

Administration. In China, there are three types of patents: invention patents, utility model patents, and design patents. Among these, we argue that invention patents best capture technological innovation, so our analysis focuses on them. In addition to the number of invention patents, we also collect the number of citations for each patent from Google Patents. We use changes in citation counts at the city-year level to measure technological growth, as both the quantity and quality of patents are important, and citations serve as an indicator of patent quality. In Appendix D, we use changes in the number of patents as an alternative measure of technological growth to verify the robustness of our results. All qualitative conclusions remain consistent. Figure 2 illustrates the changes in patent citations from 2005 to 2015 at the city level. It shows that regions experiencing the most significant growth are concentrated in the coastal areas.[4]

Figure 2: Spatial Distribution of Δ Log(Citation) (2005 - 2015)



Notes: The number of patents is obtained from the China National Intellectual Property Administration. Only invention patents are included. The number of citations of each patent is from Google Patent. The number of patent citations is aggregated at the city level and is measured in logarithms. Red color indicates a larger growth rate in the number of citations. Blue color indicates a smaller growth rate in the number of citations.

For migration and labor supply data, we utilize the 2010 population census data and the 1% population survey (also known as the "mini" census) data from 2005 and 2015. Our analysis

[4] Areas with dark grey color lack citation data.

focuses on the working population aged between 25 and 50 years.[5] We observe individuals' *hukou* registration locations and current residence. Migrants are defined as those who have left their *hukou* registration city for at least six months.[6] Additionally, we observe whether workers are employed in the agricultural or non-agricultural sector. Specifically, individuals working in rural agricultural and rural non-agricultural sectors are classified as agricultural workers, as earnings in rural non-agricultural sectors are similar to those in rural agricultural sectors due to negligible migration costs.[7] Urban workers in the non-agricultural sector are classified as non-agricultural workers. Since only about 4% of individuals in urban areas work in agriculture, we exclude them from our analysis. Consequently, all non-agricultural workers are based in urban areas, where they enjoy city amenities but also face rent payments and *hukou* policies. In this paper, the terms "agricultural" and "rural" are used interchangeably, as are "non-agricultural" and "urban."[8] Finally, we classify workers into high-skill and low-skill groups. High-skill workers are defined as those with education at the college level or above.

For city-level characteristics, including wages by skill level, housing price, and variables related to the amenities, are obtained from statistical yearbooks. Specifically, we impute the wage by skill level from city-by-industry (two-digit industry) level wages available in statistical yearbooks. First, we use census data to calculate the industrial structure of employment for high-skilled and low-skilled workers. Then, we calculate the weighted average wage according to the industrial structure of employment. We compare the imputed wages with the wage data from the Urban Household Survey (UHS), a nationally representative survey conducted by the National Bureau of Statistics of China. The correlation between these two wage measures is around 0.62–0.85 (see Appendix Table H1). Table 1 shows the summary statistics of the main variables used in our analysis at the city-year level.

Based on the city characteristics, we follow Diamond (2016) to use principal component analysis (PCA) to combine 13 characteristics, including measures of healthcare services, infrastructure, education, and environment, into a single index of amenities. Specifically, we first create amenity indexes within each amenity category, and then create an overall amenity index using the principal component of these sub-category amenity indexes. Table 2 shows

[5]The retirement age for women is 50.

[6]Throughout the paper, the term "city" refers to the prefecture, encompassing both the urban area and surrounding rural regions.

[7]If workers could move freely between agricultural and rural non-agricultural sectors, wages in the two sectors would be expected to be same.

[8]The categorization of urban and rural regions is based on census data from 2005, with rural-urban classification codes from the National Bureau of Statistics for 2010 and 2015.

Table 1: Summary Statistics

VARIABLES	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
Share of migrants among the working population	609	0.16	0.16	0.00	0.90
Share of migrants among the high-skilled working population	609	0.08	0.09	0.00	0.59
Share of migrants among the low-skilled working population	609	0.19	0.19	0.00	0.96
Citations of Patents	571	2903.20	11265.63	2.00	157306.00
Wages of workers in the agricultural sector	576	10072.41	4181.63	2638.21	26838.00
Wages of high-skilled workers in the non-agricultural sector	595	48127.27	14217.58	15928.67	122615.09
Wages of low-skilled workers in the non-agricultural sector	595	39474.81	11309.51	6007.17	91138.81
City-level average house price	570	4822.948	3086.891	1589.353	33942.34
Doctors per 10,000 residents	576	20.37	8.18	6.92	75.19
Hospitals per 10,000 residents	576	0.60	0.65	0.09	6.89
Kilometers of road per 10,000 residents	575	33.38	18.72	1.44	152.09
Highway passengers per 10,000 residents	574	24.30	121.30	1.15	2855.72
With High-speed railway stations	577	0.41	0.49	0.00	1.00
PM 2.5	572	44.64	20.05	4.15	101.19
Heavily polluted days	576	6.85	10.91	0.00	55.89
Polluted days	576	70.37	56.32	0.00	237.05
Teacher-student ratio in primary schools	577	0.06	0.01	0.00	0.13
Teacher-student ratio in middle schools	576	0.08	0.02	0.00	0.20
Number of colleges	565	8.45	14.55	1.00	90.00
Number of Project 985 universities	578	0.13	0.64	0.00	8.00
Number of Project 211 universities	578	0.38	1.75	0.00	23.00
Average uphill slope of terrain (%)	575	3.96	3.13	0.00	18.34

Notes: Shares of migrants are calculated from population census and 1% population survey data. Patents are obtained from the National Intellectual Property Administration and their citations are obtained from Google Patent. Wages are imputed with city-by-industry level average wages from Municipal Statistical Yearbooks. Housing prices are from the China Statistical Yearbook for Regional Economy. The number of doctors and hospitals, variables related to transportation, teacher-student ratios, and the number of colleges and universities are from the China City Statistical Yearbook. PM 2.5 is aggregated from ground-level fine particulate matter data estimated by the Atmospheric Composition Analysis Group at Dalhousie University (Dal U ACAG). The number of polluted days is from Tracking Air Pollution in China (TAP). Average uphill slope of terrain is from Nunn and Puga (2012).

the factor loading as well as the unexplained variance of each variable in the PCA. Intuitively, we find that the healthcare index, infrastructure index, and education index all have positive loadings, while the environment index, capturing the level of pollution of a city, has a negative loading. Unexplained variance captures a variable's variance along the direction orthogonal to the principal component. The magnitudes of unexplained variances in our study are comparable to those in Diamond (2016).

3 Descriptive Evidence

Before introducing the quantitative model, we first present several descriptive data patterns on the relationship between patent citation growth and economic development at the city level.

To better capture the exogenous patent shocks, we construct a shift-share style citation shock

Table 2: PCA Results of the Amenity Index

	Loading	Unexplained variance
Panel A: Healthcare Index		
Hospital per 10,000 residents	0.707	0.435
Doctors per 10,000 residents	0.707	0.435
Panel B: Infrastructure Index		
Kilometers of road per 10,000 residents	0.418	0.808
Highway passengers per 10,000 residents	0.599	0.605
High-speed railway	0.683	0.486
Panel C: Environment Index		
PM 2.5	0.532	0.339
Heavily polluted days	0.571	0.237
Polluted days	0.626	0.084
Panel D: Education Index		
Teacher-student ratio in primary schools	0.082	0.982
Teacher-student ratio in middle schools	0.114	0.966
Number of colleges	0.540	0.233
Number of Project 985 universities	0.589	0.088
Number of Project 211 universities	0.586	0.097
Panel E: Amenity Index		
Healthcare Index	0.643	0.439
Infrastructure Index	0.554	0.585
Environment Index	-0.234	0.926
Education Index	0.474	0.695

Notes: All amenity data is measured in logarithm. Panels A to D show the factor loadings on variables to construct each subindex. Panel E shows the factor loadings on subindexes to construct the overall amenity index.

according to Equation (1):

$$\Delta P_{kt} = \sum_{ind} (Citation_{ind,-k,t} - Citation_{ind,-k,2005}) \frac{E_{ind,k,2005}}{E_{k,2005}} \tag{1}$$

where $Citation_{ind,-k,t}$ represents the log number of patent citations in two-digit industry ind in year t in the country, excluding city k. $E_{ind,k,2005}$ measures the number of workers in industry ind in city k in the initial year, 2005, while $E_{k,2005}$ denotes the total number of workers in city k in 2005. The shift variable is the change in the log number of citations from the initial year to year t in a specific industry at the national level, and the share variable is the industry employment share for city k in the initial year. This shift-share-style patent citation shock allows us to capture a more exogenous technology shock for city k driven by its industry composition.

We plot the relationship between the citation shock and economic development indicators with 2010 and 2015 data. Variables are measured as differences from 2005 levels. To mitigate the endogeneity issue, we first regress the variables on city and year fixed effects, and then plot the relationships between the residuals.[9] Each circle represents a city in China. The size of

[9]In Appendix G, we follow Borusyak, Hull, and Jaravel (2022) to test whether the shift-share-type citation shock, as well as other shift-share-type shocks used in this study, are exogenous.

each circle corresponds to the size of the city.

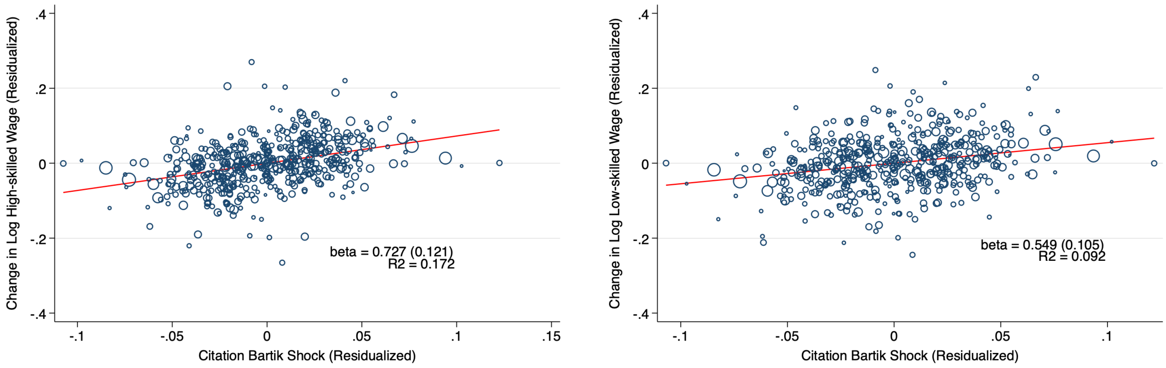
Figure 3 shows that wages are positively correlated with patent innovation shocks for both high- and low-skilled workers. That is, wages increased more in cities experiencing larger patent citation increases from 2005 to 2010 and from 2005 to 2015. Comparing the coefficients of the fitted lines, we find similar magnitudes across skill groups. Specifically, one log point increase in the predicted patent citation is associated with 0.727 log points increase in the average wages of high-skilled workers, and 0.549 log points increase in the average wages of low-skilled workers. The difference of these two coefficients is not statistically significant ($p = 0.278$). Technological progress in China benefits the wages of both high-skilled and low-skilled workers.

We further illustrate the relationship between patent citation growth and migration at the city level in Figure H1. Unlike studies in developed countries, we find little evidence of positive sorting for high-skilled workers congregating in locations with faster patent citation growth. While a one-log-point increase in the predicted patent citation is associated with 1.607 log points increase in the number of high-skilled migrants, the corresponding growth of low-skilled migrants is 3.051 log points. This difference is significant both economically and statistically. Consequently, we observe a decrease in the ratio of high-skilled workers in cities with higher patent growth, as shown in Figure 5. Noting that we focus on migrants aged between 25 and 50 years old, we potentially neglect migrants aged 16 to 25 who may have entered the labor market. In Figure 4, we include migrants aged 16 to 50. We observe that a one-log-point increase in predicted patent citation is also associated with a larger increase of low-skilled migrants than that of high-skilled migrants.

Figure 6 examines the effect of patent growth on housing prices and amenities. We find that locations with faster patent citation growth experience a faster increase in housing prices, but it has no significant effect on amenities. Appendix Table A1 provides a more rigorous empirical analysis, which uses the Bartik citation shock as an instrument for the actual citation growth, and finds consistent results on wages, migration, housing price, and amenities.

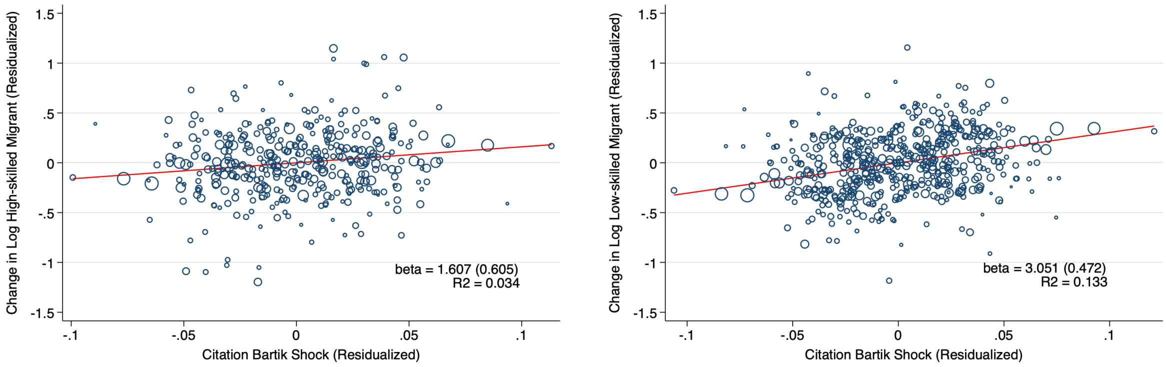
Overall, we investigate the descriptive relationships between innovation shocks, as represented by patent citation growth, and various economic development indicators. Our findings suggest that in China, technological growth increases wages for both low-skilled and high-skilled workers. However, it attracts a larger influx of low-skilled workers compared to high-skilled workers, resulting in a decline in the skill ratio. In the next section, we will introduce a quantitative general equilibrium model to elucidate the mechanism behind this inclusive growth without positive sorting.

Figure 3: Effect of Citation on Wages for High- and Low-skilled Workers



Notes: Each circle indicates the shift-share-style measure of predicted citation growth and the corresponding change of log wages of a city. Both variables are residualized by partialling out the year fixed effects and city fixed effects. The size of the circles indicates the population size of cities. The solid line is the fitted line with OLS regression. The coefficient and standard error of the variable on the x-axis and the R^2 of the regression are listed in the figure. The left panel is for wages of high-skilled workers and the right panel is for wages of low-skilled workers.

Figure 4: Effect of Citation on Number of High- and Low-skilled Migrants

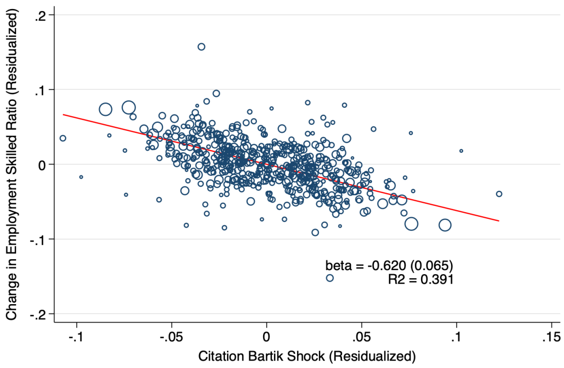


Notes: Each circle indicates the shift-share-style measure of predicted citation growth and the corresponding change in the log number of migrants of a city. Both variables are residualized by partialling out the year fixed effects and city fixed effects. The size of the circles indicates the population size of cities. The solid line is the fitted line with OLS regression. The coefficient and standard error of the variable on the x-axis and the R^2 of the regression are listed in the figure. The left panel is for high-skilled migrants and the right panel is for low-skilled migrants.

4 Model Settings

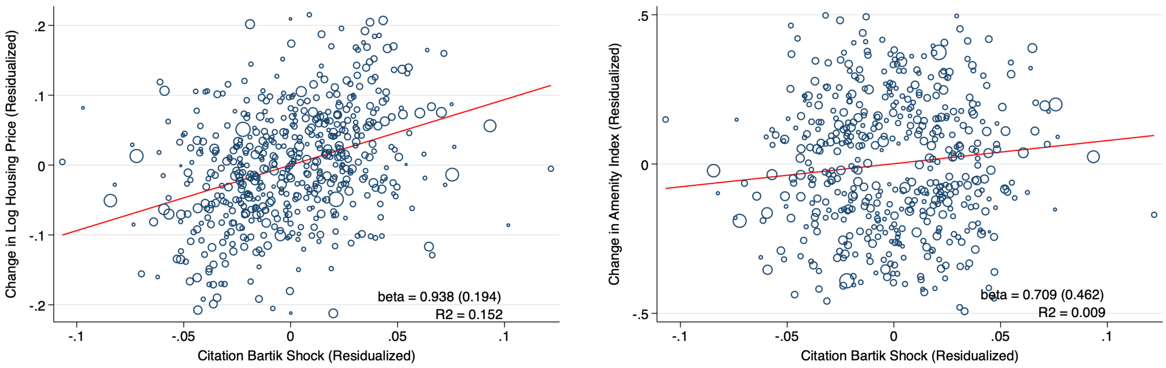
This section develops a spatial equilibrium model of local labor markets that captures the determination of labor forces, wages, housing rents, and amenities in equilibrium. Building on

Figure 5: Citation Growth and Change in Skilled Ratio



Notes: Each circle indicates the shift-share-style measure of predicted citation growth and the corresponding change in the skilled ratio of a city. The skilled ratio is defined as the ratio between high-skilled workers and all workers. Both variables are residualized by partialling out the year fixed effects and city fixed effects. The size of the circles indicates the population size of cities. The solid line is the fitted line with OLS regression. The coefficient and standard error of the variable on the x-axis and the R^2 of the regression are listed in the figure.

Figure 6: Effect of Citation on Housing Price and Amenity



Notes: Each circle indicates the shift-share-style measure of predicted citation growth and the corresponding change in log housing price, or the change in amenity index, of a city. Both variables are residualized by partialling out the year fixed effects and city fixed effects. The size of the circles indicates the population size of cities. The solid line is the fitted line with OLS regression. The coefficient and standard error of the variable on the x-axis and the R^2 of the regression are listed in the figure. The left panel is for housing prices and the right panel is for amenity index.

the framework of Diamond (2016), we enrich the model along several dimensions. First, we incorporate multiple sectors within each city, i.e., agriculture and non-agriculture. Second, we introduce city- and time-specific technological changes on the labor demand side, measured by patent growth. Third, we explicitly model migration costs as a function of *hukou* policies and migration distance.

