The Effect of Metropolitan Technological Progress on the Non-metropolitan Labor Market: Evidence from U.S. Patent Counts

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Abstract

While urban technology growth exerts a positive effect on rural development through knowledge spillovers, urban technology also raises the competitive advantage of urban firms over rural firms in product market competition. The progress in urban technology also affects the rural labor market through brain drain. Brain drain, which is often considered to be a negative effect of urban technology on rural growth, in actuality, does not have an unambiguous effect on the rural labor market. Therefore, the net effect of urban technology on the rural labor market performance is theoretically ambiguous.

Alas, these facts have not yet received serious attention in academic and political arenas. Without fully taking into account these negative effects, any place-based policy aiming at increasing local and regional jobs by technological advancement might have unintended consequences. Furthermore, one cannot ignore the effects of technology on regional labor market because interregional migration within a country is prominent. With a contentious debate regarding the future role of technology on labor market, a clearer understanding of the influence of urban technology on the rural labor market is essential. Finally, even though this paper analyzes the impacts of technology in the rural-urban context, its implications might be extended to the study of various regional contexts in which interregional or international mobility and trade occur.

Using patent counts at the county level in the United States, there is evidence that a 1 percent increase in urban technological stock, which is constructed from the perpetual inventory method and the basic inverse distance matrix, raises the rural unemployment rate by 0.1-0.2 percent in a short or medium run. A back-of-the-envelope calculation translates these numbers into about two and a half million rural jobs destroyed between 2005 and 2015 by urban technical progress. Several competing hypotheses and econometric issues have been examined. Results of the examination indicate that the main finding is highly robust. Finally, I perform a simple assessment on rural welfare and find that urban technology has a statistically significant negative impact on the average wages but not the average incomes of the rural population. This crude assessment suggests that employed workers in rural regions might suffer from welfare loss caused by the progress of urban technology, although government transfer might alleviate some of this loss.

1. Introduction

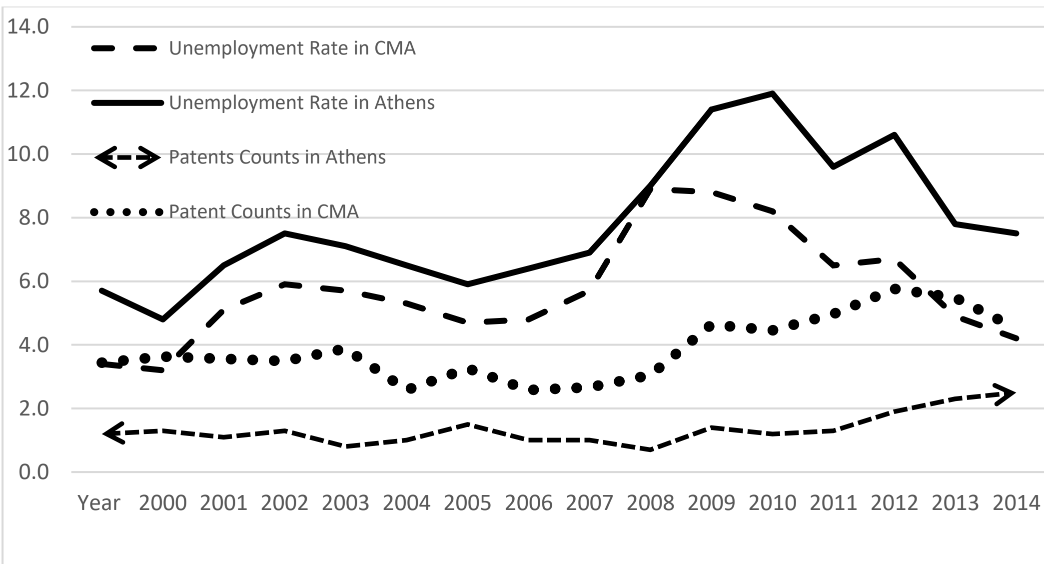
Popular belief often praises technology for its ability to create jobs and promote the economic development. The rationale used to justify this positive thought is that knowledge, which is claimed to be a nonrival and a public good, is partially or completely transferred from a frontier region to a follower.[1] There are convincing pieces of evidence that the rationale, but not the belief, is more or less correct. For instance, Athens County is located very close to the Columbus Metropolitan Area; therefore, we would expect that Athens could benefit greatly from the technological progress in this metropolitan statistical area. Indeed, Figure 1 shows that there is a strong positive correlation between the (scaled) numbers of granted patent counts filed in Athens and in the Columbus Metropolitan Area. Yet figure 1 also illustrates another surprising relationship between the unemployment rate in Athens and the (scaled) number of granted patent counts in the Columbus Metropolitan Area lagged by one year.[2] There seems to be a strong positive association between the unemployment rate in Athens and technological growth in the Columbus Metropolitan Area.[3] The latter raises an inquiry about whether there are other effects of urban technological progress, besides knowledge spillovers, that can affect the Athens labor market performance.

While urban technological progress can boost productivity and economic growth of the rural regions through knowledge spillovers, this technological progress can also increase rural

[1] In this article, knowledge and technology will be used interchangeably. Additionally, metropolitan areas are referred to as urban areas while non-metropolitan areas are referred to as rural areas.
[2] The patent counts are lagged in order to lessen the concern of simultaneous relationship between unemployment rate and technology.
[3] while the estimated correlation between the unemployment rate in CMA and the natural log of patent counts in CMA is not statistically significant, a simple regression shows a significantly positive correlation between the unemployment rate in Athens and the natural log of patent counts in CMA (the estimated correlation is 4.83 and almost significant at 1 percent level).

unemployment through product market competition.[4] In other words, the competition among urban and rural firms who produce identical or differentiate goods or services can reduce the demand of outputs produced by rural firms, and therefore, it can negatively affect labor demand of firms located in rural regions.[5] On the other hand, brain drain (which is often considered as a backwash effect of urban technology on rural economic development) can have an ambiguous influence on the rural labor. That is, brain drain can attract human capital away from rural regions, but it can also create jobs in urban areas for unemployed workers living in rural regions.

Figure 1: Relationship between Athens Unemployment Rate, Technology Growth in Athens, and Technology Growth in the Columbus Metropolitan Area



Note: the utility patent grants filed in Athens, Ohio is scaled by a factor of 0.1. The utility patent grants filed in the Columbus Metropolitan Area (CMA) are scaled by a factor of 0.01. The time series of patent counts in both regions have been lagged by a year. This patent counts data is extracted from the U.S. Patent Trademark Office (USPTO): https://www.uspto.gov/web/offices/ac/ido/oeip/taf/countyall/usa_county_gd.htm. The yearly unemployment rate of Athens and Columbus Metropolitan Statistical Area (CMA) are measured in the sixth month and can be retrieved from Federal Reserve Bank of St. Louis: https://fred.stlouisfed.org/series/OHATHE5URN.

Consequentially, the net effect of urban technology on the rural labor market is theoretically indeterminable. A fundamental question is whether urban technological growth has a net positive

[4] Following the suggestion of the U.S. Department of Agriculture (2017a), an urban area is defined as a metropolitan statistical area (MSA) while a rural region is a non-metropolitan area. MSA is delineated by using 2003 metropolitan definitions of the Office of Management and Budget (OMB).
[5] Using firm level data, Bloom, Schankerman and Reenen (2013) find that technological growth of rival firms can depress the market value of a firm.

or a net negative impact on the rural labor market. In other words, the question is whether, on average, we observe the same pattern shown in figure 1 on average. Unfortunately, this relationship between urban technological growth and the rural labor market have been largely ignored both in theoretical and empirical studies.

This relationship is particularly important for three reasons. First, without taking the negative effects of urban technology into account, any place-based policy aiming at increasing local and regional jobs by technological advancement might have unintended consequences. Second, one cannot ignore the effects of technology on regional labor markets because the interregional flow of labor within the U.S. is self-evident. Third, given that the impact of technology (particularly artificial intelligent) on future labor market is a pressing concern among policy makers, business leaders and scholars , this paper could provide a piece of evidence for the importance of technology in determining the performance of the labor market.[6]

The main contribution of this paper is an attempt to tackle the previously raised question conceptually and empirically. Although this paper specifically studies the impacts of technology in the rural-urban context, its implications could be readily extended to other regional contexts in which interregional or international mobility and trade take place.

The conservative finding of the paper is that a 1 percent increase in the urban technological stock increases the rural unemployment rate by 0.1-0.2 percent in a short or medium run. A back-of-the-envelope calculation translates these numbers into about two and a half million rural job losses due to urban technical progress between 2005 and 2015.

A number of competing hypotheses in explaining the rise of rural unemployment rate, including industry labor demand shock, mobility of low/medium skill workers, the level of automation in

[6] For instance, see Author, Levy and Murnane (2003), Frey and Osborne (2017), and Clifford (2017).

the U.S., and the level of entrepreneurship in rural regions, have been explored. Moreover, several econometric issues, such as simultaneity bias, serial correlation, lagged effect of independent variables and cross-sectional dependence, are also considered. These analyses show that the main finding of this paper is strongly robust.

Yet one may not interpret this finding as a net negative impact of urban technological progress on the welfare of rural regions. This is not necessarily true. For instance, the government can transfer income from a prosperous, urban region to a rural area, and by doing so, urban technical growth makes every region better off. The analysis of urban-rural welfare is beyond the scope of this paper as further analysis is required. Still, I also provide a basic assessment of rural welfare by studying the impact of urban technology on wages and total incomes in the rural areas. I find that the progress in urban technology could decrease wage of rural workers, but it does not significantly affect total income which contains, inter alia, wages and government transfers. Perhaps, the assessment suggests that a future increase in urban research and development funding might need to be accompanied with a higher transfer to rural areas in order to maintain the welfare of rural regions. However, rigorous analyses are needed to determine the best solution to this conundrum. This simple assessment also cannot clearly distinguish between different kinds of government transfers to a specific rural subpopulation (for instance, unemployed versus employed), it warrants future study of the impact of urban technological progress on a particular group of rural dwellers.