There are K cities in China, indexed by $k \in \{1, ..., K\}$. Each city has two sectors: agriculture and non-agriculture, denoted by $j \in \{ag, na\}$. Cities differ in wages, skill mix, housing rent, amenities, and technology. Each worker is registered to a city k_0 and assigned either an agricultural or a non-agricultural *hukou* j_0. Workers can move across cities and sectors within China. Each worker i chooses to live in city k and work in sector j to maximize her utility. Workers differ in *hukou* city k_0, resident city k, *hukou* type j_0, and skills $e \in \{L, H\}$.

4.1 Labor Demand

The production function of the agricultural sector in city k in year t is simply

$$Y_{ag,kt} = z_{ag,kt}(L_{ag,kt} + \lambda H_{ag,kt})^{\eta}$$

where $z_{ag,kt}$ is the labor productivity in the agricultural sector that can vary across cities and time. $L_{ag,kt}$ and $H_{ag,kt}$ are the number of low-skilled and high-skilled workers in the agricultural sector in city k and year t, respectively. We assume a diminishing return to labor input $\eta < 1$ to capture the fact that land supply is fixed in the agricultural sector. Aggregate labor input is the simple summation of efficient units of labor of low-skill and high-skill workers. The efficient unit of labor of low-skill workers is normalized to one and that of high-skill workers is λ.

Each city's demands for high- and low-skilled labor in the agricultural sector are derived from the F.O.C.:

$$\begin{aligned} W^H_{ag,kt} &= z_{ag,kt}(L_{ag,kt} + \lambda H_{ag,kt})^{\eta-1}\eta\lambda \\ W^L_{ag,kt} &= z_{ag,kt}(L_{ag,kt} + \lambda H_{ag,kt})^{\eta-1}\eta \end{aligned}$$

Thus, the city-level log labor demand curves in the agricultural sector are:

$$\begin{aligned} w^H_{ag,kt} &= \ln W^H_{ag,kt} = d_{ag,kt} + (\eta - 1)\ln(L_{ag,kt} + \lambda H_{ag,kt}) + \ln \lambda \\ w^L_{ag,kt} &= \ln W^L_{ag,kt} = d_{ag,kt} + (\eta - 1)\ln(L_{ag,kt} + \lambda H_{ag,kt}) \\ d_{ag,kt} &= \ln z_{ag,kt} + \ln \eta \end{aligned}$$

Now we move to the production function of the non-agricultural sector. Each city k in year t has many homogeneous firms, and they produce a homogeneous tradable good using high-skill labor ($H_{na,kt}$), low-skill labor ($L_{na,kt}$), capital (K_{kt}), and machine (C_{kt}) according to the production function:

$$
\begin{aligned}
Y_{na,kt} &= z_{na,kt} N_{na,kt}^{\alpha} (\theta_{kt}^{K} K_{kt})^{1-\alpha} \\
N_{na,kt} &= (\theta_{kt}^{L} (L_{na,kt} + \omega C_{kt})^{\rho} + \theta_{kt}^{H} H_{na,kt}^{\rho})^{\frac{1}{\rho}} \\
C_{kt} &= f_C(A_{kt}) \\
\theta_{kt}^{L} &= f_L(A_{kt}, H_{na,kt}, L_{na,kt}) \\
\theta_{kt}^{H} &= f_H(A_{kt}, H_{na,kt}, L_{na,kt})
\end{aligned}
$$

The production function is Cobb-Douglas in the labor aggregate $N_{na,kt}$ and capital K_{kt}. $z_{na,kt}$ is the Hicks-neutral technology change in the non-agricultural sector, which varies by city and time.[10] α is the output elasticity of labor. The labor aggregate combines non-routine tasks done by high-skill labor $H_{na,kt}$ and routine tasks done by low-skill labor or machines $(L_{na,kt} + \omega C_{kt})$, where the elasticity of labor substitution is $\frac{1}{1-\rho}$. In particular, we assume that low-skill labor and machines are perfect substitutes so the development of new technology could crowd out the demand for low-skill labor. A_{kt} is a vector of exogenous labor demand shocks (i.e., patent shocks in our case) that can affect the labor augmenting technology for low and high skill labor (θ_{kt}^{L} and θ_{kt}^{H}) and the supply of machines (C_{kt}). The productivities of low- and high-skill workers (θ_{kt}^{L} and θ_{kt}^{H}) also depend on the skill composition of the workforce (i.e., high-skill labor and low-skill labor) in the city. In particular, an increase in the skill ratio may enhance productivity through knowledge spillover effects.

We assume that the labor market is perfectly competitive and firms hire workers at wages that equal the marginal product of labor. We also assume that there exists a frictionless capital market that supplies capital perfectly elastically at price κ_t, which is constant across all cities. Each city's demand for labor and capital in the non-agricultural sector is:

$$
\begin{aligned}
W_{na,kt}^{H} &= z_{na,kt} \alpha N_{na,kt}^{\alpha-\rho} (\theta_{kt}^{K} K_{kt})^{1-\alpha} H_{na,kt}^{\rho-1} \theta_{kt}^{H} \\
W_{na,kt}^{L} &= z_{na,kt} \alpha N_{na,kt}^{\alpha-\rho} (\theta_{kt}^{K} K_{kt})^{1-\alpha} (L_{na,kt} + \omega C_{kt})^{\rho-1} \theta_{kt}^{L} \\
\kappa_t &= z_{kt} N_{na,kt}^{\alpha} (\theta_{kt}^{K} K_{kt})^{-\alpha} (1-\alpha) \theta_{kt}^{K}
\end{aligned}
$$

Substituting for equilibrium levels of capital, the city-level log labor demand curves in the

[10] Here we do not specify the functional form of $z_{na,kt}$. In practice, $z_{na,kt}$ can depend on the city's working population size, which captures the agglomeration effect.

non-agricultural sector are:

$$
\begin{aligned}
w_{na,kt}^{H} &= \ln W_{na,kt}^{H} = d_{na,kt} + (1-\rho)\ln N_{na,kt} + (\rho-1)\ln H_{na,kt} + \ln\theta_{kt}^{H} \\
w_{na,kt}^{L} &= \ln W_{na,kt}^{L} = d_{na,kt} + (1-\rho)\ln N_{na,kt} + (\rho-1)\ln(L_{na,kt} + \omega C_{kt}) + \ln\theta_{kt}^{L} \\
N_{na,kt} &= (\theta_{kt}^{L}(L_{na,kt} + \omega C_{kt})^{\rho} + \theta_{kt}^{H} H_{na,kt}^{\rho})^{\frac{1}{\rho}} \\
d_{na,kt} &= \ln\left(z_{na,kt}^{1/\alpha}\alpha \left(\frac{(1-\alpha)\theta_{kt}^{K}}{\kappa_t} \right)^{\frac{1-\alpha}{\alpha}} \right)
\end{aligned}
$$

In particular, A_{kt} has two effects on the log labor demand curve of the low-skill labor: 1) enhancement effect: It increases their productivity by raising θ_{kt}^{L}, 2) replacement effect: It increases the number of machines C_{kt}, which replace low-skilled workers and thus reduce the demand for low-skilled labor. We can rewrite labor demand equations as unknown functions of employment $H_{j,kt}$, $L_{j,kt}$, technology index A_{kt}, and an error term $d_{j,kt}^{e}$:

$$
\begin{aligned}
w_{ag,kt}^{H} &= g_{ag,H}(H_{ag,kt}, L_{ag,kt}) + d_{ag,kt}^{H} \\
w_{ag,kt}^{L} &= g_{ag,L}(H_{ag,kt}, L_{ag,kt}) + d_{ag,kt}^{L} \\
w_{na,kt}^{H} &= g_{na,H}(A_{kt}, H_{na,kt}, L_{na,kt}) + d_{na,kt}^{H} \\
w_{na,kt}^{L} &= g_{na,L}(A_{kt}, H_{na,kt}, L_{na,kt}) + d_{na,kt}^{L}
\end{aligned}
$$

We assume that $\lambda = 1$, which means that low- and high-skilled labors have the same production efficiency in the agricultural sector. Thus, wages for high- and low-skill labors are identical in the agricultural sector. We then approximate the above labor demand using a log-linear specification

$$w_{ag,kt}^{H} = w_{ag,kt}^{L} = \gamma_{ag}\ln(H_{ag,kt} + L_{ag,kt}) + d_{ag,kt} \tag{2}$$

$$w_{na,kt}^{H} = \gamma_{HA}A_{kt} + \gamma_{na,HH}\ln(H_{na,kt}) + \gamma_{na,HL}\ln(L_{na,kt}) + d_{na,kt}^{H} \tag{3}$$

$$w_{na,kt}^{L} = \gamma_{LA}A_{kt} + \gamma_{na,LH}\ln(H_{na,kt}) + \gamma_{na,LL}\ln(L_{na,kt}) + d_{na,kt}^{L} \tag{4}$$

Note that γ_{LA} could be either sign. If the replacement effect dominates the enhancement effect, γ_{LA} would be negative; otherwise, it would be positive. In contrast, we expect γ_{HA} to be positive, as it mainly contains the enhancement effect. $\gamma_{na,HH}$ captures both the direct effect of labor supply on wages, which should be negative, and the spillover effect of the skilled ratio on productivity, which could potentially be positive. Therefore, the sign of $\gamma_{na,HH}$ is ambiguous. The same argument applies to other γ coefficients.

We observe wages ($w^H_{j,kt}, w^L_{j,kt}$), employment ($H_{j,kt}, L_{j,kt}$) and technology shock (A_{kt}), but the error terms ($d_{j,kt}$) are unobserved. Parameters to be estimated are the reduced-form aggregate labor demand elasticities ($\gamma_{ag}, \gamma_{na,HH}, \gamma_{na,HL}, \gamma_{na,LH}, \gamma_{na,LL}, \gamma_{HA}, \gamma_{LA}$).

4.2 Sector and Location Choices

Each individual i chooses to live in city k and work in sector j to maximize her utility, which depends on demographic characteristics, wages, housing rents, amenities, and *hukou* policies. A worker inelastically supplies one unit of labor and earns a wage of (W^e_{jkt}) that differs by sector, city, and worker's skill. For simplicity, we assume that individuals with non-agricultural *hukou* do not want to work in the agricultural sector and individuals with agricultural *hukou* do not want to work in the agricultural sector outside the home city. Therefore, an individual with non-agricultural *hukou* chooses from $(na, k), k \in K^*$, where K^* is the set of all cities in our sample. For an individual with agricultural hukou, she chooses between (ag, k_0) and $(na, k), k \in K^*$. We assume a sequential choice structure for individuals with agricultural hukou. They first observe a sector-specific i.i.d. preference shock ξ^j_{it} and choose whether to work in the agricultural or non-agricultural sector (sector choice). Then, if working in the non-agricultural sector, they observe a city-specific preference shock ϵ_{ikt} and choose which city to work in (location choice). Individuals with non-agricultural *hukou* only make the location choice.

For workers i that choose to work in the non-agriculture sector in city k, and year t, the utility is as follows:

$$V_{ikt} = \beta^e_1 w^e_{na,kt} + \beta^e_2 r_{kt} + \beta^e_3 a_{kt} + MigrationCost_{ikt} + \nu^e_{kt} + \epsilon_{ikt} \tag{5}$$

The worker's utility depends on log wage rate w^e_{kt} and expenditure on housing r_{kt}, both adjusted by the CPI index. Individuals also derive utility from amenities. The endogenous amenities, a_{kt}, is a single-index that summarizes a bundle of amenities related to school quality, medical service, the environment, and transportation infrastructure in the urban area constructed using the PCA approach. We allow preferences over wages, housing rents, and amenities to vary by workers' skills, so the coefficients β depend on individual skill e.

The utility is also affected by migration costs. Migration costs contain a vector of components as follows:

$$MigrationCost_{ikt} = \sum_r \beta^e_{4rt} WithinHometown_{ikt} 1_{k\in r}$$
$$+ \sum_\tau \beta^e_{\tau 5lt} WithinProvince_{ikt} 1_{k\in\tau} + \beta^e_{6t} hukou_{ikt} + \beta^e_{7t} hukou^2_{ikt} \tag{6}$$

One aspect relates to the distance of migration, proxied by whether an individual lives within a *hukou* city ($WithinHometown$) and whether they reside within a *hukou* province ($WithinProvince$). We allow the effect of living within a *hukou* city to differ across four regions (r) of the country: the east, west, middle, and northeast regions.[11] We also allow the effect of living within a *hukou* province to vary based on the city tier τ. We consider two tiers of cities: Tier 1 includes cities with populations above 3 million, while the rest are classified as Tier 2. This helps us to capture additional cost by moving to big cities even within the same province.

The other component of migration costs arises from the *hukou* policy in the destination city k during period t, denoted as $hukou_{ikt}$. The *hukou* policy index follows Fan (2019), with higher values indicating more restrictive policies that limit migrants' access to local public resources and the acquisition of permanent *hukou* residency. For individuals working in their hometown, they are not subject to the strictness of the local *hukou*; therefore, the *hukou* index is individual-specific.[12] To capture the potential non-linear effects of *hukou* policy, we also include its quadratic term. Additionally, we allow the coefficients of migration costs to vary by workers' skill levels and over time.

There is also an exogenous amenity ν^e_{kt}, which is not observed by researchers. Individuals also draw an idiosyncratic city preference shock ϵ_{ikt} from the Type I Extreme Value distribution.

When making the location choice, individuals choose the city that gives the maximum utility, conditional on the idiosyncratic shocks. We assume that individuals do not observe the idiosyncratic shock when they choose which sector to work in, so the expected value of working in the non-agricultural sector for individual i in year t is (Train, 2009):

$$E[U^{na}_{it}] = ln[\sum_{k\in K} exp(V_{ikt})]$$

[11]The east region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan provinces. The west region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, and Xinjiang provinces. The middle region comprises Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan provinces. The northeast region includes Liaoning, Jilin, and Heilongjiang provinces.

[12]For individuals with agricultural *hukou* who choose to work in the non-agricultural sector within their hometown, they are still subject to *hukou* restrictions.

The value of working in the non-agricultural sector is

$$U_{it}^{na} = E[U_{ik_0t}^{na}] + \xi_{it}^{na}$$

where ξ_{it}^{na} is a sectoral preference shock with Type I Extreme Value distributions.

The value of working in the agricultural sector in one's hometown k_0 is defined as follows:

$$U_{it}^{ag} = \tilde{U}_{it}^{ag} + \xi_{it}^{a} = \alpha_{0k_0t} + \alpha_{1t} w_{ag,k_0t}^{e} + \xi_{it}^{a} \tag{7}$$

where α_{0k_0t} is a city-year-specific constant term. w_{a,k_0t}^{e} is the agricultural earnings for workers with education e, and we allow its coefficient α_{1t} to vary over time. ξ_{it}^{a} is an i.i.d. shock that follows a standard extreme type I distribution. In particular, the housing expenditure, *hukou* index, and amenities are set to be zero in rural areas.[13] Workers stay in the agriculture sector in their hometown city if $U_{it}^{a} > U_{it}^{na}$. By the basic property of Type I Extreme Value distribution, we can write the ex ante expected utility of workers before making sector choices as:

$$U_{it} = ln(exp(E[U_{it}^{na}]) + exp(\tilde{U}_{it}^{ag})) \tag{8}$$

4.3 Housing Supply

Following Diamond (2016), we assume that local housing expenditure R_{kt} is set through equilibrium in a competitive housing market where the price of housing equals its marginal cost.

$$R_{kt} = \iota_t \times MC(CC_{kt}, LC_{kt}) \tag{9}$$

where ι_t is the interest rate. MC is the marginal cost of constructing a house, which is a function of local construction costs CC_{kt} and local land cost LC_{kt}. Land cost depends on the geographic characteristics of the location and the total demand of housing.

In equilibrium, the housing expenditure is parametrized as

$$r_{kt} = \ln(R_{kt}) = \ln(\iota_t) + \ln(CC_{kt}) + \left[\gamma_1^{hd} + \gamma_2^{hd} geo_k\right] \ln(HD_{kt}) \tag{10}$$

$$HD_{kt} = L_{na,kt} W_{na,kt}^{L} + H_{na,kt} W_{na,kt}^{H} \tag{11}$$

[13] Rural residents can build a house with low costs on their land. There is no *hukou* restriction in rural areas.

where HD_{kt} is the aggregate local housing demand in city k in year t. It depends on the labor supply and wages of low-skill and high-skill workers in the non-agricultural sector, as shown in Equation (11). We allow the elasticity of price with respect to local good demand to vary by the geographic characteristic of the city geo. Geographic characteristic is proxied by the average altitude, which calculates the average elevation of a city from the 1km-resolution digital elevation model.

We observe employment H_{jkt}, L_{jkt}, wage $W^H_{na,kt}, W^L_{na,kt}$, and housing expenditure r_{kt}. Interest rate ι_t and construction cost CC_{kt} are unobserved. Parameters to be estimated are γ_1^{hd} and γ_2^{hd}.

4.4 Amenity Supply

There are two components of amenities, an exogenous factor ν^e_{kt} and an endogenous factor a_{kt}, and the latter can respond to the technology shock and the types of workers who choose to live in the city. The endogenous amenities are measured by the amenity index constructed using the PCA approach.

$$a_{kt} = \gamma_1^a A_{kt} + \gamma_2^a \ln\left(\frac{H_{na,kt}}{L_{na,kt}}\right) + \epsilon^a_{kt} \tag{12}$$

The innovation shock can enhance education, medical services, and infrastructure, as well as reduce pollution, thereby increasing local amenities. At the same time, highly educated households may have stronger preferences for improved amenities, and high-skill labor contributes significantly to amenities such as teachers and doctors. Previous research indicates that local amenities respond to residents' income levels (Diamond, 2016). Therefore, amenities could also depend on the skill ratio within the local population.

We observe measure of technology A_{kt}, skill quantities $H_{na,kt}, L_{na,kt}$, and endogenous amenity a_{kt}. ϵ^a_{kt} is unobserved. Parameter to be estimated are γ_1^a and γ_2^a.

4.5 Equilibrium

We denote variables with tilde as the deterministic part of the corresponding ones. We also denote $N_t^{a,e}$ and $N_t^{na,e}$ as the number of skill e people with agricultural and non-agricultural *hukou* in the country. A ***Spatial General Equilibrium*** for this economy is defined a set of working populations, wages, housing expenditures, and amenities $(H^*_{jkt}, L^*_{jkt}, w^{H*}_{jkt}, w^{L*}_{jkt}, r^*_{kt}, a^*_{kt})$ such that

- **[Worker Optimization]** Workers maximize their utility by choosing locations and sectors.
- **[Firm Optimization]** Firms maximize their profit by choosing different inputs.
- **[Housing Market Clearing]** Housing demand equals housing supply in the non-agricultural sector for all cities.

$$
\begin{aligned}
r^*_{kt} &= \ln(\iota_t) + \ln(CC_{kt}) + \gamma_1^{hd} \ln(HD^*_{kt}) + \gamma_2^{hd} geo_k \ln(HD^*_{kt}) \\
HD^*_{kt} &= L^*_{na,kt} \exp(w^{L*}_{na,kt}) + H^*_{na,kt} \exp(w^{H*}_{na,kt})
\end{aligned}
$$

- **[Labor Market Clearing for High-skill]** The high-skill labor demand equals high-skill labor supply for both sectors and all cities.

$$
\begin{aligned}
H^{na*}_{kt} &= \sum_{i \in N_t^{na,H}} \frac{\exp(\tilde{V}_{ikt})}{\sum_{\tilde{k}=1}^{K} \exp(\tilde{V}_{i\tilde{k}t})} + \sum_{i \in N_t^{a,H}} \frac{exp(\tilde{W}^{na}_{it})}{exp(\tilde{W}^{a}_{it}) + exp(\tilde{W}^{na}_{it})} \cdot \frac{\exp(\tilde{V}_{ikt})}{\sum_{\tilde{k}=1}^{K} \exp(\tilde{V}_{i\tilde{k}t})} \\
H^{a*}_{kt} &= \sum_{i \in N_{kt}^{a,H}} \frac{exp(\tilde{W}^{a}_{it})}{exp(\tilde{W}^{a}_{it}) + exp(\tilde{W}^{na}_{it})} \\
w^{H*}_{ag,kt} &= \gamma_{ag} \ln(H^*_{ag,kt} + L^*_{ag,kt}) + d_{ag,kt} \\
w^{H*}_{na,kt} &= \gamma_{HA} A_{kt} + \gamma_{na,HH} H^*_{na,kt} + \gamma_{na,HL} L^*_{na,kt} + d_{na,kt}
\end{aligned}
$$

where $\tilde{W}^{j}_{it}$ and $\tilde{V}_{ikt}$ represent the value of working in sector j and the value of working in city k in the non-agricultural sector without the idiosyncratic shock, respectively.

- **[Labor Market Clearing for Low-skill]** The low-skill labor demand equals low-skill labor supply for both sectors and all cities.

$$
\begin{aligned}
L^{na*}_{kt} &= \sum_{i \in N_t^{na,L}} \frac{\exp(\tilde{V}_{ikt})}{\sum_{\tilde{k}=1}^{K} \exp(\tilde{V}_{i\tilde{k}t})} + \sum_{i \in N_t^{a,L}} \frac{exp(\tilde{W}^{na}_{it})}{exp(\tilde{W}^{a}_{it}) + exp(\tilde{W}^{na}_{it})} \cdot \frac{\exp(\tilde{V}_{ikt})}{\sum_{\tilde{k}=1}^{K} \exp(\tilde{V}_{i\tilde{k}t})} \\
L^{a*}_{kt} &= \sum_{i \in N_{kt}^{a,L}} \frac{exp(\tilde{W}^{a}_{it})}{exp(\tilde{W}^{a}_{it}) + exp(\tilde{W}^{na}_{it})} \\
w^{L*}_{ag,kt} &= \gamma_{ag} \ln(H^*_{ag,kt} + L^*_{ag,kt}) + d_{ag,kt} \\
w^{L*}_{na,kt} &= \gamma_{LA} A_{kt} + \gamma_{na,LH} H^*_{na,kt} + \gamma_{na,LL} L^*_{na,kt} + d_{na,kt}
\end{aligned}
$$

5 Estimation

In this section, we present the estimation methods and results. We begin with the estimation of labor demand, followed by the estimation of the housing market and amenity supply. Finally, we discuss the estimation of labor supply, including location choice and sector choice decisions.

5.1 Labor Demand Estimation

Equations (2), (3), and (4) specify the parameterized labor demand functions we aim to estimate for the agricultural sector, high-skilled workers in the non-agricultural sector, and low-skilled workers in the non-agricultural sector, respectively.

For the non-agricultural sector, we proxy the technology index A_{kt} by the total number of citations in city k in year t. We estimate the following first-difference regression:

$$\Delta w^H_{na,kt} = \gamma_{HA}\Delta A_{kt} + \gamma_{na,HH}\Delta \ln H_{na,kt} + \gamma_{na,HL}\Delta \ln L_{na,kt} + \Delta\epsilon^H_{na,kt}$$
$$\Delta w^L_{na,kt} = \gamma_{LA}\Delta A_{kt} + \gamma_{na,LH}\Delta \ln H_{na,kt} + \gamma_{na,LL}\Delta \ln L_{na,kt} + \Delta\epsilon^L_{na,kt}$$

where $\Delta x = x_t - x_{t0}$ for all variables x. To address the endogeneity concern, we instrument changes in citations using the citation Bartik shock constructed in Section 3 (Equation (1)). Additionally, we instrument high- and low-skilled non-agricultural employment using a Bartik-style shift-share migrant instrument, following the approach of Card (2009). The migrant Bartik instruments are defined as:

$$\Delta B^H_{kt} = \sum_{ind}\left(Mig^H_{ind,na,-k,t} - Mig^H_{ind,na,-k,2005}\right)\frac{Mig^H_{ind,na,k,2005}}{Mig^H_{na,k,2005}} \tag{13}$$
$$\Delta B^L_{kt} = \sum_{ind}\left(Mig^L_{ind,na,-k,t} - Mig^L_{ind,na,-k,2005}\right)\frac{Mig^L_{ind,na,k,2005}}{Mig^L_{na,k,2005}} \tag{14}$$

where $Mig^H_{ind,na,k,2005}$ and $Mig^L_{ind,na,k,2005}$ denote the number of high- and low-skilled migrants in a specific 2-digit non-agricultural industry ind in city k in 2005. $Mig^H_{na,k,2005}$ and $Mig^L_{na,k,2005}$ represent the total number of high- and low-skilled migrants across all non-agricultural industries in city k in 2005. $Mig^H_{ind,na,-k,2005}$ and $Mig^L_{ind,na,-k,2005}$ denote the national counts of high- and low-skilled migrants in industry ind in 2005, excluding city k. The first term is the "shift", capturing the national-industry level migration shock, while the second term reflects the initial "share" of migrant employment in each industry within the city. Following the framework of Borusyak, Hull, and Jaravel (2022), the key identification assumption is that industry growth is not systematically correlated with the weighted average of unobserved shocks across different locations, where the weights are determined by the industry's importance in each location. For example, since the steel industry is primarily concentrated in Hebei Province, the validity of the Bartik instrument relies on the assumption that national migration growth in the steel industry is not correlated with unobserved local employment shocks in Hebei.

Table 3 presents the estimation results for labor demand in the non-agricultural sector. The first two columns display the OLS estimates for high- and low-skilled workers, respectively. Columns (3) through (5) show the first-stage results of the IV estimation. The final two columns report the second-stage estimates, separated by skill level. In the first-stage regressions, the citation Bartik instrument has a significant positive effect on changes in citations. Additionally, the migrant Bartik instrument for low-skilled (high-skilled) workers significantly correlates with changes in low-skilled (high-skilled) employment, respectively.

In both the OLS and IV specifications, citations consistently exhibit a significant positive effect on wages for both high-skilled and low-skilled workers, although the estimated effects are larger in the IV regressions. Moreover, the magnitude of these effects is similar across the two skill groups. According to the IV estimates, a one percent increase in citations is associated with a 1.10 percent rise in high-skilled workers' wages and a 1.04 percent increase in low-skilled workers' wages.

In addition, the IV estimation indicates that a one percent increase in low-skilled employment results in a 0.85 percent decrease in wages for low-skilled workers. This negative effect arises from a combination of the direct labor supply response and indirect spillover effects. Similarly, high-skilled employment also negatively impacts high-skilled wages, but the effect is much smaller in magnitude (-0.078 percent compared to -0.85 percent). These findings suggest that spillover effects increases with the skill ratio; consequently, an increase in high-skill (or low-skill) employment can enhance (or reduce) productivity and wages. For high-skilled (low-skilled) workers, the indirect spillover effect is positive (negative), which partially counteracts (or amplifies) the negative direct effect. The cross-elasticity between low-skilled employment and high-skilled wages is estimated at -0.73, while the elasticity between high-skilled employment and low-skilled wages is 0.08. This further implies that a higher skill ratio may promote overall productivity. Although these results are not statistically significant, their point estimates are plausible and consistent with our theoretical model.

Table 3: Estimation of Labor Demand in the Non-agricultural Sector

VARIABLES	(1) Δ Log High-skilled Wage	(2) Δ Log Low-skilled Wage	(3) Δ Log High-skilled Employment	(4) Δ Log Low-skilled Employment	(5) Δ Log Citation	(6) Δ Log High-skilled Wage	(7) Δ Log Low-skilled Wage
Δ Log Citation	0.033***	0.033**				1.099***	1.036***
	(0.012)	(0.013)				(0.316)	(0.302)
Δ Log High-skilled Employment	0.040*	0.041				-0.078	0.08
	(0.024)	(0.027)				(0.501)	(0.479)
Δ Log Low-skilled Employment	-0.061*	-0.067*				-0.726	-0.848
	(0.031)	(0.035)				(0.719)	(0.688)
Citation Shock			-0.190	0.110	0.566**		
			(0.137)	(0.108)	(0.240)		
Migrant Bartik for High-skilled Workers			0.627***	0.409***	0.344		
			(0.143)	(0.113)	(0.250)		
Migrant Bartik for Low-skilled Workers			-0.228	0.614***	-0.182		
			(0.255)	(0.201)	(0.446)		
Constant	0.672***	0.675***	-0.076	-0.807***	0.439	-0.824**	-0.776*
	(0.024)	(0.026)	(0.337)	(0.266)	(0.591)	(0.416)	(0.398)
Observations	468	468	468	468	468	468	468
Model	OLS	OLS	First stage	First stage	First stage	IV GMM	IV GMM
Sanderson-Windmeijer F			15.32	16.28	11.22		

Notes: This table shows results of estimating the first-difference version of Equation (3) and (4). Δ indicates the change between the sample year and the baseline year 2005. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

For the agricultural sector, we run a first difference regression following:

$$\Delta w_{a,kt} = \gamma_a \Delta \ln(H_{a,kt} + L_{a,kt}) + \Delta\epsilon_{a,kt}$$

We further instrument the working population in rural areas, $\Delta \ln(H_{a,kt} + L_{a,kt})$, using changes in the number of individuals holding agricultural *hukou* in the prefecture city.

Table 4 presents the estimation results for the agricultural sector. The first stage is strong, as indicated by a large F statistic in Column (2). Both the OLS (Column (1)) and IV (Column (3)) estimates reveal a significant negative relationship between employment and income. Specifically, the IV estimates suggest that a one percent increase in agricultural employment leads to a 0.17 percent decrease in agricultural income.

5.2 Housing Market Estimation

We now estimate the housing market equation (10) using a first-difference regression approach, following the specification:

$$\Delta r_{kt} = \left[\gamma_1^{hd} + \gamma_2^{hd} \times \ln(Altitude_k)\right] \Delta \ln(HD_{kt}) + \Delta\epsilon_{kt}^r$$

where $\Delta\epsilon_{kt}^r = \Delta \ln(\iota_t) + \Delta \ln(CC_{kt})$. In Equation (10), the variable geo_k is measured by the logarithm of the local altitude, $\ln(Altitude_k)$. Housing demand is calculated as the total income of both high- and low-skilled workers, following Equation (11). To address potential

Table 4: Estimation of Labor Demand in the Agricultural Sector

VARIABLES	(1) Δ Log Agr Income	(2) Δ Log Agr Employment	(3) Δ Log Agr Income
Δ Log Agricultural Employment	-0.044*		-0.172***
	(0.024)		(0.034)
Δ Log Agricultural Population		1.167***	
		(0.053)	
Constant	0.694***	-0.061***	0.674***
	(0.013)	(0.017)	(0.014)
Observations	468	468	468
Model	OLS	First stage	IV GMM
Sanderson-Windmeijer F		488.9	

Notes: This table shows results of estimating the first-difference version of Equation (2). Δ indicates the change between the sample year and the baseline year 2005. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

endogeneity, we further instrument housing demand using a wage Bartik instrument, constructed based on the following equation for both low- and high-skilled workers and their interactions with $\ln(Altitude_k)$.

$$\Delta W^H_{kt} = \sum_{ind} \left(w^H_{ind,na,-k,t} - w^H_{ind,na,-k,2005} \right) \frac{H_{ind,na,k,2005}}{H_{na,k,2005}} \tag{15}$$

$$\Delta W^L_{kt} = \sum_{ind} \left(w^L_{ind,na,-k,t} - w^L_{ind,na,-k,2005} \right) \frac{L_{ind,na,k,2005}}{L_{na,k,2005}} \tag{16}$$

where $w_{ind,na,-k,t}$ represents the national average log wage of high- or low-skilled workers in a 2-digit non-agricultural industry ind in year t, excluding city k. $H_{ind,na,k,2005}$ and $L_{ind,na,k,2005}$ denote the number of high- and low-skilled workers in industry ind in city k in 2005, respectively. Similarly, $H_{na,k,2005}$ and $L_{na,k,2005}$ represent the total number of high- and low-skilled workers in city k across all industries in 2005. The "shift" term captures the national-industry level wage shock, while the "share" reflects the initial employment share of each industry within the city. The underlying identifying assumption is that industry-level wage growth is not systematically correlated with unobserved, location-specific shocks to the housing market.

Table 5 presents the estimation results for the housing market. The IV estimates indicate that a one percent increase in housing demand leads to an approximate 0.91 percent increase in housing rents per square meter, calculated as 0.60 + 0.05 * ln(507) = 0.91, given that the city's altitude is at the national average of 507 meters. Additionally, we find that the housing rent elasticity increases with altitude, which is consistent with the model's prediction that cities with more mountainous terrain have less elastic land supply, resulting in higher price elasticity.

Table 5: Estimation of the Housing Market

VARIABLES	(1) Δ Log(Rent)	(2) Δ Log Housing Demand	(3) Δ Log Housing Demand * Geo	(4) Δ Log(Rent)
Δ Log Housing Demand	0.0118			0.599***
	(0.0663)			(0.120)
Δ Log Housing Demand * Log Altitude	0.0290**			0.0450***
	(0.0116)			(0.0167)
Wage Bartik IV for High-skilled Workers		-5.737***	-18.66***	
		(1.235)	(6.272)	
Wage Bartik IV for Low-skilled Workers		6.693***	17.16***	
		(1.226)	(6.228)	
Wage Bartik IV for High-skilled Workers * Log Altitude		0.956***	3.284***	
		(0.211)	(1.069)	
Wage Bartik IV for Low-skilled Workers * Log Altitude		-0.948***	-2.046*	
		(0.210)	(1.065)	
Constant	0.615***	0.203***	1.287***	-0.0548
	(0.0424)	(0.0728)	(0.370)	(0.0975)
Observations	468	468	468	468
Model	OLS	First stage	First stage	IV GMM
Sanderson-Windmeijer F		607.3	93.77	

Notes: This table shows results of estimating the first-difference version of Equation (10). Δ indicates the change between the sample year and the baseline year 2005. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.3 Amenity Supply Estimation

The endogenous amenity index is influenced by the technology shock—proxied by the total citations—as well as the high-skilled labor ratio, as specified in Equation (12). We estimate this equation using the same method as in the previous subsection, by taking the first difference:

$$\Delta a_{kt} = \gamma_1^a \Delta A_{kt} + \gamma_2^a \Delta \ln \left(\frac{H_{na,kt}}{L_{na,kt}} \right) + \Delta \epsilon_{kt}^a$$

We continue to instrument citation growth using the citation Bartik instrument. Additionally, we instrument the change in the log high-skilled to low-skilled labor ratio, $\Delta \ln \left(\frac{H_{na,kt}}{L_{na,kt}} \right)$, using the wage Bartik instrument defined above. The key identifying assumption is that local unobserved amenity shocks are uncorrelated with national industry-level citation growth and wage shocks.

Table 6 presents the estimation results. We find that both technology shocks and changes in the skilled labor ratio significantly influence local amenities. According to the IV estimates, a one percent increase in citations leads to approximately a 1.08 percent increase in the amenity index. Similarly, a 1 percent rise in the skilled ratio results in a 5.77 percent increase in the index.

In Appendix Table H2, we perform the same analysis on the four sub-indices used to construct the overall amenity index. The results indicate that each component contributes to the overall effect: citation growth tends to reduce pollution while enhancing infrastructure and health services. Likewise, a higher skilled ratio is associated with reductions in pollution and improvements in infrastructure and education services.

Table 6: Estimation of the Amenity Supply

VARIABLES	(1) Δ Amenity Index	(2) Δ Log High-skilled Ratio	(3) Δ Log Citation	(4) Δ Amenity Index
Δ Log Citation	0.152***			1.084***
	(0.034)			(0.309)
Δ High-skilled Employment Ratio	0.492			5.769**
	(0.387)			(2.345)
Citation Shock		-0.081***	0.426*	
		(0.022)	(0.251)	
Wage Bartik IV for High-skilled Workers		0.077	-1.108	
		(0.059)	(0.678)	
Wage Bartik IV for Low-skilled Workers		0.079	1.573**	
		(0.062)	(0.722)	
Constant	0.538***	0.029	0.661***	-1.196***
	(0.067)	(0.021)	(0.245)	(0.451)
Observations	468	468	468	468
R-squared	0.044			
Model	OLS	First stage	First stage	IV GMM
Sanderson-Windmeijer F		14.28	8.193	

Notes: This table shows results of estimating the first-difference version of Equation (12). Δ indicates the change between the sample year and the baseline year 2005. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.4 Estimation of Location and Sector Choices

We estimate the workers' labor supply decision model in two steps using backward induction. In the first step, we estimate the location choices for all workers who choose to work in the non-agricultural sector. In the second step, we estimate their sector choices conditioned on the value of choosing to work in the non-agricultural sector, as obtained from the first step.