Due to the nature of the study and the lack of data at the county level, one might not be able to claim that the finding is conclusive. However, I hope that the finding of this paper could ignite the interest of scholars and policy makers to put more effort in making data available and to further examine the effects of urban technological growth on rural labor market performance.

The remainder of the paper will be organized as follows. Section 2 gives a critical overview of the two strands of economic theories used in the paper. Section 3 shows some suggestive evidence of the three effects of urban technology. Next, section 4 offers a conceptual framework as the motivation of the paper. Section 5 presents the empirical strategy, the dataset, and the main finding. Section 6 compares the main finding with other competing hypotheses and conducts several econometric tests. Section 7 performs a basic rural welfare analysis. Section 8 concludes the paper.

2. The Endogenous Growth Theory of Technology and the Concept of Spread and Backwash

Due to a variety of constraints, several seminal works are omitted from this section. I only review two important strands of literature that are very crucial to this work.

Firstly, one of the most influential works on the positive impact of endogenous technological progress on output growth is written by Paul M. Romer (1990). Romer (1990) theorizes that technology endogenously accelerates economic growth of a region. Through investment in research and development (or human capital), one can promote welfare (Romer, 1990).[7] Additionally, Romer (1990) also incorporates the notion of "non-rival and partially excludable good" of technology in his model. Therefore, Romer (1990) undoubtedly contributes to the appreciation of the positive impact of technology and later to the understanding of the effect of knowledge spillovers.

It is worth to noting that Romer's endogenous growth theory has been criticized by various empirical studies and subsequent theories. Particularly, Jones (1995a, 1995b) points out that the endogenous growth theory cannot explain the growth pattern in developed countries. Jones (1995a, 1995b), along with other opponents of the full endogenous growth, contend that government

[7] There are two generations of the endogens growth models. A few notable works for the first generation are the works of Romer (1990), Aghion and Howitt (1992), and Grossman and Helpman (1991a). The second generations have been built around the works of Jones (1995a, 1995b), Kortum (1997), and Segerstrom (1998), Aghion and Howitt (1998c).

policies are ineffective in raising the economic growth rate because the rate itself depends on the exogenous rate of population growth. The argument is commonly known as the "growth without scale effects". While the debate among growth theorists centers on the scale effects, there is no doubt that technological progress always leads to an increase in economic growth.

If one allows the possibility of labor movement across regions, population growth will not be fully exogenous. Policies that leads to technological progress can incentivize labor mobility, and therefore affect labor market conditions. This issue is the main interest of the current study. Specifically, this paper focuses on brain drain and product market competition effects, in addition to knowledge spillovers of urban technology, on the rural labor market performance. Conceptually, technological change does not always benefit every place; some rural places can experience their reduction in unemployment rates while others might suffer from high unemployment.

The second strand of literature is the spread and backwash concepts proposed by Hoselitz (1955), Myrdal (1957) and Hirschman (1960). On the one hand, economists often refer to knowledge spillovers as a positive effect, which can increase efficiency in production and quality of outputs. On the other hand, backwash effects could be induced by the effects of brain drain and product market competition. Yet the classic terminology of the spread and backwash effects do not apply immediately to the study of the impacts of technology on labor market performance. Specifically, in theory, brain drain has an ambiguous effect on the rural labor market performance.

A large number of empirical works on the Hoselitz–Myrdal-Hirschman concept mainly focus on the effects of international trade between developed and underdeveloped countries. They often overlook the relationship between the technological growth of an urban area and the rural labor market. As a matter of fact, urban technological progress might be one of the primary explanations for the prosperity or destruction of rural areas.[8] While physical, legal, cultural and language barriers have prevented the flow of international labor mobility, technological migration across nations could be a minor issue. Nevertheless, we cannot ignore this issue when we look at the impact of technology on interregional migration within any country, particularly within the United States.

3. Decomposition of the Effects of Urban Technological Progress: Suggestive Evidence

It is instructive to show evidence of knowledge spillovers, brain drain and product market competition. Each of these effects of urban technology deserves separate analysis in its own right. Yet some suggestive pieces of evidence are presented here.

In the following analyses, I leave the details on how to construct knowledge stock variables, educational attainment and industry mixed employment growth to the next section. In brief, the knowledge stock variables are constructed by applying the perpetual inventory method weighted by the basic inverse distance matrix on patent counts at the county level. The education variable is the percentage of adult population with a college degree or higher, and the industry mixed employment growth is the Batik's industry mixed employment growth.

Using the firm level data, the seminal works of Jaffe (1986) and of Jaffe, Trajtenberg and Henderson (1993) have identified the existence and some aspects of knowledge spillovers. Most of subsequent empirical works have confirmed these findings. Using the county data, I have also found evidence that knowledge can be transferred from urban to rural regions.

Table 1 shows the result of the regression of the domestic technological stock of rural regions on the lagged urban technology stock.[9] The regression also includes other variables such as, other

[8] For a comprehensive discussion of the spread and backwash concepts, see Gaile (1980)
[9] The details on the construction of regional technological stocks and educational attainment can be found in section 5.

rural regions' technological stock lagged by one year, educational attainment lagged by one period, time fixed effect, county fixed effect, population, and industry mixed employment growth.[10,11] All variables are in logarithmic form. Consistent with the theory presented in the previous section and other empirical studies, there is a significant positive correlation between technological progress of urban and rural areas.[12]

Table 1. Evidence of Knowledge Spillovers

	Fixed Effects
Urban Knowledge Stock	0.75*
	(0.402)
Rural Knowledge Stock	-0.84
	(0.842)
Education	0.004
	(0.070)
Industry Mixed Employment Growth	0.38
	(0.458)
Population	-0.37
	(0.867)
Year Dummies	Yes
Countries Dummies	Yes
Observations	1,325
R-squared	0.169

Note: Robust standard errors are in parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively. The period of study is between 2004 and 2014. The dependent variable is rural, domestic knowledge stock. All variables are in logarithmic form. The variables including urban knowledge stock, rural knowledge stock and education are lagged by one year.

Another effect of urban technology is brain drain. The study of brain drain in literature mainly confines to issues of productivity and education, particularly at the firm or country level. For example, using patent citation data, Agrawal, Kapur, McHale and Oettl (2011) find that Indian skill emigration is harmful to domestic technological growth. Moreover, Stoyanov and Zubanov (2012) conclude that firms can gain higher productivity when they hire skilled worker from other

[10] Industry mixed employment growth is constructed using Batik-type instrument. More detail on the construction of this variable can be found in section 6.
[11] Population dataset are extracted from U.S. Bureau of Economic Analysis through https://www.bea.gov/.
[12]Although the relationship is not significant, we see a negative correlation between a rural technological stock and the rest of rural areas. One explanation is that rural areas might exert a strong "fishing-out" effect on one another. For a short discussion about "fishing-out" and "standing on the shoulder" effects, see Bottazzi and Peri (2007).

firms. Faggian and McCann (2008) show that a highly innovative area can attract highly educated human capital.[13]

Table 2. Evidence of Brain Drain

	Fixed Effects
Urban Knowledge Stock	0.35***
	(0.063)
Rural Knowledge Stock	-0.02
	(0.091)
Own Knowledge Stock	0.007
	(0.007)
Education	0.19***
	(0.029)
Industry Mixed Employment Growth	0.01
	(0.052)
Income	0.35***
	(0.062)
Population	0.985***
	(0.051)
Year Dummies	Yes
State Dummies	Yes
Observations	1,494
R-squared	0.80

Note: Robust standard errors are in parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively. The period of study is from 2004 to 2015. The dependent variable is out migration. All variable are in logarithmic. The variables including urban knowledge stock, rural knowledge stock, own knowledge stock and education are lagged by one year. The estimation includes amenity variables, whose results are not reported. The amenity variables are mean January sun hours, mean January temperature, mean July humidity, mean July temperature, topography score, percentage of county area cover by water, and natural amenity rank.

Table 2 presents evidence of brain drain effect of urban technology on the rural labor market. The results are obtained by regressing the total number of out migration from rural areas on the lagged urban technological stock and other control variables. The control variables are the rural and domestic knowledge stocks lagged by one year, one-year lagged educational attainment variable, industry mixed employment growth, average personal income, population, and amenity

[13] Faggian and McCann (2009) also find that human capital growth can promote regional innovations.

variables.[14,15] In addition, both dependent and independent variables are in logarithmic form, and the estimation is performed with the two-way fixed effects.

As can be seen, urban knowledge stock positively correlates with out-migration rate. The positive coefficient of high educational attainment reinforces the argument of brain drain. That is, highly educated workers tend to migrate away from rural areas (Stephens, Partridge and Faggian, 2013).

Last but not least, urban technological progress can also adversely affect the rural labor market through product market competition. Using firm level data, Bloom, Schankerman and Reenen (2003) find a strong negative effect of product market competition on a firm's market value. They conclude that innovation of neighboring firms could potentially harm the growth of a firm.[16]

Table 3 shows the results from regressing the number of current establishment in rural areas on the urban technological stock lagged by one period. I also control for other regional knowledge stocks and educational attainment. Both of them are also lagged by a one year period. The other control variables are population and industry mixed employment growth. As shown in the table, the result suggests the existence of product market competition. To put it differently, an increase in urban technological stock correlates with a reduction in rural establishment. Interestingly, there is a positive correlation between a rural region's establishment and technology growth of other rural regions. Although it is statistically insignificant, other rural regions' technological stock

[14] To make the results legible, the coefficients of the amenity variables are not reported in table 2. These variables are mean January sun hours, mean January temperature, mean July humidity, mean July temperature, topography score, and percentage of county area cover by water. All of these variables are standardized z-score. Last but not least, natural amenity rank is also included. These variables are taken from USDA's Economic Research Service: https://www.ers.usda.gov/data-products/natural-amenities-scale/.

[15] The average personal income is extracted from U.S. Bureau of Economic analysis through https://www.bea.gov/.