Equation (5) illustrates the utility that worker i derives from working in the non-agricultural sector of city k in year t. To estimate this function, we assume that the unobserved utility shock ϵ_{ijkt} follows a Type I Extreme Value distribution. Consequently, the probability of worker i choosing city k is given by:

$$Prob_{ikt} = \frac{exp(\tilde{V}_{ikt})}{\sum_{k'} exp(\tilde{V}_{ik't})}$$

We follow Berry, Levinsohn, and Pakes (2004) by employing a two-step estimator to estimate the utility function, using a sample of the working population residing in urban areas. The utility function can be divided into two components: individual-specific and city-specific. Therefore, Equation (5) becomes:

$$V_{ikt} = \delta^e_{kt} + MigrationCost_{ikt} + \epsilon_{ikt} \tag{17}$$

$$\delta^e_{kt} = \beta^e_1 w^e_{na,kt} + \beta^e_2 r_{kt} + \beta^e_3 a_{kt} + \nu^e_{kt} \tag{18}$$

In the first step, we employ a maximum likelihood estimator to estimate Equation (17) and recover the individual-specific migration costs. Part of the migration costs varies with migration distance, which differs across individuals born in different cities. Another component of migration costs is influenced by *hukou* policies; however, local residents are unaffected by the stringency of local policies. Therefore, migration costs are individual-specific and can be estimated in this first step. Additionally, we estimate the mean utility value of each city for each type of worker in each year, denoted as δ^e_{kt}. The log-likelihood function can then be expressed as:

$$LL = \sum_i \sum_t \sum_k \mathbf{1}(d_{ikt}) \times \ln Prob_{ikt}$$

where $d_{ikt} = 1$ if individual i is observed to live in city k in year t.

Table 7 presents the results of the first-step estimation of individual-specific utility parameters. As expected, remaining within one's hometown has a positive effect on utility, with this effect generally being smaller in the eastern provinces, indicating that migration costs are lower for residents of coastal regions. In addition to the migration cost associated with leaving one's hometown, moving out of one's home province incurs an additional cost, as evidenced by the positive utility associated with staying within the home province. It is also more costly to live in larger cities within the province. *Hukou* policies also influence migration costs: the more stringent the *hukou* policy, the lower the utility of moving to that city, and consequently, the higher the migration costs. However, the effect of *hukou* policy is not linear with respect to the *hukou* index; instead, it exhibits a concave relationship with a decreasing marginal effect.

In the second step, we estimate Equation (18) using the changes between year t and 2005 at the city level:

$$\Delta\delta^e_{kt} = \beta^e_1 \Delta w^e_{na,kt} + \beta^e_2 \Delta r_{kt} + \beta^e_3 \Delta a_{kt} + \Delta\nu^e_{kt} \tag{19}$$

where ν^e_{kt} captures the exogenous amenities that are not observed by researchers. We have three

Table 7: Estimation of Workers' Location Choice (First Stage)

Worker Type Year	Low-Skilled 2005	Low-Skilled 2010	Low-Skilled 2015	High-Skilled 2005	High-Skilled 2010	High-Skilled 2015
Within Hometown (East)	4.725***	3.817***	4.23***	3.832***	3.383***	3.766***
	(0.037)	(0.016)	(0.024)	(0.042)	(0.022)	(0.027)
Within Hometown (Middle)	4.892***	4.526***	4.588***	4.644***	3.94***	4.144***
	(0.043)	(0.021)	(0.033)	(0.088)	(0.037)	(0.049)
Within Hometown (West)	4.627***	3.611***	4.015***	3.987***	3.266***	3.736***
	(0.048)	(0.022)	(0.04)	(0.077)	(0.038)	(0.056)
Within Hometown (North East)	4.628***	4.223***	4.941***	4.98***	3.873***	4.39***
	(0.053)	(0.034)	(0.061)	(0.125)	(0.059)	(0.084)
Within Province × Tier1	2.977***	2.867***	4.202***	1.632***	2.478***	3.331***
	(0.05)	(0.017)	(0.042)	(0.056)	(0.03)	(0.049)
Within Province × Tier2	3.085***	3.095***	3.917***	3.701***	3.946***	4.231***
	(0.036)	(0.014)	(0.031)	(0.064)	(0.03)	(0.045)
Hukou Index	-1.194***	-1.716***	-1.105***	-1.118***	-1.262***	-1.409***
	(0.004)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)
Hukou Index^2	0.132***	0.236***	0.189***	0.139***	0.179***	0.262***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)

Notes: This table shows results of estimating Equation (17) with maximum likelihood. Each row comes from a separate estimation. Column titles indicate the independent variables. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

years of data, 2005, 2010, and 2015. So we can take the difference between 2010 and 2005, as well as between 2015 and 2005. Specifically, we calculate individuals' annual housing rent expenditure r_{kt} based on the average rent per squared meter obtained from census data and multiply it by the average housing area per capita.[14]

To solve the endogeneity problem of wage, rent, and amenity, we consider a large set of potential instrumental variables. These potential instrumental variables include citation Bartik, migrant Bartik, wage Bartik, and employment Bartik, as we introduced before. We also consider other possible demand-side Bartik shocks, such as trade shocks, constructed using a similar shift-share approach.[15] We also include the interactions of these instruments with exogenous geographic variables, including altitude, uphill slope, terrain ruggedness index (TRI), and the area of undevelopable land. Finally, exogenous land supply, measured by the area and monetary

[14] In Appendix B, we follow Diamond (2016) and interpret β_2^e as $-\beta_3^e\zeta$, where ζ captures workers' relative taste for national versus local good. We calibrate ζ to be 0.35, which is the average share of housing expenditures over total expenditures according to Urban Household Survey data. Results are qualitatively consistent with our baseline results.

[15] The trade shock is constructed as:

$$\Delta T_{kt}^H \equiv \sum_{ind} \left(Trade_{ind,-k,t} - Trade_{ind,-k,2005}\right) \frac{Emp_{ind,na,k,2005}}{Emp_{na,k,2005}}$$

where $Trade_{ind,-k,t}$ measures the import, export, net export, and total volume of trade of industry ind in cities other than k in year t. The robot shock is constructed as:

$$\Delta R_{kt}^H \equiv \sum_{ind} \left(Robot_{ind,-k,t} - Robot_{ind,-k,2005}\right) \frac{Emp_{ind,na,k,2005}}{Emp_{na,k,2005}}$$

where $Robot$ indicates the number of industrial robots used. Other notations are the same as in the main text.

value of state-owned land transfers, is also included. To select the proper instrumental variables, we use LASSO in the first-stage regression to choose a set of instruments with the most predicted power for each endogenous variable. Then, we plug in the predicted variables as regressors in the second stage, which introduces errors in statistical inference. Therefore, we report bootstrapping standard errors with 300 re-samples instead.

We now present the results from the second-step estimation for parameters related to city characteristics. The first-stage estimation results using LASSO are presented in Appendix Table B2. The selected IVs have reasonable explanatory powers for all endogenous variables, with R^2 being 0.68, 0.54, 0.30, and 0.19 for high/low-skill wages, rent, and amenity index, respectively. Moreover, the F-statistics of the first-stage estimation all approach or exceed 10.

Table 8 presents the second-stage results using the predicted city characteristics obtained from the LASSO. We find that wages positively affect utility for both skill levels, with a larger impact on low-skilled workers. Specifically, a one percentage point increase in wages raises utility by 1.67 percentage points for low-skilled workers and by 1.16 percentage points for high-skilled workers. Rent expenditure decreases utility for workers at both skill levels by a similar magnitude. Additionally, amenities positively influence utility across both groups, but the effect is more significant for high-skilled workers. A one percentage point increase in amenities increases utility by 0.37 percentage points for high-skilled workers and by 0.20 percentage points for low-skilled workers. These findings suggest heterogeneity in preferences between the two worker types. Since low-skilled workers are primarily temporary migrants, they are more sensitive to wages and are less likely to plan long-term residence in the city. Conversely, high-skilled migrants aim to become permanent residents, making city amenities a more critical factor in their utility. This is because amenities hold greater value for permanent migrants who obtain local *hukou*, granting them better access to public schools and healthcare services. This result aligns with findings from Khanna et al. (2025).

After estimating the location choice, we can recover the indirect utility of choosing the non-agricultural sector, denoted as W_{it}^{na}. Next, we proceed to estimate the sector choice. The probability of individual i in year t choosing the agricultural sector is given by:

$$P_{ag,it} = \frac{exp(W_{it}^{na})}{exp(W_{it}^{ag}) + exp(W_{it}^{na})}$$

We estimate the parameters in equation (7) using the maximum likelihood estimation (MLE)

Table 8: Estimation of Workers' Location Choice (Second Stage)

VARIABLES	(1) $\Delta\delta_{high}$	(2) $\Delta\delta_{low}$	(3) $\Delta\delta_{high}$	(4) $\Delta\delta_{low}$
Δ Log(High-skilled Wage)	0.328**		1.161**	
	(0.157)		[0.583]	
Δ Log(Low-skilled Wage)		0.322		1.673**
		(0.227)		[0.700]
Δ Log(Housing Rent)	0.148	0.165	-0.929*	-0.954*
	(0.101)	(0.128)	[0.511]	[0.504]
Δ Amenity Index	0.0656	0.0733	0.371**	0.196
	(0.0524)	(0.0615)	[0.164]	[0.266]
Constant	0.447***	0.557***	0.471***	0.358
	(0.125)	(0.167)	[0.179]	[0.260]
Observations	476	476	451	451
R-squared	0.035	0.033	0.055	0.058
Model	OLS	OLS	IV	IV

Notes: This table shows results of estimating the first-difference version of Equation (18). Δ indicates the change between the sample year and the baseline year 2005. In columns (3) and (4), independent variables are predicted values manually estimated with OLS regression on instrumental variables selected by LASSO. See text for more details. In columns (1) and (2), standard errors are in parentheses. In columns (3) and (4), bootstrapped standard errors are in brackets. *** p<0.01, ** p<0.05, * p<0.1.

method, focusing on the sample of workers with agricultural hukou. The corresponding log-likelihood function can be expressed as:

$$LL = \sum_i \sum_t \mathbf{1}(d_{it}) \times \ln P_{ag,it}$$

where $\mathbf{1}(d_{it})$ is an indicator function that equals one if individual i in year t works in the agricultural sector, and zero otherwise.

Table 9 reports the coefficient of the agricultural wage, indicating that higher agricultural wages tend to attract more individuals to remain in the agricultural sector. The estimated elasticities are similar for both low- and high-skilled workers.

Table 9: Estimation of Workers' Sector Choice

Skill	Coefficient on w^a
Low-Skilled	1.048***
	(0.005)
High-Skilled	1.016***
	(0.013)

Notes: This table shows results of estimating Equation (7) with maximum likelihood. Each row comes from a separate estimation. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.5 Baseline Equilibrium Fit in 2015

In this section, we solve the baseline equilibrium in 2015 using the contraction mapping algorithm introduced in Appendix C.1. Appendix Table E1 displays the fit of several key moments, with the first column showing the results from the equilibrium solution of the model, the second column presenting the corresponding data, and the third column indicating the percentage difference between the model's predictions and the observed data moments. Overall, our model captures the number of migrants, their geographic distribution, wages by skill and sector, as well as housing rents and amenities quite well. Additionally, Appendix Figures E1 to E4 illustrate the distributions of the working population by skill, migrants by skill, wages by skill, housing rents, and amenities across cities. In these figures, the red curve represents the density at equilibrium from the model, while the blue curve depicts the corresponding data. The model provides a reasonably good fit to these distributions.

5.6 Discussion of the Mechanism

Our estimation results reveal various mechanisms through which technology shocks can differently influence low- and high-skilled migration, as illustrated in Figure 1. First, a positive patent shock increases wages for both low- and high-skilled workers by a similar magnitude. Since low-skilled workers have higher wage elasticity, they are more responsive to wage increases than high-skilled workers. Consequently, migration increases for both groups, with a larger rise in low-skilled migration. This leads to a decline in the skill ratio, which reduces amenities and partially offsets the direct positive effect of patent growth on amenities. This disproportionally affects high-skilled migrants, further lowering the skill ratio. Meanwhile, as the number of migrants and wages rise, housing demand increases, driving up housing rents. Higher housing rents, in turn, discourage migration for both worker types.

There are some other potential alternative mechanisms to consider. One possibility is that low-skilled workers migrate more because cities experiencing faster technological growth demand more low-skilled labor. In this view, migration patterns could be primarily driven by labor demand factors. However, we argue that this is unlikely during the period under study. First, both the descriptive evidence and the estimation of the production function in our model do not support a significant effect of technological growth on the demand for low-skilled workers. Specifically, we find that cities with higher technological growth exhibit similar wage increases for both high- and low-skilled workers. To further validate our findings, we examine the impact of technology shocks on local employment, as shown in Figure H2. The results indicate that cities experiencing larger technology shocks are positively associated with employment increases for both high- and low-skilled local workers. Importantly, the effect is significantly stronger for high-skilled workers, not low-skilled ($p = 0.014$ for the difference in effects), suggesting that the demand-driven migration hypothesis is less plausible in this context.

Another possible mechanism is that high-skilled workers are more sensitive to *hukou* restrictions than low-skilled workers, and that *hukou* policies are more restrictive in cities experiencing faster technological growth.[16] However, in our estimation of the utility function, we explicitly account for the effect of *hukou* policies by incorporating them into the migration costs. Additionally, we do not find any significant differences in the coefficients of the *hukou* index between high- and low-skilled workers. Therefore, *hukou* restrictions are unlikely to be the primary driver of the observed migration patterns associated with technology shocks.

6 Counterfactual

6.1 Eliminate Innovation Growth in China

In this counterfactual analysis, we take the economy in 2015 as the baseline and set the patent citation levels in each city to those of 2005. This scenario effectively eliminates the innovation growth in China from 2005 to 2015. In this counterfactual, other primitives remain at the 2015 level, including the residuals in the wage equation $\epsilon_{ag,kt}$, $\epsilon^H_{na,kt}$, $\epsilon^L_{na,kt}$, residuals in the housing market equation ϵ^r_{kt}, residuals in the amenity supply ϵ^a_{kt}, and exogenous amenities v^e_{kt}. This allows us to evaluate the impact of technology change on China's economic outcomes.

Table F1 presents the changes in patent citations across different regions. On average, the national mean of patent citations decreases by 1.748 log points. Among the 222 cities in our sample, 213 experience a decline in patent citations. Of the 9 cities with increased patent citations, most are located in the northeastern region, commonly referred to as China's rust belt.[17] The northeastern region experienced significant population loss between 2005 and 2015, primarily due to stagnation in economic growth.

Table 10 presents the counterfactual results for migration, the urban skill ratio, and the urban workforce ratio. The urban skill ratio is defined as the number of high-skilled workers divided by the total number of workers in urban areas. The urban workforce ratio is calculated as the number of workers in the non-agricultural sector divided by the total workforce. Several key

[16]The correlation between the change in *hukou* policy index and the change in citation growth is 0.1 with a significance level at 1.6%.

[17]Patents from earlier years tend to have more citations than those from later years, and our regressions always control for year fixed effects to account for this systematic bias.

Table 10: Eliminating Innovation Growth: Changes in Migration, Skill Ratio, and Urban Workforce

	Original Eq	Counterfactual	Change
Panel A. Migration across Cities			
Total Migration	26644290	19039122	-28.54%
High-skilled Migration	5746083	5499044	-4.30%
Low-skilled Migration	20898208	13540079	-35.21%
Migrants in East	17942248	12422673	-30.76%
Migrants in Middle	3952603	2585766	-34.58%
Migrants in NE	1076804	1223492	13.62%
Migrants in West	3672636	2807192	-23.56%
Panel B. Urban Skill Ratio			
National Skill Ratio	0.360	0.421	16.94%
Skill Ratio in Urban East	0.376	0.449	19.35%
Skill Ratio in Urban Middle	0.326	0.392	20.23%
Skill Ratio in Urban NE	0.359	0.370	3.16%
Skill Ratio in Urban West	0.350	0.405	15.70%
Panel C. Urban Workforce Ratio			
National Urban Ratio	0.412	0.335	-18.69%
High-skilled in East	0.871	0.826	-5.15%
High-skilled in Middle	0.832	0.776	-6.82%
High-skilled in NE	0.939	0.926	-1.34%
High-skilled in West	0.860	0.821	-4.49%
Low-skilled in East	0.389	0.281	-27.82%
Low-skilled in Middle	0.237	0.158	-33.04%
Low-skilled in NE	0.372	0.352	-5.27%
Low-skilled in West	0.267	0.200	-25.21%

Notes: This table presents the migration, urban skill ratio, and urban workforce changes across different regions if innovation growth in China between 2005 and 2015 were eliminated. The first column shows the levels in the original equilibrium, the second column displays the levels in the counterfactual equilibrium, and the third column reports the percentage changes. Panel A presents the migration changes. Panel B displays the changes in the urban skill ratio, calculated as the number of high-skilled workers divided by the number of low-skilled workers in the non-agricultural sector. Panel C illustrates the changes in the urban workforce ratio, calculated as the number of workers in the non-agricultural sector divided by the number of total workers in both agricultural and non-agricultural sectors.

findings emerge: First, total migration declines by 28.5% nationally, driven by a significant drop in non-agricultural sector wages, which reduces the incentive for workers from rural and less developed urban areas to migrate in pursuit of higher incomes. Second, low-skilled migration is particularly affected, decreasing by 35.2%, whereas high-skilled migration is less sensitive to this change. Third, since most rural migrants are low-skilled workers, their increased retention in their hometowns leads to a rise in the urban skill ratio, which increases by 16.9% at the national level. Fourth, urban workforces across all regions, except the northeastern region, experience substantial declines. Overall, the proportion of workers in urban sectors decreases by 18.7% nationwide, with low-skilled workers being more affected than high-skilled workers. Specifically, the low-skilled urban workforce ratio drops by 27.8% in the eastern region and by 33.0% in the middle region.

Table F2 reports the changes in wages by skill groups and regions. In the non-agricultural sector, wages decrease by approximately 70-80% across all regions except the northeastern region, primarily due to the elimination of innovation. In contrast, wages in the agricultural sector decline by less than 5%, as patent changes do not directly impact agricultural productivity. The reduction in wages significantly narrows the urban-rural wage gap, which further discourages migration. Notably, the wage decreases are similar for both high- and low-skilled workers.

Table F3 examines changes in housing rents and amenities under the counterfactual scenario. Housing rents decline by approximately 70% across all regions except the northeastern region, primarily due to the substantial reduction in workers' incomes. Similarly, amenities decrease by around 60% as a result of the elimination of technological progress.

To evaluate welfare changes, we calculate the changes in utility values (wage equivalent) for switching from the origin 2015 equilibrium to the counterfactual equilibrium for individuals with different skills and *hukou* registration statuses, that is, $(U_{i2015} - U_{i2005})/\beta_1^e$. Here, U_{i2005} and U_{i2015} represents the ex ante expected utility value in the counterfactual and the original equilibrium for individual i, as calculated in equation (8). β_1^e represents the skill-specific wage elasticity as in Equation (5).

Table 11 presents the results. The negative welfare change estimates indicate that eliminating innovation growth significantly harms all groups, with the most pronounced effects observed among low-skilled workers holding non-agricultural Hukou. For this group, their welfare reduces as high as 22%. In contrast, workers with agricultural Hukou experience much smaller losses, with a welfare reduction of 1-4%. This disparity arises because individuals with agricultural Hukou can remain in their hometowns and engage in farming, an option unavailable to non-agricultural Hukou workers.

Table 11: Eliminating Innovation Growth: Changes in Welfare

Skill	*hukou* Type	Region	Welfare Change
Low-skilled	Agr	East	-1.87%
		Middle	-1.82%
		Northeast	-0.72%
		West	-1.89%
	Non-agr	East	-15.70%
		Middle	-22.04%
		Northeast	-9.79%
		West	-18.31%
High-skilled	Agr	East	-4.56%
		Middle	-4.67%
		Northeast	-3.58%
		West	-4.41%
	Non-agr	East	-13.00%
		Middle	-17.32%
		Northeast	-9.29%
		West	-13.34%

Notes: This table presents the utility changes (wage equivalent) for various types of workers across different regions if innovation growth in China between 2005 and 2015 were eliminated.

Table 12 illustrates the changes in overall inequality in terms of wages and welfare. After eliminating innovation growth, both the Gini coefficient and the 90th/10th percentile ratio decrease. In contrast, inequality of welfare increases.[18] This finding further highlights the differences between China and other developed countries. Notably, we find no evidence that amenities amplify inequality through skill sorting. On the contrary, our results suggest that although income inequality increased with technological growth, the technological advancements in China over the past decade have helped reduce welfare inequality. This is because more low-skilled workers have been attracted to migrate to urban regions to enjoy improved amenities.

In summary, innovation and patent growth have been key drivers of migration and structural transformation in China. Patent growth has played a crucial role in facilitating rural-urban migration by attracting both high- and low-skilled workers to developed regions, thereby benefiting both groups. However, low-skilled workers are particularly responsive to wage changes but less sensitive to amenities. Consequently, technological growth has significantly contributed to migration without leading to positive skill sorting or divergence, aligning with our descriptive

[18]One concern is that utility levels are not directly comparable across *hukou* types due to differences in choice structures. Specifically, individuals with agricultural *hukou* have an additional option—they can choose to remain in the agricultural sector of their hometown. Therefore, we examine welfare inequality by *hukou* type in Table F4, and the results are similar.

Table 12: Eliminating Innovation Growth: Changes in Inequality

	Original Eq	Counterfactual	Change
Panel A. Wage Inequality			
Gini Coefficient	0.430	0.253	-41.2%
P90/P10	7.396	2.759	-62.7%
Panel B. Welfare Inequality			
Gini Coefficient	0.0965	0.103	6.7%
P90/P10	1.516	1.547	6.0%

Notes: This table presents the income and welfare inequality changes across different regions if innovation growth in China between 2005 and 2015 were eliminated. The first column reports the levels in the original equilibrium, the second column shows the levels in the counterfactual equilibrium, and the third column displays the percentage changes. Panel A presents the changes in wage inequality. Panel B shows the changes in welfare inequality. Two inequality measures are used: the Gini Coefficient and the 90th percentile/10th percentile ratio.

findings from 2005 to 2015.

6.2 Channel Analysis

In Diamond (2016), it is argued that economic growth in the US led to positive sorting of high-skilled workers, who subsequently displaced low-skilled workers from high-productivity and high-amenity locations. Amenities play a crucial role in this process by attracting high-skilled workers to desirable areas, where these amenities are then endogenously enhanced through the agglomeration of such workers. This reinforcing mechanism amplifies welfare inequality beyond what wage inequality alone would produce. However, our analysis suggests that this mechanism does not operate in the same way in China. In this section, we examine the roles of wages, amenities, and skill ratios in workers' migration decisions and compare our findings with those of Diamond (2016) to highlight key differences in the underlying mechanisms.

In our model, technological growth influences worker migration through four channels: 1) Wage effect: Technological growth raises wages, attracting workers to regions experiencing larger technology shocks. 2) Rent effect: Technological growth raises housing demand by increasing residential population and their income, which in turn leads to an increase in housing rents and reduces migration inflow. 3) Direct amenity effect: Technology shocks directly enhance amenities, increasing the desirability of certain locations. 4) Indirect amenity effect via skill ratio: Technological growth affects skill ratios by influencing migration across skill groups, which in turn indirectly impacts local amenities.

To disentangle these channels, we start by repeating the counterfactual analysis from the previous section, replacing the 2015 patent data with the 2005 level. This approach allows us to assess how technology growth from 2005 to 2015 influences skill sorting. Subsequently, we explore four counterfactual scenarios, each designed to deactivate one of the four channels individually. In the first scenario, we identify the wage effect by fixing wage levels at their 2015 values while allowing rent, amenities, and skill ratios to vary with patents. In the second scenario, we identify the rent effect by fixing rent levels at their 2015 values while allowing wage, amenities, and skill ratios to vary with patents. In the third scenario, we isolate the direct amenity effect by holding the impact of patents on amenities constant at its 2015 levels — specifically, setting the patent value in the amenity equation to its 2015 level. In the final scenario, we capture the indirect amenity channel by assuming that the effect of skill ratios on amenities remains at the 2015 level — that is, we hold skill ratios in the amenity equation constant.

Next, we use simulated data from each counterfactual scenario and regress the changes in migration (the difference between the original 2015 equilibrium and the counterfactual equilibrium) on patent shocks (the difference between 2015 patent levels and 2005 patent levels). These regression coefficients measure the impact of technology shocks on high- and low-skilled migration, with each scenario effectively shutting down one of the channels.

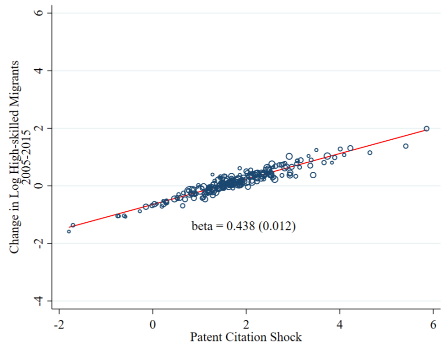
Figure 7 presents the results for high-skilled migration. Subfigure (a) illustrates the impact of patent growth on high-skilled migration in the original counterfactual without shutting down any channel, with an estimated elasticity of 0.438.

Subfigure (b) illustrates a counterfactual scenario in which the wage effect is removed. When wages remain unchanged with patent growth, the impact of patents on high-skilled migration becomes relatively weaker, with the elasticity decreasing from 0.438 to 0.309. Nonetheless, the positive relationship persists, indicating that other channels, beyond wage effects, primarily drive high-skilled workers toward high-growth cities.

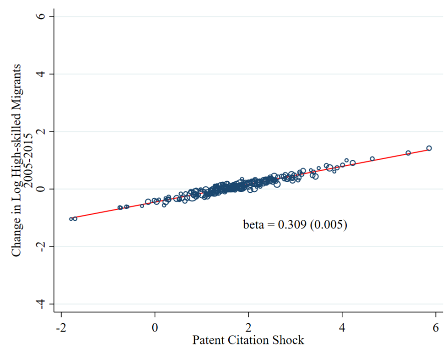
Subfigure (c) shows a counterfactual scenario in which the rent effect is eliminated. When rents do not change with patent growth, the resistance force to prevent people from migrating to fast-growing cities is weakened. Therefore, the impact of patents on high-skilled migration becomes much larger, with the elasticity increasing from 0.438 to 0.970.

Subfigure (d) indicates that when the direct amenity effect is shut down, the positive impact of patent growth on high-skilled migration disappears, with the elasticity dropping to 0.135. This occurs because amenities decline in cities experiencing high patent growth due to a decrease in the skill ratio. As a result, the positive wage effect is almost fully offset by the negative indirect amenity effect, leading to an overall minimal impact on high-skilled migration.

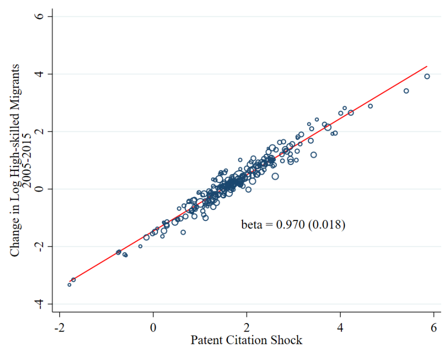
Figure 7: Mechanism Analysis of Patents' Impact on High-skilled Migration



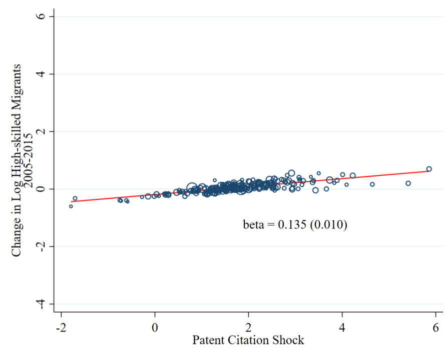
(a) Original Counterfactual



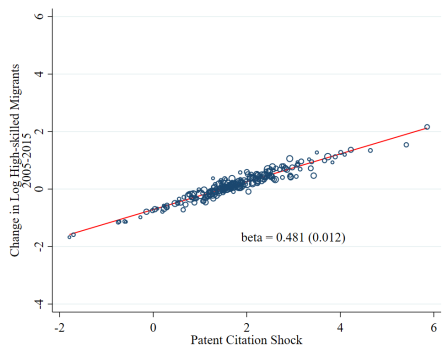
(b) Fixed Wage



(c) Fixed Rent



(d) Fixed Direct Amenity



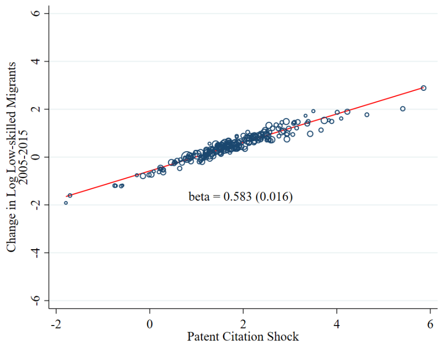
(e) Fixed Skill Ratio

Notes: This figure illustrates the impact of patents on high-skilled migration. Each subfigure shows the correlation between patent citation shocks and changes in the logarithm of high-skilled migration. In subfigure (a), we present results from the original counterfactual model that sets patents to the 2005 level. Subfigure (b) displays results from the model with a fixed housing rent at the 2015 level, effectively shutting down the rent channel. Subfigure (c) displays results from the model with a fixed wage at the 2015 level, effectively shutting down the wage channel. In subfigure (d), we show results from the model with a fixed effect of patents on amenities at the 2015 level, which eliminates the direct amenity channel. Finally, subfigure (e) presents results from the model with a fixed effect of skill ratio on amenities at the 2015 level, effectively shutting down the indirect amenity channel.

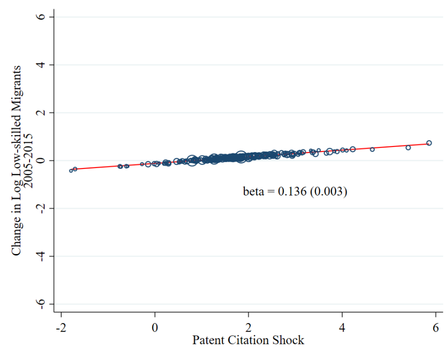
Subfigure (e) presents the counterfactual in which the indirect amenity effect is removed. In this scenario, the decline in the skill ratio does not lead to a reduction in amenities, resulting in a stronger effect of patent growth on high-skilled migration, with the elasticity increasing from

0.438 to 0.481.

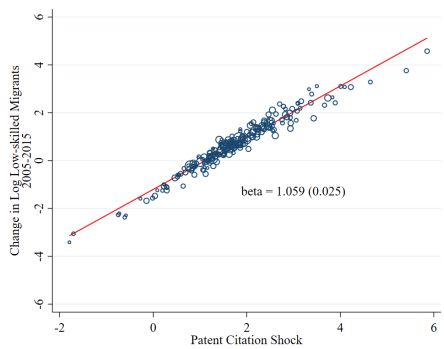
Figure 8: Mechanism Analysis of Patents' Impact on Low-skilled Migration



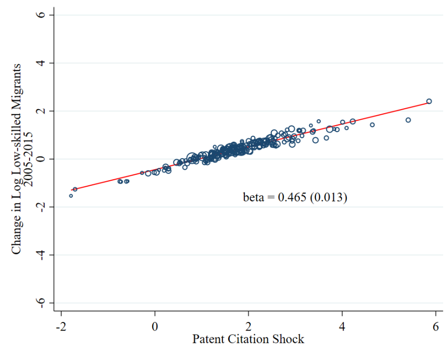
(a) Original Counterfactual



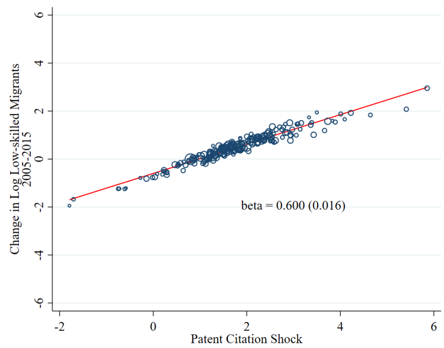
(b) Fixed Wage



(c) Fixed Rent



(d) Fixed Direct Amenity



(e) Fixed Skill Ratio

Notes: This figure illustrates the impact of patents on low-skilled migration. Each subfigure shows the correlation between patent citation shocks and changes in the logarithm of low-skilled migration. In subfigure (a), we present results from the original counterfactual model that sets patents to the 2005 level. Subfigure (b) displays results from the model with a fixed housing rent at the 2015 level, effectively shutting down the rent channel. Subfigure (c) displays results from the model with a fixed wage at the 2015 level, effectively shutting down the wage channel. In subfigure (d), we show results from the model with a fixed effect of patents on amenities at the 2015 level, which eliminates the direct amenity channel. Finally, subfigure (e) presents results from the model with a fixed effect of skill ratio on amenities at the 2015 level, effectively shutting down the indirect amenity channel.

Figure 8 presents the counterparts for low-skilled migration. Consistent with the findings in Section 3, patent growth has a much stronger impact on low-skilled migration than on high-skilled migration, with an elasticity of 0.583 compared to 0.438, as shown in subfigure (a). When the wage effect is eliminated, as presented in subfigure (b), the elasticity is reduced to 0.136, indicating that the wage channel plays a major role. Similar to high-skilled workers, the sorting of the low-skilled workers will also be heavily amplified when housing rent is fixed. As shown in subfigure (c), fixing rent will increase the elasticity from 0.583 to 1.059. However, removing either the direct amenity effect (subfigure (d)) or the indirect amenity effect (subfigure (e)) has minimal influence on the coefficient, suggesting that low-skilled migration is not primarily driven by changes in amenities.

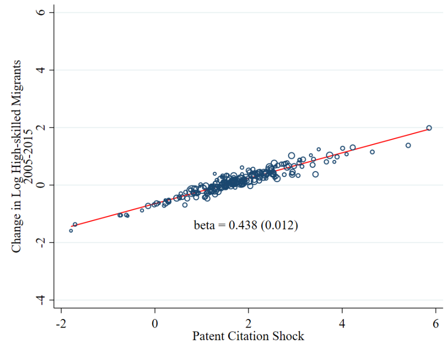
These counterfactuals underscore a key conclusion: although the impact of rent is similar across workers with different skill levels, high-skilled migration is significantly more responsive to amenities, while low-skilled migration is more sensitive to wage variations.

6.3 Importance of Preferences

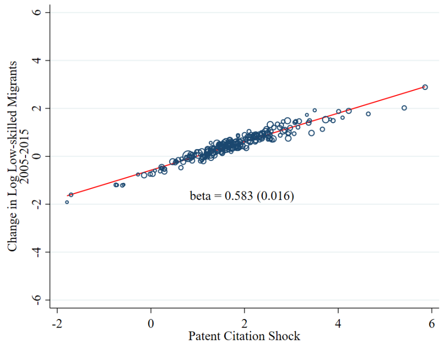
To better understand why our model yields different results from Diamond (2016), we consider a counterfactual in which the preferences for wages, rents, and amenities are equalized across all workers, aligning either with the high-skilled or the low-skilled level. Subfigures (a) and (b) of Figure 9 present the same counterfactual as in subfigure (a) of Figures 7 and 8, which analyze how changing the patent level from 2015 to 2005 affects high- and low-skilled migration. We observe that patent growth from 2005 to 2015 has a larger impact on low-skilled migration than on high-skilled migration, with elasticities of 0.583 and 0.438, respectively. In subfigures (c) and (d) of Figure 9, we set the preferences over wages, rents, and amenities of low-skilled workers to match those of high-skilled workers. Under this scenario, the impact of patent growth on low-skilled migration becomes very similar to that for high-skilled workers, with elasticities of 0.496 versus 0.505. Similarly, aligning high-skilled workers' preferences to those of low-skilled workers significantly diminishes the differential impact of patent growth on migration between the two groups. This highlights the crucial role of heterogeneous worker preferences in explaining the skill sorting patterns observed in China.

In summary, the channel analysis provides insights into the differing findings between our study and Diamond (2016). Although Diamond (2016) also finds that high-skilled workers in the US value amenities more and wages less than low-skilled workers, she also identifies strong skill-biased technological growth, which results in significantly higher wage increases for high-skilled workers. This wage growth offsets the lower wage elasticity of high-skilled workers,

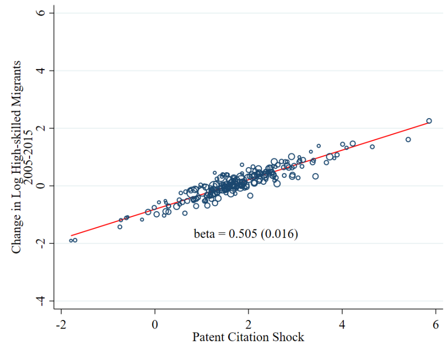
Figure 9: Equalizing Preferences across Skills and Patents' Impact on Migration



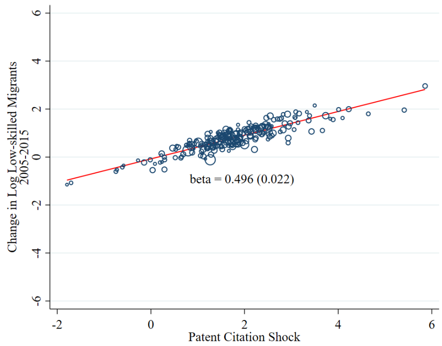
(a) Original Counterfactual (High-skilled)



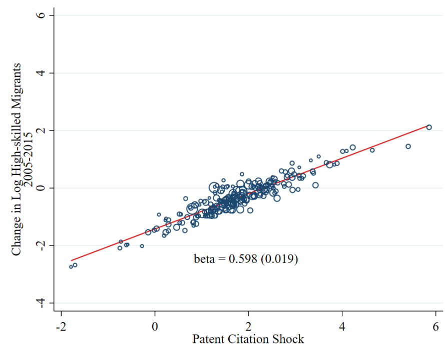
(b) Original Counterfactual (Low-skilled)



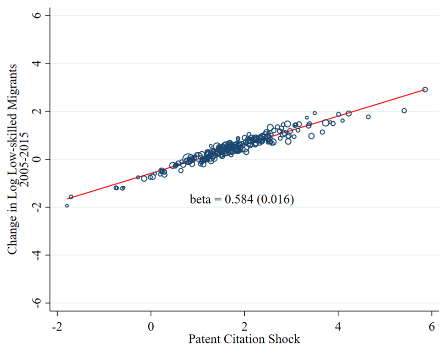
(c) Equalize Preference as High (High-skilled)



(d) Equalize Preference as High (Low-skilled)



(e) Equalize Preference as Low (High-skilled)



(f) Equalize Preference as Low (Low-skilled)

Notes: This figure illustrates the impact of patents on low-skilled migration when we equalize the preferences of people with different skills. Each subfigure shows the correlation between patent citation shocks and changes in the logarithm of high- (subfigures a, c, e) and low-skilled (subfigures b, d, f) migration. In subfigures (a) and (b), we present results from the original counterfactual model that sets patents to the 2005 level. Subfigures (c) and (d) display results from the model with an equalized preference at the high-skilled worker's level. Subfigures (e) and (f) display results from the model with an equalized preference at the low-skilled worker's level.

leading to pronounced skill-based sorting in the US. In contrast, technological innovation in China tends to be less skill-biased compared to the US. Combined with high wage elasticity and low amenity elasticity among low-skilled workers, this results in a higher migration inflow of low-skilled workers than high-skilled workers, thereby reducing the skill ratio in faster-growing cities.