[16] Yet Bloom, Schankerman and Reenen (2003) also find that social return (knowledge spillovers effect) from technological investment dominates private return (that is, product market competition effect).

could improve a rural region's labor market performance. Therefore, products from rural areas could be complementary to one another.

Table 3. Evidence of Product Market Competition

	Fixed Effects
Urban Knowledge Stock	-0.15***
	(0.025)
Rural Knowledge Stock	0.12*
	(0.066)
Own Knowledge Stock	0.014**
	(0.005)
Education	-0.0068
	(0.00949)
Industry Mixed Employment Growth	0.36***
	(0.042)
Population	0.49***
	(0.079)
Year Dummies	Yes
Countries Dummies	Yes
Observations	1,494
R-squared	0.74

Note: Robust standard errors are in parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively. The period of study is between 2004 and 2015. The dependent variable is rural, domestic knowledge stock. All variable are in logarithmic form. The variables includes urban knowledge stock, rural knowledge stock and education are lagged by one year.

4. Conceptual Framework

The theoretical model presented here is built on the work of Romer (1990) in addition to insight provided by the spread-backwash notion of Hoselitz (1995), Myrdal (1957) and Hirschman (1960). While there are critics of Romer's model regarding the scale effects of technology, the model is sufficient to the current analysis in illustrating the effects of urban technology on the rural labor market. In fact, it is reasonable to believe that one could arrive at the same conclusion about the relationships between regional wages, regional outputs and technological progress with other endogenous growth models. Since the current analysis is all about labor markets, this paper only focuses on the effect of technological progress on regional wages and outputs. That is to say, the analysis solely emphasizes the effect of technology on the labor market which is often ignored in the endogenous growth literature.

Several extensions, such as unemployment benefits, frictional unemployment and mobility cost, are added to Romer's model in order to capture labor participation and interregional labor movement in the model. These extensions can help us focus on labor market performance. Yet the purpose of this simple model is to convey a straightforward understanding on the effects of knowledge spillovers, brain drain, and market product competition of urban technology. A much more elegant and comprehensive theoretical model is left for future work.

The key idea behind the model is threefold. First, knowledge spillovers from urban regions raise the total employment in rural regions by increasing the growth rate of wages offered. Second, urban technological progress exerts brain drain effect which has an ambiguous impact on the rural labor market. Particularly, urban technology can reduce the total unemployment in the rural regions by creating jobs in urban areas for those who are unemployed and living in rural regions. However, urban technology can also attract human capital away from rural regions, and therefore, it deteriorates the ability of rural regions to raise wages over time. Third, the progress in urban technology increases the output of goods and services of the urban region. The ample production of urban goods puts pressure on world prices of both rural goods and services, and hence, it diminishes the wages of rural workers. To express it differently, the progress in urban technology enhances the competitive advantage of urban firms against rural firms in product market competition.

4.1. Description of the Theoretical Model

In this model, there are two regions, an urban region and a rural region. These regions are denoted by “U” and “R”, respectively. À la Romer (1990), there are four sectors operating in the economy of each region.

The first sector is a manufacturing sector which produces final goods. These goods produced in both region are assumed to be substitutable. Yet I assume consumers favor urban goods to rural goods because urban firms produce higher quality goods with better technology.[17] First, I solve the model by assuming that there is no trade between these two regions. Then, I give an explanation on how trade can affect the results of the model. To be specific, trade in the final outputs could give rise to the effect of product market competition.

At any time t, the maximization problem of the representative manufacturing firm in region $i \in \{U, R\}$ is given by,

$$\max_{L_{i,t}, \{x_{i,t}(k)\}} Y_{i,t} \equiv L_{i,t}^{\alpha} \int_0^{A_{i,t}} [x_{i,t}(k)]^{1-\alpha} dk - w_{i,t,L} L_{i,t} - \int_0^{A_{i,t}} x_{i,t}(k) p_{i,t}(k) dk. \quad (1)$$

I normalize the price of final output produced in region *i* and at time *t* to be one. $A_{i,t}$ is an available stock of knowledge up until time *t* in region *i*. $L_{i,t}$ is an amount of human capital used in the manufacturing sector, and $\{x_{i,t}(k)\}$ are capital goods employed to produce the final output.[18] Moreover, the final goods market is competitive, so the representative firm takes the prices of labor and capital goods (that is, $w_{i,t,L}$ and $p_{i,t}(k)$, respectively) as given.

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[17] That is the utility function of a consumer can be formulated as, $utility(Y_{U,t}, Y_{R,t}) = Y_{U,t} + \gamma_{t,q} Y_{R,t}$, where $Y_{U,t}$ and $Y_{R,t}$ are manufacturing goods (or services) produced in the urban and rural regions, respectively. $\gamma_{t,q} \in (0,1)$ is the taste parameter which reflects the concept of the Central Place Theory. This parameter is assumed to be a function of urban and rural technological stocks.

[18] A specific variety of capital goods is denoted by k, and $\{x_{i,t}(k)\}$ denotes a vector of capital goods in region *i* and time *t*.

Next, another sector is capital-goods market. Each variety of capital goods in region i is produced by a monopolist who owns a patent acquired with one-time price of $P_{A,i,t}$(k).[19] For the time being, let us also assume that capital goods are not tradable across regions.[20] As in Aghion and Howitt (1990a) and Jones (2005), it is safe to assume that one unit of capital good can be produced by a unit of raw capital. At any time *t*, in region *i* and for capital goods of a variety k, a monopolist solves:

$$\max_{x_{i,t}(k)} \ \pi_{\mathrm{i,t}}(k) \equiv x_{i,t}(k)p_{i,t}(k) - rx_{i,t}(k) \tag{2}$$

$p_{i,t}(k)$ is a price of capital good in region *i* at time *t*, and *r* is an exogenous interest rate of capital (that is, *r* might be determined by the federal government).

The third sector is a research and development sector. Following Romer (1990), I maintain the linearity assumption for the growth rate of technology. Specifically, I assume that

$$\frac{\dot{A}_{i,t}}{A_{i,t}} = \delta_i H_{i,t} \phi_i, \tag{3}$$

where δ_i is the productivity parameter of region i, and $H_{i,t}$ is the human capital employed in the research and development sector. ϕ_i is the absorptive capacity of region *i* in capturing interregional knowledge spillovers; I assume that it is constant and is greater than or equal to one. The assumptions imposed on ϕ_i are by no means able to successfully reflect the nature of knowledge spillovers across regions. These assumptions are maintained only for analytical convenience. I hope future research can effectively identify factors affecting this parameter and channels through

[19] That is, $P_{A,i,t}$(k) is a sunk cost that a monopolist has to pay for when it enters the capital market.

[20] Aghion and Howitt (1990) provide a comprehensive treatment on the effect of trade in capital goods on economic growth. The formal treatment of these models can be found in the works of Grossman and Helpman (1991a) and Grossman and Helpman (1996).

which this parameter affects the technological growth rate.[21,22] Finally, as in Romer (1990), the market for patents, which are the products of R&D sector, is assumed to be competitive.

The last sector concerns the labor market. The total population in both regions sums up to a constant. For simplicity, let assume that everyone is endowed with a unit of labor. I assume that each person can either supply a unit or none of his or her labor to the market. Define *f(m,n)* and *d(m,n)* for *m,n >0* as follow,

$$f(m,n) = \frac{m-n}{m+n} \tag{4}$$

$$\begin{cases} d(m,n) = & 1 \quad if\ m > n \\ d(m,n) = & 0, \quad otherwise \end{cases} \tag{5}$$

It is straightforward to show that for *m*, *n>0*, $(m,n) = -f(n,m)$, $f(m,n) \in (-1,1)$, $\frac{\partial f(m,n)}{\partial m} > 0$ and $\frac{\partial f(m,n)}{\partial n} < 0$. One can also establish that $f(m,m) = 0$; $\lim_{n\to 0} f(m,n) = \lim_{m\to 0} -f(m,n) = 1$, and $\lim_{m\to\infty} f(m,n) = \lim_{n\to\infty} -f(m,n) = 1$. Furthermore, for $m < m', n < n'$, and $|m-n| = |m'-n'| \neq 0$, we have $|f(m,n)| < |f(m',n')|$. In what follows, I use $f(m,n)$ to capture the flow rate of labor into and out of the labor market. For instance, if *m*, *n* are wages in region *i* and *j*, respectively and if $m > n$, the flow of labor force from *j* to *i* is proportional to the difference between these wages (the nominator of $f(m,n)$). The rate is between zero and one, and it approaches one when the wage in region *j* approaches zero or when the wage in region *i* approaches infinity. Finally, it is getting harder to attract more labor from region *j* as both wages grow higher given that the difference between these wages is constant over time.

[21] For a comprehensive review of knowledge transfer function, see Sakar (1998). For empirical studies on the relationship between the knowledge spillovers and the absorptive capacity, see Girma (2005), Girma and Görg (2005), and Falvey, Foster and Greenaway (2007).
[22] For in-depth treatment of a knowledge production function, see Griliches (1979).

For the sake of model tractability, I will specify the change in population in each region as follow,

i. the change in total unemployment in region *i* and at time *t* that is due to labor participation or job quit of agents living in region *i* and at time *t*:

$$\dot{Pop}_{ue,i,t} = f(w_{ue,i}, w_{e,i,t})[d(w_{e,i,t}, w_{ue,t})(Pop_{i,t} - Pop_{e,i,t}) + d(w_{ue,t}, w_{e,i,t})Pop_{e,i,t}] \quad (6)$$

$\dot{Pop}_{ue,i,t}$ is the change of total unemployment in region *i* and at time t. $w_{e,i,t}$ is the highest wage offered in region *i* at time *t*; $w_{ue,t}$ is the unemployment benefit in both regions. Assume that the unemployment benefit grows at the constant rate such that $w_{ue,t} = (\gamma_{ue})^t w_{ue,0}$, where $w_{ue,0}$ is a given unemployment benefit at the beginning of time. The growing unemployment benefit encompasses the idea that the unemployed agents have received higher unemployment benefit over time. $Pop_{i,t}$ and $Pop_{e,i,t}$ are the total population and total employment in region *i* at time *t*.

Condition (6) states that change in the total unemployment in region *i* and at time *t* is proportional to the difference between the unemployment benefit and the highest wage offered. If the wage is above the unemployment benefits, a fraction of unemployed people will be employed in the next period. If the wage is below the unemployment benefits, some workers will quit the job. Otherwise, there is no change in the total unemployment. This condition which is imposed by setting $f(m,n) \in (-1,1)$ reflects rigidity or friction in the labor market which cannot fully adjust in response to changes in wage and unemployment benefits.[23] It also captures an idea that there are heterogeneous responses of workers to changes in labor conditions. That is, workers might have idiosyncratic unemployment benefits.

[23] This condition shares the spirit of Burdett and Mortensen (1998).

ii. the change in total unemployment in region *i* and at time *t* that is due to out migration of the unemployed agents to region *j*:

$$\dot{Pop}'_{ue,i,t} = M_{ue,i} d\left(w_{e,j,t}, w_{e,i,t}\right) d\left(w_{e,j,t}, w_{ue,t}\right) f\left(w_{ue,t}, w_{ue,j,t}\right) [Pop_{i,t} - Pop_{e,i,t}] \qquad (7)$$

This condition says that the unemployed agents living in region *i* will move to work in region *j* whenever the highest wage offered in region *j* is higher than the highest wage offered in region *i* and the unemployment benefits. Unlike equation (6), the mobility of migrants is restricted by the ease of mobility captured by $M_{ue} \in (0,1)$. That is, $(1 - M_{ue,i})$ are mobility costs, such as travel distance, socio-psychological costs and amenity values, that migrants living in region *i* incur when they decide to work in region *j*. The low M_{ue} reflects a case where the costs of labor mobility of unemployed migrants to be very high, and therefore, the flow of unemployed migrants to be very low.

iii. the change in total employment in region *i* and at time *t* that is due to migration of the employed workers in region *j* and at time *t*:

$$\begin{aligned} \dot{Pop}_{e,i,t} = f(w_{e,i,t}, w_{e,j,t}) [M_{e,j} d\left(w_{e,i,t}, w_{e,j,t}\right) Pop_{e,j,t} \\ + M_{e,i} d\left(w_{e,j,t}, w_{e,i,t}\right) Pop_{e,i,t}] \end{aligned} \qquad (8)$$

Equation (8) required a fraction of the employed agents living in region *j* to work in region *i* when the highest wage offered in region *i* is higher than the highest wage offered in region *j*. Equation (8) also requires the number of workers gained by region *i* to be equal to the number of employed agents leaving from region *j*. Similar to condition (7), the mobility of migrants is restricted by ease of mobility, $M_e \in (0,1)$. That is, $(1 - M_{e,j})$ captures a variety of costs, such as travel distance, social costs and amenity values for migrants who are employed and living in region *j* and at time *t*. The low M_e corresponds to a situation in which the costs of labor mobility of employed migrants to be very high, and therefore, the flow of employed migrants to be very low.

Heretofore, I have ignored the situation where there is job mobility across sectors within any region. That is, workers can switch from the manufacturing sector to the R&D sector. For this model, this situation is not necessarily for the analysis for two reasons. Firstly, job mobility across the sectors within a region does not affect the unemployment rate in that region. Second, it turns out that there is no job mobility in this model when both sectors are operating. This is because the wages offered in both sectors are equal in an equilibrium. This condition is discussed in more detail in the solution section.

To reiterate, in this model I add two extensions to that of Romer (1990). First, the analysis focuses on two regions, instead of one country. Second, the interaction between these regions is conducted through three channels: interregional knowledge spillovers, mobility of labor and trades. The economy of each region can be summarized as follows:

i. The manufacturing sector produces final goods using labor and capital. This market is competitive, so each manufacturing firm takes all prices as given.

ii. The capital market is a monopolistic market where each monopolist holds the right to a patent. A monopolist produces a capital good using raw materials and its technology, and it faces a downward demand curve.

iii. The research and development sector produces new knowledge by using human capital, existing knowledge in the region that this sector belongs to and knowledge spillovers. In this sector, the existing knowledge in each region is a public good that everyone doing research in that region can use, and the final output is new knowledge that can be patented in that region.

iv. Agents choose whether to work, for which sector to work, and in which region to work. His or her decision is subject to differential in wages, unemployment benefits, mobility costs and rigidity of the labor market.

4.2. Equilibrium of Labor Market with No Trade

I drop unnecessary subscripts to avoid clutter of notations. With no trades, the analysis of this model is straightforward as the analyses of Romer (1990) and of Aghion and Howitt (1998a). One can prove the following conditions in an equilibrium:

i. There is no arbitrage between workers employed in the manufacturing sector and R&D sector in each region and at any time if both sectors are to operate:

$$w_{L,i,t} = w_{H,i,t}, \tag{8}$$

where $w_{L,i,t}$ and $w_{H,i,t}$ are wages offered to employees working in the manufacturing goods and R&D sector in region *i* and at time *t*, respectively.

ii. Due to symmetry of all capital goods, in region *i* and at time *t* we have :

$$x_{i,t}(k) = x_{i,t}, \tag{9}$$

$$P_{A,i,t}(k) = P_{A,i,t}, \tag{10}$$

iii. Since the existing knowledge is available for everyone in the R&D sector to use, in region *i* and at any time *t*, we have the following condition:

$$w_{H,i,t} = P_{A,i,t}\delta_i \phi A_{i,t}, \tag{11}$$

iv. The total workers in region *i* and at any time *t* is

$$Pop_{e,i,t} = L_{i,t} + H_{i,t}, \tag{12}$$

v. The total employment in the sector producing manufacturing goods in region *i* and at *t* is constant,

$$L_{i,t} = \frac{r}{(1-\alpha)\delta\phi_i} \tag{13}$$

vi. The competitive market in the manufacturing sector will equalize the labor wage and the marginal productivity of labor. That is,

$$w_L = \alpha L^{\alpha-1} A x^{1-\alpha}, \qquad (14)$$

vii. The price of each variety of capital goods must be equal to the marginal product of each capital in the manufacturing sector:

$$p(x) = (1-\alpha) L^{\alpha} x^{-\alpha}. \qquad (15)$$

Corollary 1. ***High stock of technology leads to high wage.***

Proof. By substituting (11) into (2) and solving for *x*, the solution to a monopolistic optimization problem will be:

$$x = \left[\frac{r}{(1-\alpha)^2}\right]^{-1/\alpha} L. \qquad (16)$$

Then, using (5), (8) and (10), we can derive the following condition,

$$P_A = \frac{\alpha}{\delta\phi} L^{\alpha-1} x^{1-\alpha}. \qquad (17)$$

Next, through substituting (12) into (13), we have the following equation,

$$P_A = \frac{\alpha}{\delta\phi}\left[\frac{r}{(1-\alpha)^2}\right]^{-1/\alpha}. \qquad (18)$$

Now, by substituting the value of P_A in equation (14) into (8), we can solve for w_H such that,

$$w_H = \alpha \left[\frac{r}{(1-\alpha)^2}\right]^{-1/\alpha} A \qquad (19)$$

▪

Equation (15) is the regional wage equation. It states that raising technological stock in region *i* and at any time *t* will increase wage.[24] This is because technology increases productivity of human capital (both in the R&D and manufacturing sectors).

[24] Since $w_L = w_H$, technology also raises the wage for workers employed in the manufacturing sectors.

Proposition 1. ***The growth rate of wages increases with the technological progress rate which depends on the degree of knowledge spillovers or the absorptive capacity.***

Proof. Taking logs and time derivative of (15) gives us the following condition,

$$\frac{\dot{w}_H}{w_H} = \frac{\dot{A}}{A} - \frac{\dot{r}}{\alpha r} = \delta H \phi - \frac{1}{\alpha}\frac{\dot{r}}{r} \qquad (21)$$

▪

Corollary (1) shows that the growth rate of wages in a region increases with the growth rate of technological stock in that region. From this corollary, urban technology can increase the rural technology through interregional knowledge spillovers (that is, ϕ_R). Knowledge spillovers increase the growth rate of rural technology (that is, $\frac{\dot{A}}{A}$), and so they raise the knowledge stock of the rural region. By raising the rural knowledge stock, urban knowledge spillovers increase wages of the rural workers, limit the out flow of human capital and raise the labor participation rate. Precisely, by raising the wage, urban technology effectively reduces the rural unemployment rate by two channels: first, decreasing employed migrants who are living in the rural region ($\frac{\partial \dot{Pop}_{e,U,t}}{\partial w_{e,R,t}} < 0$) and therefore will increase the growth wage in the next period ($\frac{\partial}{\partial H_{R,t}}\left(\frac{\dot{A}}{A}\right) > 0$); second, raising the participation of unemployed agents in the rural labor market ($\frac{\partial \dot{Pop}_{ue,R,t}}{\partial w_{e,R,t}} > 0$).[25] However, urban technology can also give rise to brain drain which has an ambiguous net effect on rural labor.

Proposition 2. ***Given that $A_U > A_R$ and $w_{e,U,t} > w_{ue,t}$, brain drain caused by the progress of urban technology has an ambiguous effect on the unemployment rate in the rural region.***

Proof. If $A_U > A_R$ and $w_{H,U,t} > w_{ue,t}$, by corollary 1 equation (6) becomes,

$$\dot{Pop}'_{ue,R,t} = M_{ue,R} f(w_{ue,t}, w_{H,U,t})[Pop_{R,t} - Pop_{e,R,t}] < 0 \qquad (22)$$

[25] Knowledge spillover could also prevent the out flow of unemployed agents living in the rural region whenever $A_R \geq A_U$. This phenomenon will increase the unemployment rate in the rural region. However, this condition should not hold empirically because most urban regions in the U.S. are technological leaders.