7 Conclusion

In this paper, we examine the impact of innovation shocks on high- and low-skilled migration in China between 2005 and 2015. Using a quantitative spatial general equilibrium model, we find that patent shocks in local labor markets led to wage increases for both high-skilled and low-skilled workers, with broadly comparable magnitudes. However, since low-skilled workers derive greater utility from wage gains, they were more responsive to these shocks and more likely to migrate from underdeveloped rural regions to more developed urban centers. This migration pattern reduced the high-skill ratios in destination cities and, consequently, diminished urban amenities. In contrast, high-skilled workers, who value amenities more highly, were less inclined to move to cities experiencing rapid technological growth, as the relative stagnation in amenities offset the utility gains from higher wages.

Using both descriptive statistics and counterfactual simulations, we find no evidence of positive geographic skill sorting—a pattern commonly observed in developed countries. Between 2005 and 2015, China‘s growth was broadly inclusive, with no divergence in skill composition across cities. Technological progress benefited both high- and low-skilled workers. Although wage inequality widened during this period, we find no evidence of a growing welfare gap between skill groups once changes in cities' wages, rents, and endogenous amenities are accounted for. These findings underscore the distinct spatial economic dynamics in China, the world's largest developing country, and contrast sharply with trends in developed economies. The striking absence of skill sorting during China's urbanization and economic development highlights the influence of institutional factors, such as the rural-urban divide and the hukou policy, which shape migration patterns and differentially influence workers' preferences by skill level. Future research could aim to quantify the effects of these institutional factors and investigate whether similar patterns are present in other developing countries. Finally, our findings suggest that local governments attempting to stimulate innovation may unintentionally lower the local high-skill ratio, raising important policy considerations.

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APPENDIX

A Additional Results of Descriptive Analysis

In this section, we provide the complete results of the descriptive analysis, showing the relationships between patent citation growth and wages, migration, employment, skill ratio, housing price, and amenities. Except for regressing the dependent variables on the Bartik-style measure of predicted change of patent citation, we use the change of patent citation (in logarithm, same below) as the independent variable and the Bartik-style measure of predicted change of patent citation as the instrumental variable. The reduced form regression equations are as follows:

$$\Delta Y_{kt} = \beta_0 + \beta_1 \Delta P_{kt} + \gamma_t + \delta_k + \epsilon_{kt}$$

The first stage and the second stage of the IV regressions are as follows:

$$\Delta Citation_{kt} = \alpha_0 + \alpha_1 \Delta P_{kt} + \gamma_t + \delta_k + \epsilon_{kt} \tag{20}$$

$$\Delta Y_{kt} = \beta_0 + \beta_1 \Delta \widehat{Citation}_{kt} + \gamma_t + \delta_k + \epsilon_{kt} \tag{21}$$

where Y indicates different independent variables, including the number of workers by skills, the number of migrants by skills, the average wages by skills, the skilled ratio, and the housing price, all in logarithm, as well as the amenity index. $Citation_{kt}$ and ΔP_{kt} follows the same definition as in Equation (1). γ_t and δ_k are year fixed effects and city fixed effects, respectively. ϵ_{kt} is the error term. The first equation indicates the reduced-form regression while the second one indicates the 2SLS regression equation.

Results are shown in Appendx Table A1. Specifically, Panel A shows the results of the reduced-form regression. By construction, this set of results aligns with the figures in Section 3. Panels B and C show the IV regression results. Accounting for the endogeneity issue, the IV regression results are qualitatively consistent with the reduced-form results.

Table A1: Citation growth and labor supply, wage, housing price, and amenity

VARIABLES	(1) Δ Log Employment	(2) Δ Log High-Skilled Employment	(3) Δ Log Low-Skilled Employment	(4) Δ Log High-skilled Migrants	(5) Δ Log Low-skilled Migrants
Panel A: Reduced Form					
Citation shock	1.837***	-0.304	2.898***	1.607***	3.051***
	(0.312)	(0.291)	(0.346)	(0.605)	(0.472)
Panel B: OLS					
Δ Log(Citation)	0.0477	-0.003	0.0644	0.0545	0.0921
	(0.033)	(0.031)	(0.039)	(0.076)	(0.057)
Panel C: IV					
Δ Log(Citation)	1.739**	-0.369	2.836**	1.056*	3.044**
	(0.772)	(0.357)	(1.240)	(0.565)	(1.441)
Year FE	X	X	X	X	X
City FE	X	X	X	X	X
VARIABLES	Δ Employment Skilled Ratio	Δ Log High-skilled Wage	Δ Log Low-skilled Wage	Δ Log(Housing Price)	Δ Amenity Index
Panel A: Reduced Form					
Citation shock	-0.620***	0.727***	0.549***	0.938***	0.709
	(0.0654)	(0.121)	(0.105)	(0.194)	(0.462)
Panel B: OLS					
Δ Log(Citation)	-0.013*	-0.010	-0.014	-0.024	0.089
	(0.008)	(0.016)	(0.017)	(0.016)	(0.063)
Panel C: IV					
Δ Log(Citation)	-0.626**	0.727**	0.560*	1.017	0.955
	(0.276)	(0.352)	(0.292)	(0.623)	(0.688)
Year FE	X	X	X	X	X
City FE	X	X	X	X	X

Notes: This table shows results of estimating the relationships between labor supply, wage, housing price, amenity, and patent citation growth. Δ indicates the change between the sample year and the baseline year 2005. Each cell comes from a separate regression. City-level populations are used as weights in the regression. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

B Additional Results of BLP Estimation

Appendix Table B1 shows the selection of IVs with LASSO regarding each endogenous independent variable. A 15-fold cross-validation is used in the LASSO estimation. Each row indicates a category of potential IVs. For example, "geographics" indicate altitude, uphill slope, terrain ruggedness index (TRI), and the area of undevelopable land. Each endogenous variable is predicted with different IVs. Therefore, we manually conduct the first-stage estimation to get the predicted values for second-stage regressions.

The first-stage results are shown in Appendix Table B2. For all endogenous variables, we obtain a high R^2 in predicting them with the selected IVs. Moreover, the F-statistics are all above 9.92, suggesting that the selected IVs satisfy the relevance condition of valid instruments.

Table B1: Second Step: LASSO for each endogenous variable

Variables	Wage (Low-Skilled)	Wage (High-Skilled)	Rent	Amenity
Employment Bartik	✓		✓	
Migrant Bartik				✓
Export Bartik	✓			
Citation Bartik		✓		
Patent Bartik	✓			✓
Patent IV		✓	✓	✓
Import Bartik	✓		✓	✓
Net Export Bartik		✓	✓	✓
Trade Volume Bartik	✓		✓	✓
Altitude			✓	✓
TRI	✓	✓		
Undevelopable Land	✓			
Land Supply	✓		✓	✓
Export Bartik × Land Supply	✓			✓
Trade Volume Bartik × Land Supply			✓	✓
Robot Bartik × TRI			✓	
Migrant Bartik × Robot Bartik			✓	
Land Supply × Altitude	✓	✓		
Land Supply × TRI	✓			✓
Land Supply × Undevelopable Land	✓	✓	✓	✓
Wage Bartik × Altitude			✓	
Wage Bartik × Undevelopable Land				✓
Patent Bartik × Slope	✓			
Patent Bartik × Undevelopable Land				✓
Export Bartik × Slope		✓		
Export Bartik × TRI				✓

Notes: This table shows the selection of instrumental variables by LASSO. "✓" indicates that at least one of the potential instrumental variables of a category, indicated by the first column, is selected.

Table B2: First stage statistics of BLP second stage IV regression

VARIABLES	(1) First Stage R-squared	(2) First Stage F-statistics
Δ Log(High-skilled Wage)	0.677	159.77
Δ Log(Low-skilled Wage)	0.539	45.07
Δ Log(Housing Rent)	0.301	19.82
Δ Amenity Index	0.189	9.92

Notes: This table shows the first stage results of BLP second stage IV regression. R-squared indicates the out-of-sample R-squared. F-statistics are obtained by regressing the endogenous variables on selected IVs with OLS.

Table B3: Estimation of Workers' Location Choice (Second Stage): Combining Wage and Rent

VARIABLES	(1) $\Delta\delta_{high}$	(2) $\Delta\delta_{low}$	(3) $\Delta\delta_{high}$	(4) $\Delta\delta_{low}$
Δ Log(High-skilled Wage) - 0.35*Δ Log(Rent)	0.245*		0.274	
	(0.146)		[0.490]	
Δ Log(Low-skilled Wage) - 0.35*Δ Log(Rent)		0.267		1.724**
		(0.218)		[0.813]
Δ Amenity Index	0.0979**	0.105*	0.369**	0.0735
	(0.0464)	(0.0573)	[0.147]	[0.224]
Constant Constant	0.665***	0.775***	0.465***	0.133
	(0.0752)	(0.108)	[0.158]	[0.251]
Observations	476	476	451	451
R-squared	0.017	0.017	0.045	0.066
Model	OLS	OLS	IV	IV

Notes: This table shows results of estimating the first-difference version of Equation (18). Δ indicates the change between the sample year and the baseline year 2005. In columns (3) and (4), independent variables are predicted values manually estimated with OLS regression on instrumental variables selected by LASSO. See text for more details. In columns (1) and (2), standard errors are in parentheses. In columns (3) and (4), bootstrapped standard errors are in brackets. *** p<0.01, ** p<0.05, * p<0.1.

C Solve the Equilibrium

C.1 Contraction Algorithm

Given exogenous variables and parameters, we need to calculate the responses of endogenous variables resulting from policy changes. The endogenous variables of city k in year t include $\mathbf{\Delta_0} = \{\mathbf{H_0}, \mathbf{L_0}, \mathbf{W_0}, \mathbf{R_0}, \mathbf{x_0}\}$ (number of high-skilled workers, number of low-skilled workers, wages for high-skilled and low-skilled workers, housing rents, and amenities).

We select the equilibrium that is the closest to the one in the real world. Thus, the initial values of the endogenous variables are set to be equal to the data. Starting from the initial values of the endogenous variables, we use the following algorithm to find the new equilibrium.

Let $N_{k_0}^{a,e}$ and $N_{k_0}^{na,e}$ be the number of skill e agricultural and non-agricultural *hukou* workers from hometown city k_0, which is an exogenously given endowment of the economy. To simplify the notation, we suppress subscript t for year. Let q denote the iteration time. Within each iteration, we use $v\hat{a}r$ to denote the temporary updating result of some variable var. At the beginning of the q-th iteration, we have $\mathbf{\Delta_{q-1}}$. Given this, we update the endogenous variables one by one:

1. Workers' utility values

In the first step, we update workers' utility values using endogenous variables derived from the last iteration $(q-1)$:

$$\hat{\delta}_k^e = \beta_1^e w_{na,k|q-1}^e + \beta_2^e r_{k|q-1} + \beta_3^e a_{k|q-1} + \nu_k^e$$

$$\hat{V}_{ik}^{k_0} = MigrationCost_{ik|q-1} + \hat{\delta}_k^e$$

$$E[\hat{W}_{ik_0}^{na}] = ln[\sum_{k\in K} exp(\hat{V}_{ik}^{k_0})]$$

$w_{na,k|q-1}^e$, $r_{k|q-1}$, $hukou_{k|q-1}$, and $a_{k|q-1}$ come from the last iteration $(q-1)$. ν_k^e is the BLP second stage residual which will be used as an exogenous parameter in this matching and not updated during the contraction.

2. Updating migration flows

In the second step, we update migration flows using the logit-form migration equations:

$$\hat{H}_k^{na} = \sum_{i\in N^{na,H}} \frac{\exp(\hat{V}_{ik})}{\sum_r^K \exp(\hat{V}_{ir})} + \sum_{i\in N^{a,H}} \frac{exp(\hat{W}_{ik_0}^{na})}{exp(\hat{W}_i^a) + exp(\hat{W}_{ik_0}^{na})} \cdot \frac{\exp(\hat{V}_{ik})}{\sum_r^K \exp(\hat{V}_{ir})}$$

$$\hat{H}_k^{a} = \sum_{i\in N_k^{a,H}} \frac{exp(\hat{W}_i^a)}{exp(\hat{W}_i^a) + exp(\hat{W}_{ik}^{na})}$$

$$\hat{L}_{kt}^{na} = \sum_{i\in N^{na,L}} \frac{\exp(\hat{V}_{ik})}{\sum_r^K \exp(\hat{V}_{ir})} + \sum_{i\in N^{a,L}} \frac{exp(\hat{W}_{ik_0}^{na})}{exp(\hat{W}_i^a) + exp(\hat{W}_{ik_0}^{na})} \cdot \frac{\exp(\hat{V}_{ik})}{\sum_r^K \exp(\hat{V}_{ir})}$$

$$\hat{L}_{kt}^{a} = \sum_{i\in N_k^{a,L}} \frac{exp(\hat{W}_i^a)}{exp(\hat{W}_i^a) + exp(\hat{W}_{ik}^{na})}$$

3. Updating wages

In the third step, we update wages in each city using the wage equilibrium equation:

$$\hat{w}_{ag,k}^H = \hat{w}_{ag,k}^L = \gamma_{ag} \ln(\hat{H}_{ag,k} + \hat{L}_{ag,k}) + \epsilon_1$$

$$\hat{w}_{na,k}^H = \gamma_{HA} A_k + \gamma_{na,LH} \ln \hat{H}_{na,k} + \gamma_{na,LL} \ln \hat{L}_{na,k} + \epsilon_2$$

$$\hat{w}_{na,k}^L = \gamma_{LA} A_k + \gamma_{na,LH} \ln \hat{H}_{na,k} + \gamma_{na,LL} \ln \hat{L}_{na,k} + \epsilon_3$$

$\hat{H}$ and $\hat{L}$ come from the second step updating. We use regression constants and residuals as exogenous parameters to match $\epsilon_1, \epsilon_2, \epsilon_3$. They will not be updated during the contraction.

4. Updating housing rents

In the fourth step, we update the housing rent in each city using housing equilibrium equation:

$$\hat{r_k} = \left[\gamma_1^{hd} + \gamma_2^{hd} \times \ln(Altitude_k)\right] \ln(\hat{L}_k^{na} exp(\hat{w}_{na,k}^L) + \hat{H}_k^{na} exp(\hat{w}_{na,k}^H)) + \epsilon_4$$

$\hat{H}$, $\hat{L}$, $\hat{w}^L$, and $\hat{w}^H$ come from the first and the third step updatings. We use regression the residual as an exogenous parameter to match ϵ_4. They will not be updated during the contraction.

5. Updating amenity

In the fifth step, we update the amenity in each city using the amenity determination equation:

$$\hat{a}_k = \gamma_1^a A_k + \gamma_2^a \ln\left(\frac{\hat{H}_k^{na}}{\hat{L}_k^{na}}\right) + \epsilon_5$$

where $\hat{H}$ and $\hat{L}$ come from the second and the third step updatings. We use regression the residual as an exogenous parameter to match ϵ_5. They will not be updated during the contraction.

Having these predicted values of the endogenous variables, we use the following updating rule to get the values of all variables for the next iteration:

$$\mathbf{\Delta_q} = \zeta \mathbf{\Delta_{q-1}} + (1 - \zeta) \mathbf{\hat{\Delta}_{q-1}} \tag{22}$$

where $0 < \zeta < 1$. We iterate until convergence is achieved, that is, $\frac{|\mathbf{\Delta_q} - \mathbf{\Delta_{q-1}}|}{|\mathbf{\Delta_{q-1}}|} < \delta$, where the numerator is the L-1 norm of the difference of the endogenous vectors at q and $q - 1$. In the main context, we choose $\zeta = 0.2, \delta = 0.1\%$. We check the robustness of the algorithms by changing these parameters and the difference is minimal.

D Robustness Check Using the Number of Patents

In our baseline specification, we use the number of citations of patents to measure technology growth. This measure takes into account both the quantity and quality of new technology developments. Nonetheless, citations may be mechanically correlated with how long a patent has been granted. In this robustness check, we use the number of patents instead of citations as the measure of technology growth. Accordingly, the Bartik-type predicted technology growth is constructed as follows:

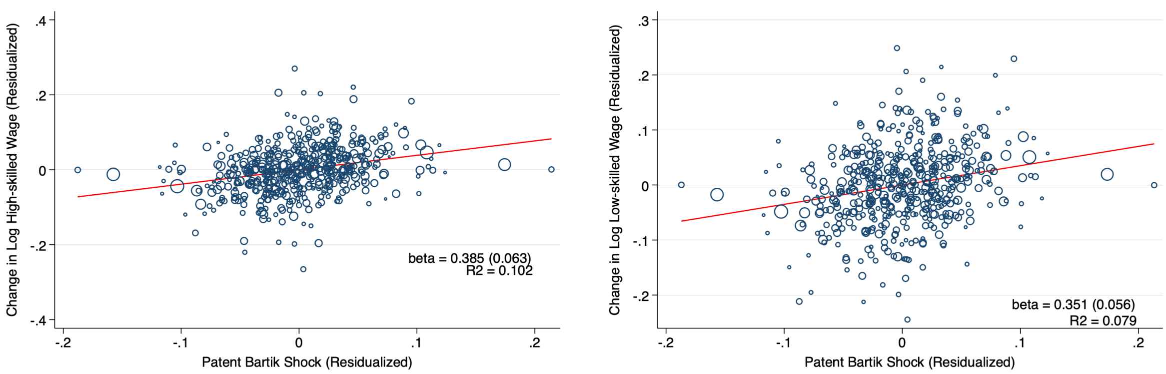
$$\Delta P_{kt} = \sum_{ind} (Patent_{ind,-k,t} - Patent_{ind,-k,2005}) \frac{E_{ind,k,2005}}{E_{k,2005}}$$

Where $Patent_{ind,-k,t}$ indicates the total number of patents (in logarithm) of industry ind in year t in cities other than k. Other notations are the same as in Equation (1).