Equation (22) states that a fraction of unemployed agents will move to work in the urban area. Take derivative of (22) with respect to A_U,

$$\frac{\partial}{\partial A_U}\left(\dot{Pop'}_{ue,R,t}\right) = \frac{\partial f(.)}{\partial w_{H,U,t}} \cdot \frac{\partial w_{H,U,t}}{\partial A_U} [M_{ue,R}\left(Pop_{R,t} - Pop_{e,R,t}\right)] < 0 \tag{23}$$

That is, the progress in urban technology can reduce the total number of unemployment. Yet given that $A_U > A_R$, by corollary 1 equation (8) can be written as,

$$\dot{Pop}_{e,R,t} = f(w_{H,R,t}, w_{H,U,t})(M_{e,R} \cdot Pop_{e,R,t}) < 0 \tag{24}$$

As urban technology progresses faster than rural technology, wages offered in the urban area exceed wages in the rural area. In response, rural workers move to work in the urban area. Take the derivative of (24) with respect to A_u,

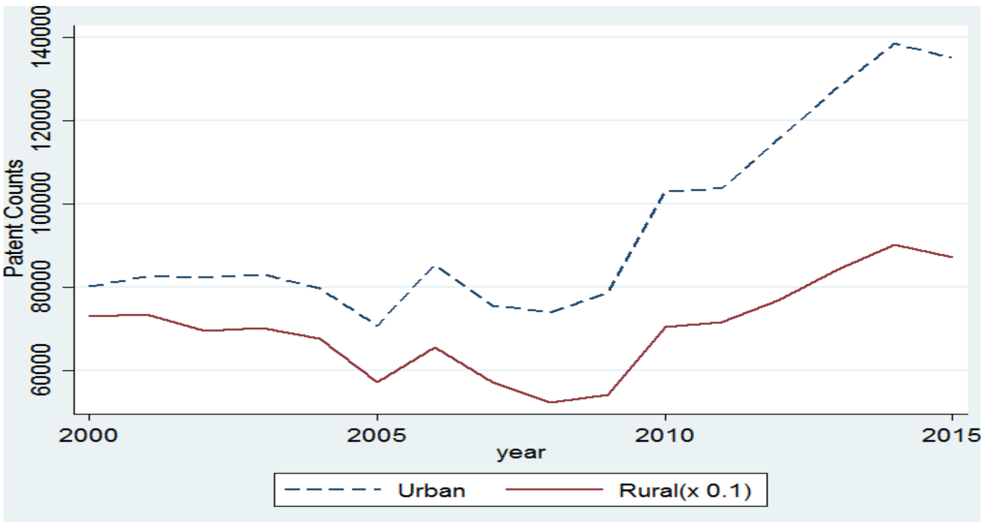
$$\frac{\partial}{\partial A_U}\left(\dot{Pop}_{e,R,t}\right) = \frac{\partial f(.)}{\partial w_{H,U,t}} \cdot \frac{\partial w_{H,U,t}}{\partial A_U}\left(M_{e,R} \cdot Pop_{e,R,t}\right) < 0 \tag{25}$$

Equation (25) indicates that a rise in urban technological stock can reduce the total rural employment in the R&D sector through raising the wage offered in the urban region. As shown in proposition 1, a reduction in employment in R&D sector can slow down the growth of rural wages. In addition, given that unemployment benefit grows over time and the change in total unemployment is an increasing function of unemployment benefit ($\frac{\partial \dot{Pop}_{ue,i,t}}{\partial w_{ue,,t}} > 0$), the decline in wage growth in the rural area can lead to an increase in the total unemployment in this area.

▪

Generally, urban regions are technological leaders while rural regions are followers (Morril, Gaile & Thrall, 1988; Milner, 2003). Figure 2 shows the total number of patent counts in each region in the U.S. from 2000 to 2015. As can be seen in the figure, there are disproportionately more patent counts in the urban region than in the rural region. This figure illustrates the fact that urban regions have higher technological stock than the rural regions.[26] Intuitively, the ample technological stock of the urban region (that is, $A_U > A_R$) leads to higher wages in the urban region. Therefore, the urban region can attract the rural workers by offering higher wages. This phenomenon will reduce the availability of human capital in the rural area, and therefore, it reduces the growth rate of rural technology. Through this mechanism, it reduces the growth rate in labor wage and manufacturing output in the rural region.

Figure 2: Total Urban and Rural Utility Patent Counts



Note: each observation is the utility patent counts. The rural patent counts have been scaled up by a factor of 10. The urban areas are the metropolitan statistical areas defined by the 2003 definitions of the official Office of Management and Budget (OMB). On the other hand, the rural regions are the rest of the counties that are non-metropolitan. The data is extracted from U.S. Patent Trademark Office (USPTO) and can be retrieved from https://www.uspto.gov/web/offices/ac/ido/oeip/taf/countyall/usa_county_gd.htm

In an extreme situation, brain drain could also reduce labor availability for the manufacturing sector, and therefore, urban technology will reduce the manufacturing outputs.[27] Nevertheless, the brain drain effect can also reduce the unemployment rate in the rural region because urban

[26] By a quick inspection on figure 1, one can observe that a relationship between urban and rural patent counts is very stable over the periods. This is a strong sign of cointegration between urban and rural patent counts. If there exist knowledge spillovers from the urban to the rural regions, this relationship does not seem to be spurious. Unfortunately, due to a small number of observations (that is, 15 years), any formal statistical tests of random walk and cointegration are difficult to conduct. However, with a few eyeballing tests, both regional patent counts seem to be I(1) and are cointegrated.

[27] That is, when the optimal solution of labor input for the manufacturing sector is more than the available labors in a region.

technology can create jobs for those who are unemployed and have sufficiently low mobility costs.[28]

To sum up, progress in urban technology can reduce the total unemployment in the rural area by creating jobs for those unemployed agents. However, it can also increase rural unemployment rate by slowing down the growth wages in the rural region. Therefore, brain drain of urban technology has a net ambiguous effect on the rural labor market performance.

4.3. Equilibrium of Labor Market with Trades

Now, we consider the product market competition effect on the rural labor market. By relaxing the assumption of no trade in the previous subsection, we are able to derive the product market competition effect. Let us consider a situation where the manufacturing output can be traded across the regions with no transportation cost. I assume that the final outputs of both regions are perfectly substitutable. However, I add an extra assumption regarding the taste of consumers over those goods.

Since the urban region is the technological leader and is likely to have more human capital (due to higher wages offered by firms in the urban region), it is very likely that urban regions can produce higher quantity (and more varieties) of good and services in rural areas. Consequently, the urban goods and services are usually in higher demanded for both rural and urban regions.[29]

Let us assume that the unemployed agents only consume what comes from the unemployment benefit whose price is measured in terms of the urban manufacturing output price. Therefore, manufacturing goods will be consumed only by the employed workers. To meet the

[28] A decision to work in another region depends on mobility cost, outside wage, current and future wage differentials. Historically, given that the rural-urban wage differentials have been growing over time, brain drain effect could have a significant impact on the rural labor market.
[29] In this analysis, I have ignored the complementary effect between urban and rural goods. In the next section, I show that there is suggestive evidence that the product market competition effect dominates the complementary effect.

aforementioned assumptions of the demand function of manufacturing goods and for an expositional purpose, I specify the inversed demand functions of both regions as follow,

$$p_{R,t,q} = \gamma_{t,q}(A_U, A_R) \cdot p_{U,t,q} = p_{t,q}(Pop_{e,R,t} + Pop_{e,U,t}, Y_{R,t}, Y_{U,t}), \qquad (26)$$

where $\frac{\partial p_{t,q}}{\partial(Pop_{R,t}+Pop_{U,t})} > 0$ and $\frac{\partial p_{t,q}}{\partial Y_{R,t}}, \frac{\partial p_{t,q}}{\partial Y_{U,t}} < o$. $p_{R,t,q}$ and $p_{U,t,q}$ are the prices of manufacturing goods for the rural and urban products, respectively.

$\gamma_{t,q}(A_U, A_R) \in (0,1]$ captures the concept of Central Place Theory which postulates that consumers favor urban goods and services which have higher quality.[30] It is the taste parameter that adjusts the prices of goods to the quality improvement by technology. I will assume that $\frac{\partial \gamma_{t,q}}{\partial A_U} = -\frac{\partial \gamma_{t,q}}{\partial A_R} < 0$ for $\forall A_U, A_R \geq 0$. That is to say, an increase in urban technology make urban goods and services more attractive to consumers. To put it in another way, a progress in rural technology makes urban goods and services less attractive. One can think of this assumption as an improvement in technology of a region leads to an improvement in the qualities of products of that region. Consequently, if the change in urban technology is greater than the change in rural technological stock ($\dot{A}_{t,U} > \dot{A}_{t,R}$), the change in the taste parameter is negative, $\dot{\gamma}_{t,q} < 0$.[31] In other words, urban goods and services become more attractive over time when urban technology advances faster than rural technology.

Equation (26) requires prices to be high when the world demand is high and low when the supply of goods is plenty. By assuming perfect substitutability between these goods, I intentionally ignore complementarity between some goods and services offered in both regions. In the empirical

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[30] For empirical evidence of the Central Pace Theory, see Partridge, Rickman, Ali & Olfert (2008, 2009)

[31] $\dot{\gamma}_{t,q} = \frac{\partial \gamma}{\partial A_U}\dot{A}_{t,U} + \frac{\partial \gamma}{\partial A_R}\dot{A}_{t,R}$. Hence, if $\dot{A}_{t,U} > \dot{A}_{t,R}$, we have $\dot{\gamma}_{t,q} < 0$.

section, I show suggestive evidence that the substitution effect seems to be more pronounced than the complementarity effect.