We replicate three sets of empirical analysis with this alternative measure: (1) descriptive analysis showing the relationships between new technology and city-level characteristics; (2) estimation of the labor demand equation; (3) estimation of the amenity supply.

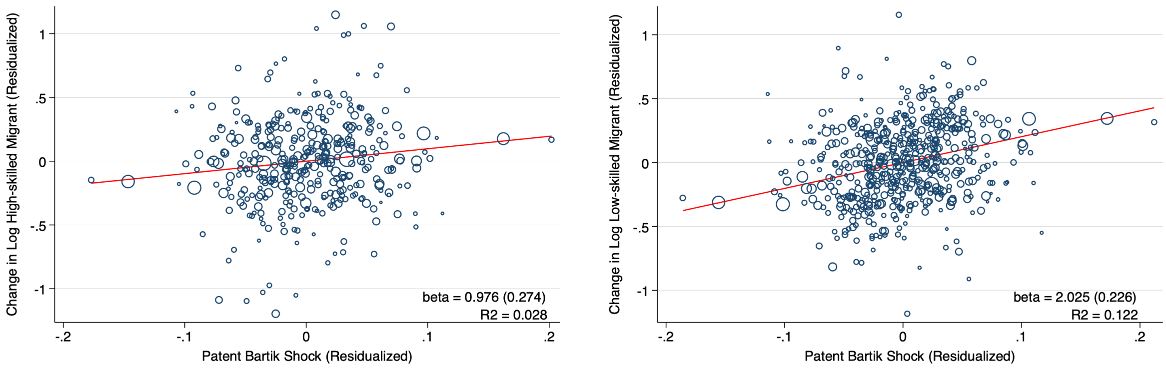
For the first set of results, we can see in Appendix Figures D1 to D4 that the qualitative patterns are identical to those in our main text (see Figures 3 to 6). Specifically, we find that technology shocks increase wages for both high-skilled and low-skilled workers. However, the growth of low-skilled migration exceeds the growth of high-skilled migration, leading to a decrease in the high-skill ratio of cities with a large technology shock. Finally, we find that technology shocks do not significantly improve the amenities of cities.

Figure D1: Effect of Patent on Wages for High- and Low-skilled Workers



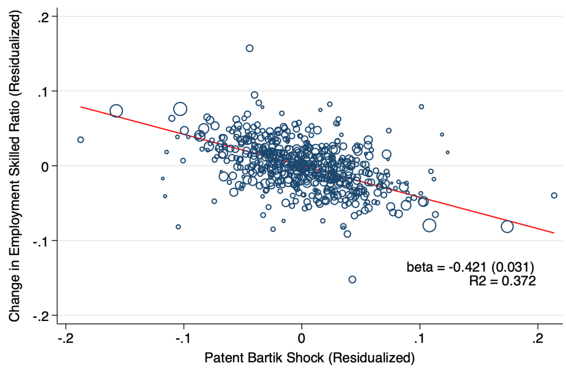
Notes: See notes of Figure 3. Each circle indicates the Bartik-style measure of predicted patent growth and the corresponding change in log wages of a city.

Figure D2: Effect of Patent on Number of High- and Low-skilled Migrants



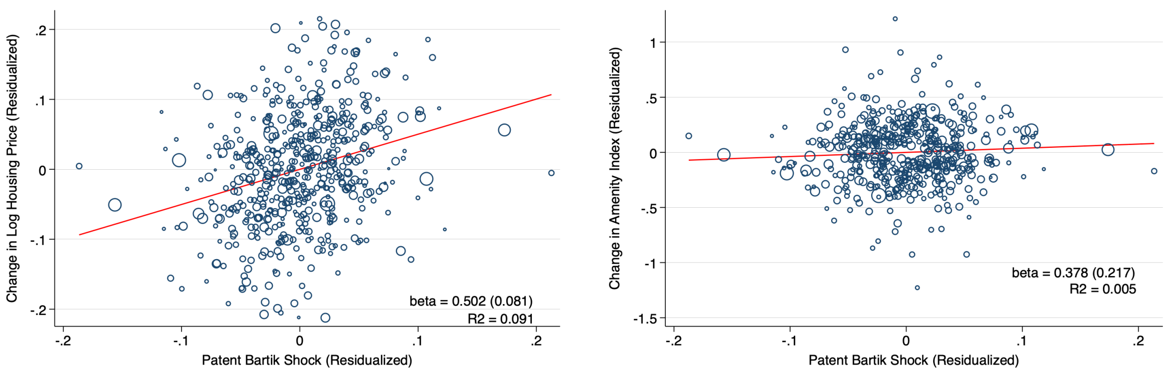
Notes: See notes of Figure H1. Each circle indicates the Bartik-style measure of predicted citation growth and the corresponding change in log number of migrants of a city.

Figure D3: Patent Growth and Change in Skilled Ratio



Notes: See notes of Figure 5. Each circle indicates the Bartik-style measure of predicted citation growth and the corresponding change in the skilled ratio of a city.

Figure D4: Effect of Patent on Housing Price and Amenity



Notes: See notes of Figure 6. Each circle indicates the Bartik-style measure of predicted citation growth and the corresponding change in log housing price, or the change in amenity index, of a city.

For the second set of results, Appendix Table D1 indicates that technology growth increases high-skilled and low-skilled wages, while the labor supply of high-skilled workers drives down the wages for high-skilled workers. The labor supply of low-skilled workers has no significant impact on wages.

Table D1: Estimation of the Labor Demand in the Non-agricultural Sector

VARIABLES	(1) Δ Log High-skilled Wage	(2) Δ Log Low-skilled Wage	(3) Δ Log High-skilled Employment	(4) Δ Log Low-skilled Employment	(5) Δ Log Patent	(6) Δ Log High-skilled Wage	(7) Δ Log Low-skilled Wage
Δ Log Patent	0.114***	0.114***				0.514***	0.481***
	(0.012)	(0.013)				(0.088)	(0.080)
Δ Log High-skilled Employment	0.003	0.006				-0.777*	-0.556
	(0.022)	(0.025)				(0.435)	(0.394)
Δ Log Low-skilled Employment	-0.058**	-0.064**				0.107	-0.086
	(0.028)	(0.032)				(0.426)	(0.387)
Patent Shock			-0.021	0.100	0.978***		
			(0.125)	(0.099)	(0.175)		
Migrant Bartik for High-skilled Workers			0.564***	0.404***	0.659***		
			(0.142)	(0.112)	(0.199)		
Migrant Bartik for Low-skilled Workers			-0.162	0.721**	-0.253		
			(0.357)	(0.282)	(0.500)		
Constant	0.543***	0.545***	-0.226	-0.832***	-0.371	0.185*	0.174*
	(0.023)	(0.026)	(0.348)	(0.275)	(0.488)	(0.098)	(0.089)
Observations	484	484	484	484	484	484	484
R-squared	0.174	0.142					
Model	OLS	OLS	First stage	First stage	First stage	IV GMM	IV GMM
Sanderson-Windmeijer F			6.819	9.238	9.247		

Notes: This table shows results of estimating the first-difference version of Equation (3) and (4). Δ indicates the change between the sample year and the baseline year 2005. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Finally, for the amenity market, technology growth significantly increases amenities (see column (4) of Appendix Table D2). The skilled ratio also has a positive coefficient, yet is statistically insignificant.

Table D2: Estimation of the Amenity Supply

VARIABLES	(1) Δ Amenity Index	(2) Δ Log High-skilled Ratio	(3) Δ Log Patent	(4) Δ Amenity Index
Δ Log Patent	0.266***			0.580***
	(0.036)			(0.096)
Δ High-skilled Employment Ratio	0.027			1.596
	(0.383)			(1.872)
Patent Shock		-0.081***	0.723***	
		(0.024)	(0.220)	
Wage Bartik IV for High-skilled Workers		0.087	-0.523	
		(0.058)	(0.536)	
Wage Bartik IV for Low-skilled Workers		0.145**	1.529**	
		(0.072)	(0.672)	
Constant	0.325***	-0.028**	0.00193	-0.312**
	(0.073)	(0.014)	(0.130)	(0.132)
Observations	484	484	484	484
R-squared	0.104			
Model	OLS	First stage	First stage	IV GMM
Sanderson-Windmeijer F		12.05	19.40	

Notes: This table shows results of estimating the first-difference version of Equation (12). Δ indicates the change between the sample year and the baseline year 2005. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

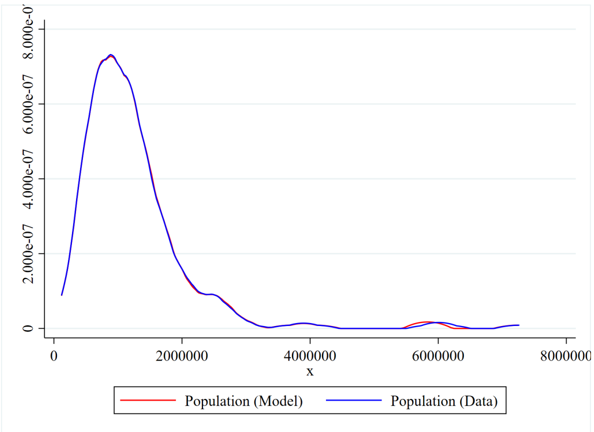
E Model Fitting Tables and Figures

Table E1: Model Fit

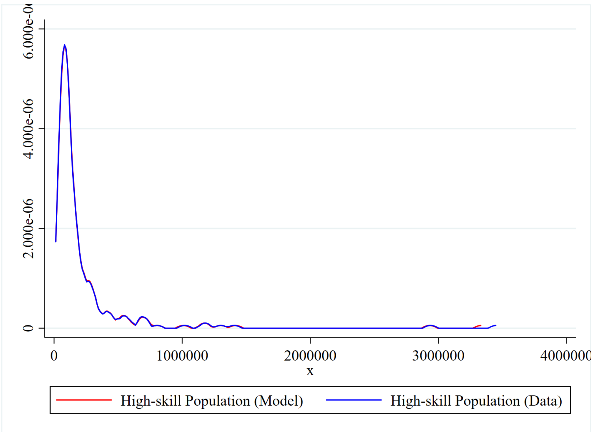
Variables	Model	Data	Difference
Panel A. Migration across Cities			
Total Migrants	26644291	26738972	-0.35%
Total High-skill Migrants	5746082	5830542	-1.45%
Total Low-skill Migrants	20898208	20908432	-0.049%
Panel B. Average Wages			
Mean Wages of High-skill in Agr	12651	12664	-0.11%
Mean Wages of High-skill in Non-agr	57090	56844	-0.43%
Mean Wages of Low-skill in Agr	12651	12664	-0.11%
Mean Wages of Low-skill in Non-agr	47076	46812	-0.57%
Panel C. Average Housing Rent and Amenity			
Mean Housing Rent	3343.6	3340.9	-0.08%
Mean Amenity	1.356	1.351	0.38%

Notes: This table presents the model fitting for the baseline economy in 2015. The first column shows the equilibrium outcomes as solved within the model. The second column shows the corresponding moments from the data. The third column shows the differences between the model predictions and the observed data.

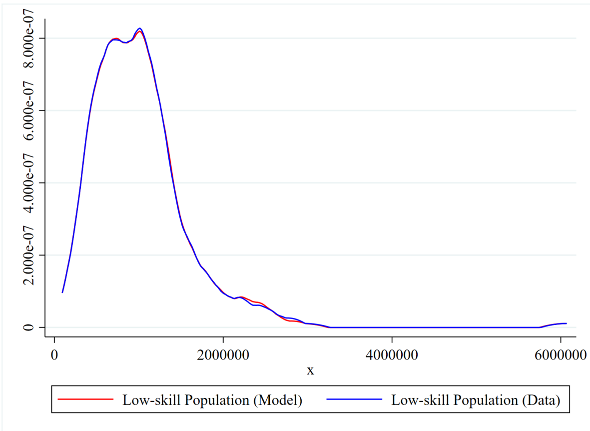
Figure E1: Model Fit of the Distribution of Working Population



(a) City Working Population



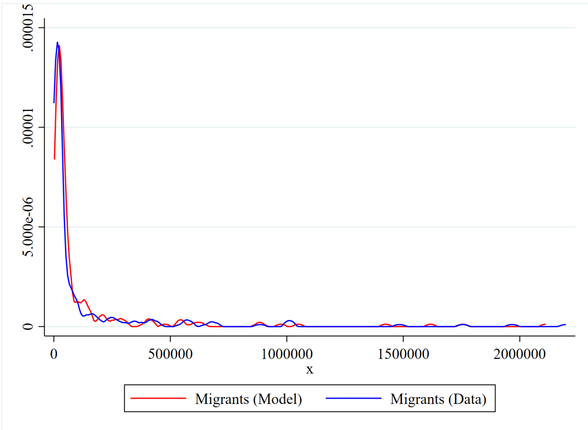
(b) City Working High-skilled Population



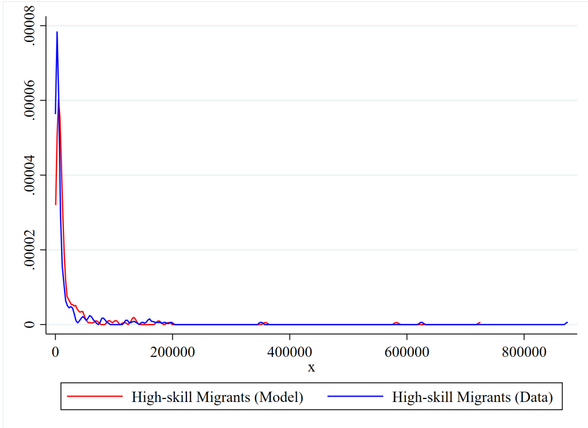
(c) City Working Low-skilled Population

Notes: This figure shows the working populations in different cities. The red curve represents the density at equilibrium from the model. The blue curve represents the density of the data.

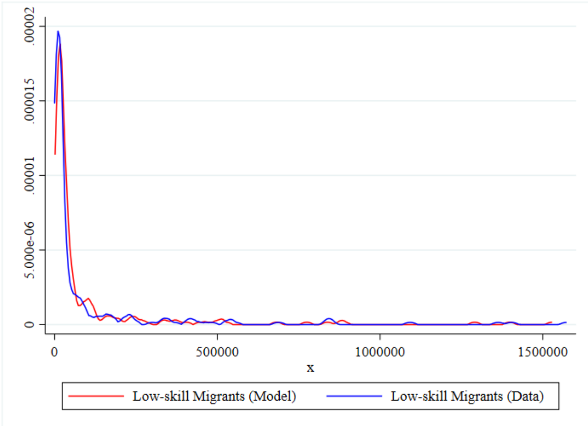
Figure E2: Model Fit of the Distribution of Migrants



(a) City Migrants



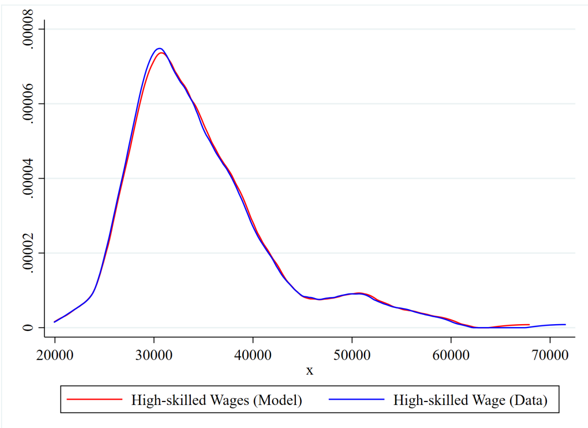
(b) City High-skilled Migrants



(c) City Low-skilled Migrants

Notes: This figure shows the number of migrants in different cities. The red curve represents the density at equilibrium from the model. The blue curve represents the density of the data.

Figure E3: Model Fit of the Distribution of Wages

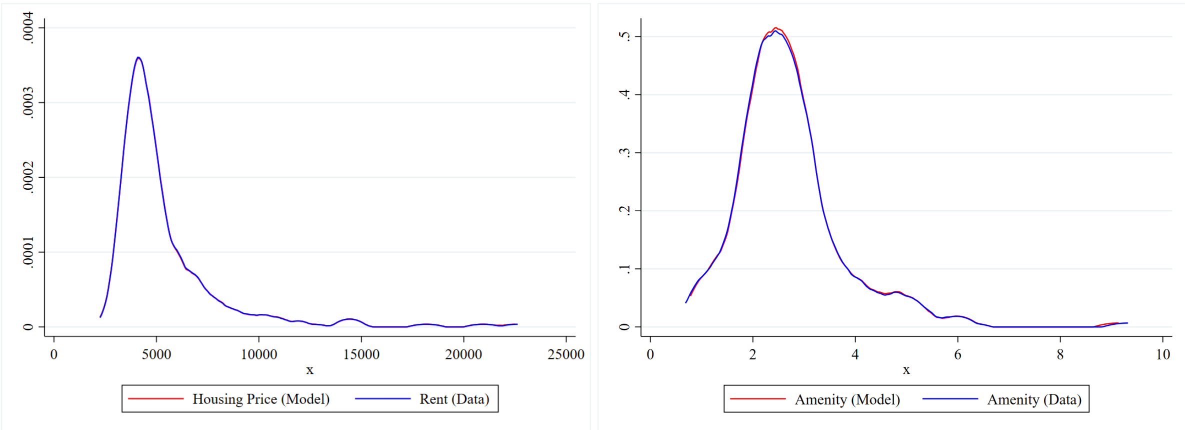


(a) High-skilled Wages

(b) Low-skilled Wages

Notes: This figure shows the wages in different cities. The red curve represents the density at equilibrium from the model. The blue curve represents the density of the data.

Figure E4: Model Fit of the Distribution of Housing Rent and Amenity



(a) Housing Rent

(b) Amenity

Notes: This figure shows the housing rent and the amenity index in different cities. The red curve represents the density at equilibrium from the model. The blue curve represents the density of the data.

F Additional Counterfactual Figures and Tables

Table F1: Eliminating Innovation Growth: Patent Citation Change in Log Points

	Mean	Std Dev	Maximum	Minimum
National	-1.748	1.048	1.792	-5.857
Eastern Region	-1.864	0.699	-0.231	-3.734
Middle Region	-2.105	0.993	0.274	-5.857
Northeastern Region	-0.646	0.879	1.792	-1.861
Western Region	-1.747	1.213	1.705	-5.412

Notes: This table illustrates the change in patent citations across different regions if the innovation growth in China between 2005 and 2015 were eliminated. The unit of measurement is y log points, which can be interpreted as a $(e^y - 1)$ percent change. For small values of y, this approximation simplifies to $(e^y - 1) \approx y$.

Table F2: Eliminating Innovation Growth: Wage Changes

Skill	Sector	Region	Original Eq	Counterfactual	Change
Average Wage of Low-skilled	Agr	East	15343.37	14853.93	-3.19%
		Middle	11655.62	11395.11	-2.24%
		Northeast	12043.63	11932.22	-0.93%
		West	10456.14	10268.65	-1.79%
	Non-agr	East	51675.43	11893.68	-76.98%
		Middle	43910.63	9307.324	-78.80%
		Northeast	43229.81	29697.35	-31.30%
		West	47038.16	14960.44	-68.20%
Average Wage of High-skilled	Agr	East	15343.37	14853.93	-3.19%
		Middle	11655.62	11395.11	-2.24%
		Northeast	12043.63	11932.22	-0.93%
		West	10456.14	10268.65	-1.79%
	Non-agr	East	64892.29	13117.79	-79.79%
		Middle	51292.6	9577.579	-81.33%
		Northeast	50522.05	35371.1	-29.99%
		West	57640.47	17279.09	-70.02%

Notes: This table presents the wage changes for workers with different skill levels across each sector and region if innovation growth in China between 2005 and 2015 were eliminated. The fourth column reports the wage levels in the original equilibrium, the fifth column shows the wage levels in the counterfactual equilibrium, and the sixth column displays the percentage changes. "Agr" refers to the agricultural sector, while "Non-agr" denotes the non-agricultural sector.

Table F3: Eliminating Innovation Growth: Housing Rent and Amenity Changes

	Original Eq	Counterfactual	Change
Panel A. Housing Rent			
Average Housing Rent in East	3971.4	1017.8	-74.37%
Average Housing Rent in Middle	2868.9	627.5	-78.13%
Average Housing Rent in Northeast	2866.0	2417.9	-15.63%
Average Housing Rent in West	3368.7	1208.7	-64.12%
Panel B. Amenities			
Average Amenity in East	2.688	1.030	-61.68%
Average Amenity in Middle	2.571	0.641	-75.08%
Average Amenity in Northeast	2.826	2.194	-22.38%
Average Amenity in West	2.871	1.284	-55.27%

Notes: This table presents the changes in housing rents and amenities across different regions if innovation growth in China between 2005 and 2015 were eliminated. The first column reports the levels in the original equilibrium, the second column shows the levels in the counterfactual equilibrium, and the third column displays the percentage changes. Panel A highlights the changes in housing rents, while Panel B illustrates the changes in amenities.

Table F4: Eliminating Innovation Growth: Welfare Inequality by *hukou* Type

	Original Eq	Counterfactual	Change
Panel A. Agricultural Hukou			
Gini Coefficient	0.0720	0.0737	2.4%
Panel B. Non-agricultural Hukou			
Gini Coefficient	0.136	0.162	19.1%

Notes: This table presents the welfare inequality (Gini Coefficient) changes by *hukou* type across different regions if innovation growth in China between 2005 and 2015 were eliminated. The first column reports the levels in the original equilibrium, the second column shows the levels in the counterfactual equilibrium, and the third column displays the percentage changes. Panel A highlights the changes for people with agricultural Hukou. Panel B illustrates the changes for people with non-agricultural Hukou. We use Gini Coefficient to represent inequality.

G Testing the Validity of Bartik Instruments

In this study, we rely extensively on Bartik-type predicted values of patent citation growth, wage growth, migration growth, and other economic characteristics to generate exogenous variations for identification. The identification assumptions in this study require that the national industry-level shocks are not correlated with the dependent variable other than their correlations with the endogenous independent variables. To test this assumption, we follow Borusyak, Hull, and Jaravel (2022) to conduct two analyses. First, we show that the industry-level shocks are not concentrated in a small number of particular industries. Second, we conduct a set of industry-level balance tests to show that the industry-level shocks are not correlated with potential confounders that affect the outcome variables.

As shown in Appendix Table G1, in which we focus on the Bartik-type shocks of citation, migrants by skill, and wages by skill, the standard deviation of industry-level shocks are non-trivial, meaning that there are sufficient variations for identification. Moreover, the effective sample size of estimation, which is calculated as the inverse of HHI of industry shares in employment, lies in a reasonable range, especially for the Bartik-type shock of citation.

Table G1: Summary Statistics of Bartik Shock

Bartik	(1) Citation	(2) Migrant High-Skilled	(3) Migrant Low-Skilled	(4) Wage High-Skilled	(5) Wage Low-Skilled
Panel A: 2010					
Mean	1.269	0.727	0.729	0.669	0.665
Standard deviation	0.326	0.269	0.277	0.102	0.102
Effective Sample Size (1/HHI)	13.834	7.168	4.295	10.131	5.763
Panel B: 2015					
Mean	1.481	0.741	0.724	1.143	1.136
Standard deviation	0.533	0.434	0.447	0.099	0.097
Effective Sample Size (1/HHI)	19.058	8.999	5.228	10.597	6.046

Notes: This table shows the summary statistics of national industry-level shocks following Borusyak, Hull, and Jaravel (2022). HHI is the Herfindahl–Hirschman Index of industry-level employment shares.

For the second set of analyses, we show that the industry-level shocks are not systematically correlated with local confounding shocks. We first aggregate the city-level potential confounding factors to industry-level based on the following equation, which uses the same share as we construct the Bartik-type predicted variables as weights.

$$\Delta\bar{v}_{ind,t} = \frac{\sum_k \frac{E_{ind,k,2005}}{E_{k,2005}} \cdot \Delta v_{kt}}{\sum_k \frac{E_{ind,k,2005}}{E_{k,2005}}}$$

where v_{kt} is potential confounding factors. In this study, we consider several indicators that are correlated with economic development and affect wages or amenities, including GDP growth rate, population density, fiscal expenditure, retail sales, profits of above-scale firms, and the number of college students. $\frac{E_{ind,k,2005}}{E_{ind,k,2005}}$ is the employment share of industry ind in city k in year 2005. Here we use this share variable as an example. In practice, the share used in constructing the industry-level confounding factors depends on the focal Bartik shock (e.g., use the share of migrants when testing for Bartik-type predicted growth of migrants). This equation essentially calculates the weighted average exposure of different industries on confounding local shocks in different cities. The weight is larger if the industry is more important for a specific local market.

As shown in Appendix Table G2, national industry-level growth of patent citations is not correlated with a wide range of covariates. Similar patterns can also be documented for industry-level growth of migration and wages (see Appendix Table G3 and G4). One exception is that the Bartik shock of wages of high-skilled workers is correlated with the log number of college students. To ensure that such a correlation does not affect our results, we conduct robustness checks by adding the changes in log number of college students when estimating the first differences of Equations (11) and (12). Results are shown in Appendix Tables G5 and G6, respectively.

For both the summary statistics and the balance tests, we perform the same analysis for the number of patents, international trade, and robots as well. Shift-share-type shocks of these variables are also not correlated with potential confounding factors. Results are available upon request.

Table G2: Balance Test of Bartik-type Shock of Citation

VARIABLES	2010 Coefficient	S.E.	2015 Coefficient	S.E.
GDP Growth Rate	0.002	(0.003)	0.001	(0.002)
Log Population Density	0.002	(0.009)	-0.003	(0.005)
Log Fiscal Expenditure	0.017	(0.023)	-0.004	(0.028)
Log Retail Sale	-0.001	(0.013)	-0.014	(0.009)
Log Above-Scale Firm Profit	-0.096	(0.087)	0.029	(0.108)
Log Number of College Students	-0.004	(0.020)	-0.004	(0.020)

Notes: This table shows the results of balance test regressions with Bartik-type predicted growth of citations as the independent variables. See the text for the construction of industry-level confounding factors. Each coefficient comes from a separate regression. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table G3: Balance Test of Bartik-type Shock of Migrants

VARIABLES	2010		2015	
	Coefficient	S.E.	Coefficient	S.E.
Panel A: High-Skilled				
GDP Growth Rate	-0.003	(0.007)	0.003	(0.005)
Log Population Density	-0.008	(0.008)	-0.020*	(0.011)
Log Fiscal Expenditure	-0.042	(0.057)	-0.017	(0.094)
Log Retail Sale	0.020	(0.050)	-0.015	(0.067)
Log Above-Scale Firm Profit	-0.011	(0.118)	0.075	(0.106)
Log Number of College Students	0.725	(0.476)	0.258	(0.559)
Panel B: Low-Skilled				
GDP Growth Rate	-0.006**	(0.002)	-0.004	(0.003)
Log Population Density	0.002	(0.002)	0.006	(0.005)
Log Fiscal Expenditure	-0.038	(0.025)	-0.036	(0.040)
Log Retail Sale	-0.009	(0.012)	-0.043*	(0.023)
Log Above-Scale Firm Profit	-0.079	(0.068)	0.048	(0.138)
Log Number of College Students	0.403	(0.245)	0.143	(0.261)

Notes: This table shows the results of balance test regressions with Bartik-type predicted growth of migrants as the independent variables. See the text for the construction of industry-level confounding factors. Each coefficient comes from a separate regression. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table G4: Balance Test of Bartik-type Shock of Wages

VARIABLES	2010		2015	
	Coefficient	S.E.	Coefficient	S.E.
Panel A: High-Skilled				
GDP Growth Rate	-0.006	(0.008)	-0.005	(0.005)
Log Population Density	0.004	(0.012)	-0.015	(0.013)
Log Fiscal Expenditure	0.022	(0.070)	-0.014	(0.117)
Log Retail Sale	-0.005	(0.030)	-0.037	(0.066)
Log Above-Scale Firm Profit	-0.114	(0.273)	0.144	(0.289)
Log Number of College Students	-1.807**	(0.683)	-2.081***	(0.688)
Panel B: Low-Skilled				
GDP Growth Rate	0.012	(0.011)	0.004	(0.007)
Log Population Density	-0.007	(0.005)	-0.012*	(0.006)
Log Fiscal Expenditure	-0.002	(0.077)	-0.049	(0.113)
Log Retail Sale	-0.013	(0.036)	-0.047	(0.053)
Log Above-Scale Firm Profit	-0.212	(0.220)	0.102	(0.377)
Log Number of College Students	-0.672*	(0.327)	-0.653	(0.444)

Notes: This table shows the results of balance test regressions with Bartik-type predicted growth of wages as the independent variables. See the text for the construction of industry-level confounding factors. Each coefficient comes from a separate regression. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table G5: Estimation of the Housing Market

VARIABLES	(1) Δ Log(Housing Rent)	(2) Δ Log Housing Demand	(3) Δ Log Housing Demand * Geo	(4) Δ Log(Housing Rent)
Δ Log Housing Demand	0.0141			0.596***
	(0.0661)			(0.121)
Δ Log Housing Demand * Log Altitude	0.0263**			0.0441***
	(0.0116)			(0.0168)
Δ Log Number of College Students	0.101**	0.0389	0.171	0.0149
	(0.0432)	(0.0470)	(0.239)	(0.0568)
Wage Bartik IV for HS Workers		-5.777***	-18.84***	
		(1.239)	(6.294)	
Wage Bartik IV for LS Workers		6.724***	17.29***	
		(1.230)	(6.248)	
Wage Bartik IV for HS Workers * Log Altitude		0.958***	3.290***	
		(0.211)	(1.072)	
Wage Bartik IV for LS Workers * Log Altitude		-0.951***	-2.057*	
		(0.210)	(1.068)	
Constant	0.571***	0.193***	1.246***	-0.0549
	(0.0464)	(0.0740)	(0.376)	(0.0977)
Observations	466	466	466	466
R-squared	0.055			
Model	OLS	First stage	First stage	IV GMM
Sanderson-Windmeijer F		578	89.44	

Notes: This table shows results of estimating the first-difference version of Equation (10). Δ indicates the change between the sample year and the baseline year 2005. “Geo” indicates log(Altitude). “HS” means “High-skilled”. “LS” means “Low-skilled”. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table G6: Estimation of the Amenity Supply

VARIABLES	(1) Δ Amenity Index	(2) Δ Log High-skilled Ratio	(3) Δ Log Citation	(4) Δ Amenity Index
Δ Log Citation	0.137***			1.036***
	(0.035)			(0.368)
Δ High-skilled Employment Ratio	0.502			4.950**
	(0.394)			(2.400)
Δ Log number of college students	0.266***	-0.023**	0.168	0.093
	(0.080)	(0.009)	(0.106)	(0.182)
Citation Shock		-0.072***	0.306	
		(0.021)	(0.251)	
Wage Bartik IV for High-skilled Workers		0.069	-1.012	
		(0.057)	(0.672)	
Wage Bartik IV for Low-skilled Workers		0.089	1.511**	
		(0.061)	(0.715)	
Constant	0.406***	0.029	0.696***	-1.147**
	(0.078)	(0.021)	(0.243)	(0.467)
Observations	479	479	479	479
R-squared	0.062			
Model	OLS	First stage	First stage	IV GMM
Sanderson-Windmeijer F		9.432	5.386	

Notes: This table shows results of estimating the first-difference version of Equation (12). Δ indicates the change between the sample year and the baseline year 2005. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

H Additional Tables and Figures

Table H1: Correlation between Imputed Wages and Wages of UHS Data

Year	High-Skilled	Low-Skilled
2005	0.851	0.778
2010/2009	0.802	0.620

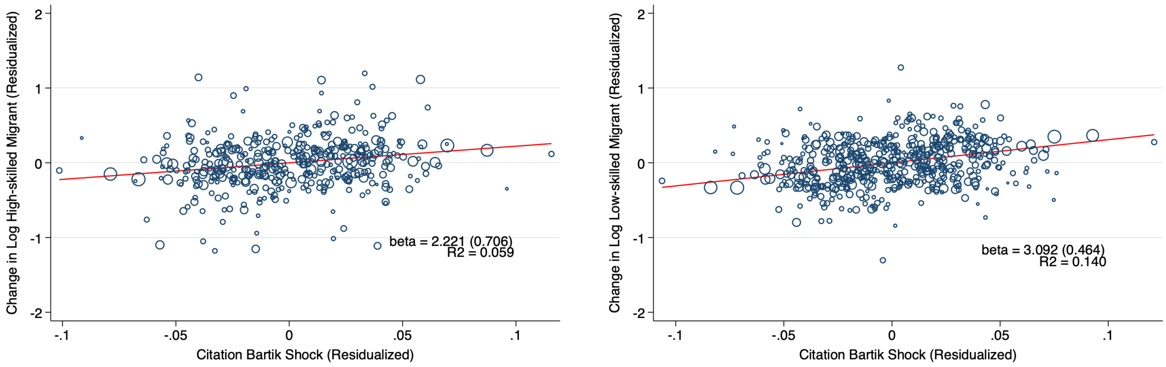
Notes: UHS data ends in 2009. We adjust the wage data in 2009 to the 2010 price level and calculate its correlation with the imputed wages in 2010.

Table H2: Estimation of Amenity Market (Sub-indexes)

VARIABLES	(1) Δ Infrastructure Index	(2) Δ Environment Index	(3) Δ Health Index	(4) Δ Education Index
Δ Log(Citation)	0.968***	-0.782***	0.797**	-0.062
	(0.289)	(0.235)	(0.317)	(0.091)
Δ High-skilled Ratio	4.777**	-4.425**	1.292	2.696***
	(2.207)	(1.797)	(2.418)	(0.693)
Constant	-0.903**	1.420***	-0.879*	0.153
	(0.418)	(0.340)	(0.458)	(0.131)
Observations	481	481	481	481
Model	IV GMM	IV GMM	IV GMM	IV GMM
Kleibergen-Paap rk LM	14.600	14.600	14.600	14.600
Cragg-Donald Wald F	4.978	4.978	4.978	4.978

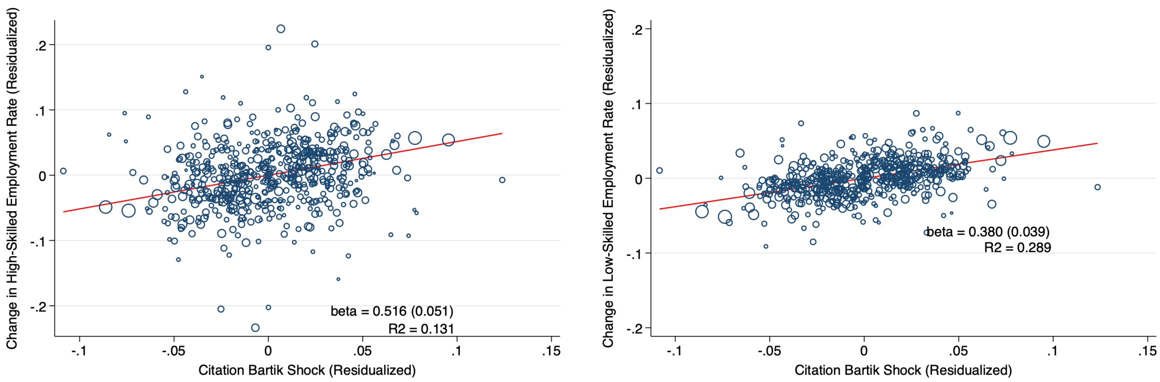
Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure H1: Effect of Citation on Number of High- and Low-skilled Migrants Aged 16 to 50



Notes: Each circle indicates the shift-share-style measure of predicted citation growth and the corresponding change in the log number of migrants of a city. Both variables are residualized by partialling out the year fixed effects and city fixed effects. The size of the circles indicates the population size of cities. The solid line is the fitted line with OLS regression. The coefficient and standard error of the variable on the x-axis and the R^2 of the regression are listed in the figure. The left panel is for high-skilled migrants and the right panel is for low-skilled migrants.

Figure H2: Local Employment by Skills



(a) Local High-skill Employment

(b) Local Low-skill Employment

Notes: Each circle indicates the shift-share-style measure of predicted citation growth and the corresponding change in the employment rate of local labor force in a city. Both variables are residualized by partialling out the year fixed effects and city fixed effects. The size of the circles indicates the population size of cities. The solid line is the fitted line with OLS regression. The coefficient and standard error of the variable on the x-axis and the R^2 of the regression are listed in the figure. The left panel is for high-skilled migrants and the right panel is for low-skilled migrants.