Proposition 3. ***Through product market competition, the progress of urban technology decreases the wages offered to workers in the rural region.***

Proof. Given the price of rural manufacturing goods is $p_{R,t,q}$, from corollary 1 we can rewrite the wages offered to employees in the rural region as,

$$w_{H,R,t} = \alpha \left[\frac{r}{(1-\alpha)^2}\right]^{-1/\alpha} A_{R,t} p_{R,t,q}. \tag{27}$$

Take derivative of (15) with respect to $A_{U,t}$,

$$\frac{\partial w_{H,R,t}}{\partial A_{U,t}} = \alpha \left[\frac{r}{(1-\alpha)^2}\right]^{-1/\alpha} A_{R,t} \cdot \left(\frac{\partial p_{R,t,q}}{\partial Y_{U,t}}\right)\left(\frac{\partial Y_{U,t}}{\partial A_{U,t}}\right) < 0 \tag{28}$$

▪

Technological development in the urban region could translate into the glut of urban manufacturing goods into the world. Urban technological progress also raises demand of urban goods and services due to an improvement in their qualities. Per equation (28), this situation reduces the output price of rural products relative to the output price of urban products. This reduction in output price leads to a reduction in wages in the rural region. Therefore, urban technology could enhance the effects of brain drain. A reduction in wages in the rural region can also lead to an increase in total unemployment whenever the wages fall below the unemployment benefits.[32] In short, urban technology could harm firms operating in the rural area, and so product market competition could increase the rural unemployment rate.

[32] The unemployment benefit is measured relative to the urban output price. If urban technological progress deflates the price of urban product, the unemployment benefit also decreases over time. However, the price of urban goods is protected by the favorable taste of consumers toward urban goods, and therefore, the price of urban goods and the unemployment benefit might not necessarily decline over time.

It is noteworthy to mention that the price of urban manufacturing goods is shielded from the adverse effects of technological progress by the increase in wage due to urban technological progress and the favorable taste of consumers toward urban goods.[33] It is also important to note that we have only differentiated goods in this model, and therefore, urban technology might be able to completely wipe out rural production completely. Yet in real world, there are some goods and services that are mainly produced in rural regions and not in urban areas (one possible cause is different factors of endowment). So, rural firms which produces those goods and services do not compete directly with urban firms. Therefore, the progress of urban technology is more likely to lead each region to specialize in producing different goods and services.

Suppose now that trade in capital goods is also allowed. As shown in Aghion and Howitt (1998b), the trade in capital goods in this type of model will lead to higher wages of workers. That is because increasing varieties of capital goods will enhance the productivity of labor in the manufacturing sector. However, trade in capital goods generally also increases competition faced by each producer (Grossman & Helpman, 1991b; Aghion & Howitt, 1998b). Unfortunately, the type of model presented here cannot yield this competitive effect (that is, product market competition effect in capital goods) because the manufacturing technology is additively separable in capital goods (Aghion & Howitt, 1998b).

To recap, while knowledge spillover can improve the performance of the rural labor market, product market competition can adversely affect this market. On the other hand, the effect of brain drain is ambiguous. Therefore, the net effect of urban technology on the rural labor market is theoretically ambiguous. An empirical study is needed to identify this net effect.

5. The Net Effect of Urban Technology on the Rural Labor Market

[33] It is also important to note that urban technological progress

The theoretical model tells us that technological stocks of a rural region (that is, A_R) and of other regions (which include both rural and urban areas) can affect the level of unemployment rate of that region. Unfortunately, the theoretical model does not lend itself explicitly to be used in empirical estimation. The restrictive structures, such as mobility costs, unemployment benefits, and demand function of services and goods, are required for the model in order to make it accessible for empirical study.

To study the net effect of urban technological progress on the rural labor market, I instead adopt a modified version of the frameworks used by Bottazzi and Peri (2007), Van Pottelsberghe de la Potterie and Lichtenberg (2001), and Ertur and Musolesi (2017). These authors have studied the impacts of international knowledge stock on domestic productivity, economic growth and technological growth.[34] I also conduct several sensitivity analyses to check the robustness of the main finding of the paper. These analyses could also address the aforementioned shortcoming regarding the link from the theoretical model to the empirical estimation.

The empirical framework used in this paper takes the following equation:

$$\begin{aligned} Unemployed_{i,t} = \hat{\theta}_i + \hat{\theta}_t + \beta_i^{urban} Ustock_{i,t-1} + \beta_i^{rural} Rstock_{i,t-1} \\ + \beta_i^{own} Ostock_{i,t-1} + \gamma_i Educ_{i,t-1} + e_{i,t} \end{aligned} \tag{29}$$

$Unemployed_{i,t}$ represents the logarithmic of the unemployment rate of a rural county i at any time t. As in Bloom, Schankerman and Reenen (2013), all independent variables are lagged one year to avoid simultaneity and to lessen the concern of endogeneity bias. As a robustness check, I also lag the technological stock variables and educational attainment variable by longer periods in the section of sensitivity analysis. The result is robust to this modification.

[34] These studies are conducted at the country level.

$Ostock_{i,t}, Ustock_{i,t}$ and $Rstock_{i,t}$ stand for the logarithmic of own (domestic), the urban and the rural technological stocks, respectively. Following Bottazzi and Peri (2007) and Aghion, Bloom, Blundell, Griffith and Howitt (2005), I use utility patent counts as a measure of regional knowledge. As in Bottazzi and Peri (2007), I construct these knowledge stock variables using the perpetual inventory method, which is usually used to construct a stock of assets in macroeconomics literature.

The domestic (own) knowledge stock in region i and at a time t is given by:

$$Ostock_{i,t} = Patent_{i,t} + \left(1 - \bar{\delta}\right) Ostock_{i,t-1} \tag{30}$$

and

$$Ostock_{i,t_0} = \frac{Patent_{i,t_0}}{(\bar{g}_i + \bar{\delta})} \tag{31}$$

$\bar{g}_i$ is the average growth rate of patenting in county i between year $t_0 = 2000$ and $t_0 + 5 = 2005$.[35,36] Following Bottazi and Peri (2007), $\bar{\delta}$, which is the depreciation rate of technology, is set to be 0.1. To account for localization of knowledge, mobility cost and transportation cost of goods, $Ustock_{i,t}$ and $Rstock_{i,t}$ are the summation of $Ostock_{j,t}$ weighted by the basic inverse distance matrix for all counties $j \neq i$ and all j belongs to the metropolitan and nonmetropolitan areas, respectively.[37,38,39,40]

[35] I follow Grifftith and Simpson (2004) to set all of the stocks containing negative values at any time t to zero. In addition, to avoid the issue of a reference year, I used the average patent counts between the two years as a base to calculate the annual patent growth rate. That is, $g_{i,(t,t+1)} = (Patent_{i,t+1} - Patent_{i,t})/0.5(Patent_{i,t} + Patent_{i,t+1})$, and $\bar{g} = \frac{1}{5}\sum_{2000}^{2005} g_{i,(t,t+1)}$. If county i has not been granted any patents in either year t or t+1, I assume $g_{i,(t,t+1)} = 0$.

[36] For more details on how to use the perpetual inventory method, see Young (1995, footnote 16 p. 652).

[37] For "geographic localization of knowledge spillovers", see Jaffe, Trajtenberg and Henderson (1993).

[38] In the spirit of Keller (2002), I use the exponential decay function instead of the inverse distance function as a weighted matrix in a separate analysis. All distances between counties have been scaled up to avoid too many zero weights in the construction of the weighted matrix. Then, I conduct the same analyses as those presented in the main finding subsection. Despite being statistically insignificant in some estimations, the coefficients of *Ustock* range from +0.12 to +5.34. Yet the results indicate that an application of exponential decaying function is less robust than that of inverse distance function in the setting of this study. Therefore, it could be a sign of functional misspecification.

[39] For a few examples of the applications of the spatial weights matrices in the studies of knowledge spillovers, see Anselin, Varga and Acs (1997) and Crescenzi, Rodríguez-Pose and Storper (2007).

[40] Several studies include the number of citations as a weight to capture the market value or the quality of each patent (for instance, see Hall, Jaffe & Trajtenberg, 2005). However, the patent citations include noises. For example, patents

$Educ_{i,t}$ is logarithmic of the percentage of adult population (age 25 and above) with a college degree or higher in county i at a time t. Next, the $Others$ variable which consists of lags of the dependent variables are included (in Blundell-Bond estimation) to reflect the dynamics of the system.

$\hat{\theta}_i$ and $\hat{\theta}_t$ are regional and year dummies. They could account for unobserved regional and annual heterogeneity, such as natural amenities and financial crisis. $e_{i,t}$ captures all of the unobservable factors including unobserved common shocks and an idiosyncratic error.

To estimate the net effect of urban technological growth on the rural unemployment rate, I apply various estimation techniques and conduct several sensitivity analyses. Beside simultaneity bias, I also try to account for both serial autocorrelation and cross-sectional dependence by employing the two-way fixed effect, first difference, and Blundell-Bond estimators. The Blundell-Bond estimator, which is a seminal work of Blundell and Bond (1998), can significantly improve the estimation of the celebrated work of Arellano and Bond (1991).

Another group of estimators which perform well in dealing with cross-sectional dependence are the common correlation effects estimators of Pesaran (2006). Unfortunately, the short time span, multicollinearity and unbalanced panel data prevent me from effectively employing most of these estimators in this study. Despite that, we can utilize the static version (no lags of the dependent and the independent variables) of the common correlation effect pooled estimators (SCCEP) as a robustness check to the preferred result estimated by the Blundell-Bond estimator.

are selected to be cited by a patent examiner, not by an inventor. Second, Bottazzi and Peri (2007) find that the uses of an unweighted and citations-weighted matrix yield similar magnitudes of the effect of international knowledge spillovers on domestic productivity. Third, we expect patents filed in urban areas to receive more citations than the ones filed in rural areas. Therefore, the citation-weighted patent counts will increase the importance of urban knowledge stock, and the effect of the simple patent counts will be the lower bound of the actual effect of urban technology. Finally, since each unit of the observations in this article includes the sum of a fairly large number of patent counts, the quality of each patent is likely to be averaged out.

There is a concern related to the use of granted patent counts because there could be a lag between the date of application and the date of grant. Unfortunately, the data of patent applications at the county level is limited. Yet we should expect the two measure of technology to be strongly correlated. As a matter of fact, using the available data of 377 counties between 2007 and 2014, the correlation between the two measurements of technology is 0.97.[41] Regardless, there are also advantages of employing granted patent counts rather than the number of patent applications. First, granted patent counts data are less noisy because these patents can be considered genuine and new knowledge that can be accumulated into technological stock of any county. Second, the lags between the year of application and the year of grant could further help us lessen the concern of simultaneity bias between the unemployment rate and technology.

Another general concern related to the use of regional patents data is the assignment of a patent to each county. Following the literature on innovation, a patent is assigned to each region based on a residence of the first-named inventor at the time of grant. If the first-named inventor lives and works in different counties, the use of patents will introduce measurement error. Therefore, the estimated effect of urban technology can be downward biased and can be considered at the lower bound.

An issue related to R&D expenditure also deserves a discussion. Often in the literature, patent counts or R&D investment is used as a proxy for knowledge. In fact, patent count is a fairly reliable indicator to be used in the study of regional innovation (Acs, Anselin & Varga, 2002). It would be a good exercise to do a sensitivity analysis using R&D in place of patent counts. Unfortunately, data on total R&D spending at the county level is scarce. Even so, the previous empirical studies

[41] Patent application data can be found on SAGE stats (Web site) through http://data.sagepub.com.proxy.lib.ohio-state.edu/sagestats/13890. The data of patent granted can also be found at http://data.sagepub.com.proxy.lib.ohio-state.edu/sagestats/14122.

have shown that past R&D is captured by knowledge stocks constructed from patent counts (Hall, Grilliches & Hausman, 1986; Bottazzi & Peri, 2007). Additionally, a correlation exercise between the logarithmic of total patent granted and the logarithmic of total expenditure on R&D lagged one period at the city level yields the coefficient of 0.57.[42]

There might also be a concern that R&D expenditure, aside from increasing patent counts, might have a direct effect on the labor market. Therefore, omitting this variable will lead to a biased and inconsistent result. However, if the direct effect of R&D expenditure reduces the unemployment rate, the estimation of the effect of $Ustock_{i,t}$ might be biased downward whenever the coefficient $\beta_i^{urban} > 0$. In fact, this is the case in my empirical finding. That is, the estimated coefficient in my finding is conservative.[43]

Finally, there is a concern about other omitted variables that can bias the estimated coefficients here. Unfortunately, besides R&D expenditure and educational attainment, theories and empirical studies have shed little light on the roles of other factors.[44] Therefore, I test the presented theory with other competitive hypotheses. The examination should alleviate some of these concerns. The results of these analyses and several econometric tests show that the main finding is highly robust.

5.1. Data

The dataset used in this paper is discussed in this subsection; the results of the estimation and sensitivity analyses are presented in the subsequent subsections. The data sample is at the county level across the United States except for Hawaii and Puerto Rico. Since the interest lies in the

[42] The data is composed of 469 cities and spans from 2011 to 2014. The data on total R&D expenditure at the city level can be found on SAGE stats (Web site): http://data.sagepub.com.proxy.lib.ohio-state.edu/sagestats/15926. The data of total number of patent granted at the city level is at http://data.sagepub.com.proxy.lib.ohio-state.edu/sagestats/14121.

[43] For comprehensive econometric analysis of omitted variable bias, see Greene (2003)

[44] Crescenzi, Rodríguez-Pose and Storper (2007) find some evidence that social and economic conditions can affect the growth rate of knowledge. Data limitations at the county level prevents me from effectively controlling for these conditions. Yet I use educational attainment, fixed effects and Blundell-Bond estimators to control for these conditions.

socio-economic condition (that is, the unemployment rate) of rural regions, the use of metropolitan and nonmetropolitan statistical areas as the definitions of the urban and the rural regions is appropriate (United States Department of Agriculture, 2017). The delineation of metro/nonmetropolitan statistical areas is based on the 2003 definitions given by the Office of Management and Budget (OMB).[45]

Table 4: Summary Statistics of the Data Sample

	Mean	S.D.	Minimum	Maximum
Unemployment Rate	7.534337	2.717396	2.4	19
Own Knowledge Stock	134.1683	257.9672	0.81	4746.843
Rural Knowledge Stock	50123.11	2379.275	46713.84	55184.17
urban Knowledge Stock	1193384	88175.5	1114030	1384417
Percentage of Adults with Higher Education	19.5577	6.788147	8	49.9
Number of Observations		1494		

Note: All observations are in level form.

The patent dataset can be found on the U.S. Patent and Trademark Office website. The patent data are the granted utility patent counts from 2000 to 2015. A patent is assigned to each region based on a residence of the first-named inventor at the time of grant.[46] I used all the available patent count data to construct the knowledge stock variables. The unemployment rate and the education data are taken from the U.S. Census Bureau and the U.S. Department of Agriculture (USDA).[47] Last but not least, the distance dataset between counties comes from the National Bureau of Economic Research and is compiled by Jean Roth (2014).

[45] The OMB metro/non-metro dataset can also be found on the USDA(2017b) website, https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/

[46] For the dataset and detailed information on this dataset, see https://www.uspto.gov/web/offices/ac/ido/oeip/taf/countyall/usa_county_gd.htm

[47] The U.S. census provides the educational attainment and unemployment data from the American Community Survey from 2005-2015 (1-year estimates). I use USDA 2000 educational attainment data as a substitute for 2004 educational attainment data.

After dropping all missing observations, the dataset contains 1494 observations ranging from 2005 to 2015. Table 4 contains descriptive statistics for the data sample used in the empirical analysis.

5.2. Results

5.2.1. Main Finding

Table 5: The Net Effect of Urban Technology on the Rural Labor Market

	FE (1)	FD (2)	BB (3)	BB (4)
Urban Knowledge Stock	0.22*	0.25*	0.22***	0.21***
	(0.125)	(0.145)	(0.0549)	(0.0713)
Rural Knowledge Stock	-0.04	-0.38	-0.09	-0.12
	(0.236)	(0.399)	(0.0767)	(0.088)
Own Knowledge Stock	0.02	-0.03	-0.05***	-0.03*
	(0.031)	(0.029)	(0.015)	(0.018)
Education	0.01	-0.004	-0.01	-0.0003
	(0.067)	(0.023)	(0.03)	(0.032)
Number of Lags of DV	0	0	1	2
Year Dummies	Yes	Yes	Yes	Yes
County Dummies	Yes	-	-	-
Number of Instruments	0	0	68	66
AB Test AR(1)	-	-	0.00	0.00
AB Test AR(2)	-	-	0.01	0.31
Sargan Test	-	-	0.17	0.34
CD Test	0.71	0.41	0.84	0.46
Observations	1,494	1,325	1,325	1,180

Note: Robust standard errors are in parenthesis. *, ** and *** are significant at 10%, 5% and 1% levels, respectively. The dependent variable (DV) is ln (unemployment rate). All Blundell-Bond estimators (BB) include two lags of the dependent variable. AB (Arellano-Bond) test for Ho of no residual serial correlation (p-value is reported). The cross-sectional dependence (CD) test for Ho of no/weak cross-sectional dependent residual (p-value is reported). The Sargan test of overidentifying restrictions (p-value is reported).

Table 5 presents the main finding of this article. Column 1 and 2 show the estimation results using the two-way fixed effects (FE) and the first difference (FD) estimators. Columns 3 and 4 present the results of the Blundell-Bond (BB) models with one and two lags of dependent variables, respectively. These variables are assumed to be strictly exogenous; however, we will relax this assumption later for a sensitivity analysis. Since the interest is in the short/medium run, I omit the coefficient(s) of the lag(s) of dependent variables from the both columns 3 and 4.[48]

The estimated coefficients of the urban knowledge stock are very robust across estimators. In column 4, which is the preferred model, the Arellano and Bond test for an AR (2) process supports the null hypothesis of no residual serial correlation.[49] This estimator also passes the overidentification restrictions test.[50] In addition, the test of no/weak cross-sectional dependence of Pesaran (2004, 2015) cannot be rejected for all the models.

The estimations indicate that there is a positive association between urban technological stock and the rural unemployment rate.[51] The rural technological stock, the domestic knowledge stock and the education variables weakly correlate with the rural unemployment rate (though, the result is not robust and is sometimes insignificant).[52]

From table 5, a one percent increase in urban technology can raise the rural unemployment rate by 0.2 percent. A back-the-envelope-calculation translates these numbers into around two and a half million rural job losses, on average, due to urban technical progress between 2005 and 2015.[53]

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[48] In column 3, the coefficient of the first lag of log (unemployment rate) is 0.86 and is significant at any conventional level. In column 4, the coefficient of the first lag is 0.83 and is significant at any conventional level. For the second lag, the coefficient is -0.08 and is significant at 5 percent level. These results from both columns suggest that the effect of urban technology on the rural unemployment rate is greater in the long -term than the short-term.

[49] When the idiosyncratic errors are independently and identically distributed, it is expected that the first difference errors are first-order serially correlated. Therefore, it is important to examine AB test AR (2) for a valid use of the Blundel-Bond estimator.

[50] To performance a robust check on the choice of number of instruments for the preferred estimator (whose result is tabulated in column 4 of table 5), I (arbitrarily) limit the numbers of instruments to be 56 and 45. Comparing to the baseline results (whose number of instruments is 66), the coefficients of the variables of interest are almost identical up to two decimal points.

[51] In a separate analysis, I also control for deeper lags of the dependent variables; however, the quality of the results remain unchanged.

[52] The statistical insignificance results of *Ostock, Rstock and Educ* might be due to the short time span of the data and multicollinearity.

[53] That is, the predicted number of job losses= $\sum_t \sum_i \{ \exp[\frac{\partial \log(Unemployment\ Rate)}{\partial \log(Urban\ Patent)} \cdot (Urban\ Technology)_{it}] \cdot (Total\ Worker)_{it}\} \approx 2.6\ \times 10^6$, where i denotes a county and t denotes a year.

Table 6: The Net Effect of Urban Technology on Total Employment and Unemployment

	(1)	(2)
Dependent Variable	Total Employment	Total Unemployment
Urban Knowledge Stock	-0.058**	0.057
	(0.026)	(0.076)
Rural Knowledge Stock	0.125*	-0.025
	(0.073)	(0.084)
Own Knowledge Stock	0.029**	-0.028
	(0.012)	(0.018)
Education	0.0043	-0.017
	(0.011)	(0.027)
Number of Lags of DV	3	3
Year Dummies	Yes	Yes
County Dummies	-	-
Number of instruments	62	62
AB Test AR(1)	0.00	0.00
AB Test AR(2)	0.48	0.27
Sargan Test	0.00	0.00
CD Test	0.82	0.52
Observations	1,038	1,038

Note: Robust standard errors are in parenthesis. *, ** and *** are significant at 10%, 5% and 1% levels, respectively. The dependent variable (DV) is ln (unemployment rate). Both dependent and independent variables are in logarithmic. Both estimations use Blundell-Bond estimators (BB), which include three lags of the dependent variable. AB (Arellano-Bond) test for Ho of no residual serial correlation (p-value is reported). The cross-sectional dependence (CD) test for Ho of no/weak cross-sectional dependent residual (p-value is reported).

There might be a question whether using the unemployment rate could lead to a misleading conclusion. Consider a scenario where urban technology destroys existing jobs while it also creates new jobs. If the number of jobs it destroy is far more than the number of jobs it creates, the unemployment rate will increase. To determine the channels through which urban technology increases rural unemployment rate, I reevaluate the baseline estimation utilizing the Blundell-Bond estimator and replacing the unemployment rate with the total employment or total unemployment weighted by the inverse of county total population as the dependent variable. All variables are in logarithmic form. To reiterate, I omit the results of the lags of dependent variables since the focus is on the short or medium run.[54,55]

The results of both estimations are tabulated in table 6. The results conforms to a scenario such that urban technology reduces availability of jobs and might increases total unemployment in rural areas. Therefore, urban technology increases the rural labor unemployment rate.[56,57]

6. Sensitivity analysis

6.1. Competing Hypotheses

There are multiple factors, besides urban technology, that could worsen or improve rural labor market performance. Those factors includes labor demand shock, mobility of low/medium skill to rural regions, automation in the U.S., and entrepreneurship.

To lessen a concern of labor demand shock, I control for Batik's industry mixed employment growth (in logarithmic form) in the preferred Blundell-Bond estimation.[58] This industry mixed variable comes from shift-share analysis (Bartik, 1991; Blanchard & Katz, 1992), and the construction is as follow:

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[54] The Blundell-Bond estimator is chosen to estimate the effects of urban technology on the total employment and total unemployment in rural regions because this estimator is the preferred estimator in the main analysis. I use three lags of the dependent variables because the estimations with two lags of the dependent variables barely pass the autocorrelation test for AR (2).

[55] For the total employment estimation, the coefficients of lags of dependent variables are 0.84, -0.01 and -0.03. While the first and second lags are statistically significant at the 1 percent level, the third lags of employment is not significant at any conventional level. For the total unemployment estimation, the coefficients of lags of the dependent variables are 0.83, -0.11 and 0.03. The first lag is statistically significant at the 1% level, and the second lag is significant at the 5 percent level. However, the third lag of the unemployment variable is not statistically significant at any conventional level.

[56] In the regression of the total employment, the estimated coefficients of the urban technology using two or three lags are almost identical. However, both estimations reject the hypothesis of the Sargan test. I also estimate the effect of urban technology on the rural total unemployment by other estimators, including the fixed effects and the first-difference, yield similar results. The coefficients of urban technology in both estimations are about 0.2 but not statistically significant at any conventional level.

[57] Using two lags of the total unemployment, the Blundell-Bond estimator fails the AB test for AR (2). Using different estimators, including the fixed effects and the first-difference, the coefficients of urban technology in the total unemployment estimations are about 0.2. The fixed effect yields a statistically significant coefficient of the urban technology while the first-difference estimation provides the insignificant (almost significant at 10 percent level) coefficient.

[58] Controlling for Batik's industry mixed employment growth in level form does not change the results.

$$Industry\ Mixed\ Employment\ Growth_{i,t} = \sum_{s} Share_{s,i} Emp_{national,s,t} \quad (32)$$

where, s represents a one-digit industry sector, s. $Share_{s,i}$ is the share of industry s in county i, and $Emp_{national,s,t}$ is the national growth rate of sector, s in year t relative to year 2005.[59]

Table 7: Assessment of Industry Labor Demand Shock

	(1) (Baseline)	(2)
Urban Knowledge Stock	0.21***	0.22***
	(0.071)	(0.084)
Rural Knowledge Stock	-0.12	-0.26**
	(0.088)	(0.131)
Own Knowledge Stock	-0.03*	-0.03
	(0.018)	(0.029)
Education	-0.0003	0.006
	(0.032)	(0.0347)
Industry Mixed Employment Growth	-	-0.49***
		(0.131)
Number of Lags of DV	2	2
Year Dummies	Yes	Yes
County Dummies	-	-
AB Test AR(1)	0.00	0.00
AB Test AR(2)	0.31	0.63
CD Test	0.46	0.52
Observations	1,180	1,180

Note: Robust standard errors are in parenthesis. *, ** and *** are significant at 10%, 5% and 1% levels, respectively. The dependent variable (DV) is ln (unemployment rate). Both dependent and independent variables are in logarithmic. Both estimations use Blundell-Bond estimators (BB), which include two lags of the dependent variable. AB (Arellano-Bond) test for Ho of no residual serial correlation (p-value is reported). The cross-sectional dependence (CD) test for Ho of no/weak cross-sectional dependent residual (p-value is reported).

Table 7 compares the results from the baseline estimation to the results of the new estimation when I control for labor demand shock. Panel (1) is the baseline estimation, and Panel (2) is the new estimation. The results from both estimations are comparable, and therefore, the baseline results are reasonably robust.

While urban technology can increase the unemployment rate through the aforementioned channels, urban technology, particularly automation, might displace low/medium skilled worker from urban to rural regions through “jobs polarization”.[60] That is, technology can benefit urban

[59] Employment data is taken from the Bureau of Economic Analysis: https://www.bea.gov/.
[60] See Acemoglu and Autor (2011) and Autor and Dorn (2013) for issues related to “job polarization”.

skilled worker by increasing productivity, but it can also harm low/medium skilled workers through automation. Although it is conceptually possible, it seems unlikely for this situation to occur within the urban-rural interrelationship context.

Figure 3: The Evolution of Low and Medium Skilled Workers in Rural Regions

Note: the low skill worker is measured by the average share of adults with education of nine to twelve years of general education but without high school diploma. The medium skill is measured by the average share of high school graduate or the share of adult with equivalent degree. The data of educational attainment is extracted from American Community Survey. It is accessible through https://factfinder.census.gov/faces/nav/jsf/pages/download_center.xhtml.

Firstly, on average the share of low/medium skill workers is decreasing over time in these rural regions. Figure 3 shows the average share of adults with nine to twelve years of formal education but without high school diploma and the average share of adults with a high school diploma as proxies of low and medium skilled worker in rural regions, respectively.[61] If urban technology increases out migration of low/medium skilled workers to rural regions, we should see a reversed pattern shown by figure 3. Given that there is little growth or no growth of total rural population, with drops in some areas (Kusmin, 2016), we would expect the same pattern to emerge when we consider the total number of low and medium skill workers in rural regions. It is indeed the case for the data used in this paper.

[61] The data of educational attainment is extracted from American Community Survey. It is accessible from https://factfinder.census.gov/faces/nav/jsf/pages/download_center.xhtml

Second, to explicitly account for this concern, I re-estimate the baseline result by controlling for low and medium skill workers.[62] As in baseline estimation, these control variables are lagged by a year to avoid simultaneity bias. The results tabulated in Table 8 show the robust result of the baseline estimation. That is, urban technology still manifest a significant negative effect on the rural unemployment rate.

Table 8: Assessment of Low/Medium Skill Workers

	(1) (Baseline)	(2)
Urban Knowledge Stock	0.21***	0.21***
	(0.071)	(0.071)
Rural Knowledge Stock	-0.12	-0.12
	(0.088)	(0.086)
Own Knowledge Stock	-0.03*	-0.03*
	(0.018)	(0.018)
Education	-0.0003	-0.004
	(0.032)	(0.033)
Low Skill		0.005
		(0.0178)
High Skill		0.026
		(0.043)
Number of Lags of DV	2	2
Year Dummies	Yes	Yes
County Dummies	-	-
AB Test AR(1)	0.00	0.00
AB Test AR(2)	0.31	0.32
CD Test	0.46	0.54
Observations	1,180	1,180

Note: Robust standard errors are in parenthesis. *, ** and *** are significant at 10%, 5% and 1% levels, respectively. The dependent variable (DV) is ln (unemployment rate). Both dependent and independent variables are in logarithmic. Both estimations use Blundell-Bond estimators (BB), which include two lags of the dependent variable. AB (Arellano-Bond) test for Ho of no residual serial correlation (p-value is reported). The cross-sectional dependence (CD) test for Ho of no/weak cross-sectional dependent residual (p-value is reported).

To further assess the effect of automation on the rural area job market, I control for automation activities using the total number of patents in controls granted in the United States. [63,64] This control

[62] To reiterate, the low skill worker is measured by the share of adults with education of nine to twelve years of general education but without a high school diploma. The medium skill is measured by the share of high school graduates or the share of adults with equivalent degree.

[63] Because the share of patents in controls are very stable over time, using share of patents in control can cause a multicollinearity.

[64] The data on patents in controls is retrieved October 25 from National Science Foundation through https://www.nsf.gov/statistics/2016/nsb20161/#/data.

variable has also been lagged by a year to lessen concern of simultaneity bias. The results which are tabulated in table 9 show that the baseline result is robust to the inclusion of automation in the United States. The robust result is not surprising given that the share of patents in controls and automation in the U.S., which is shown in figure 4, has been steady (or slightly declining) over time.[65]

Table 9: Assessment of Automation

	(1) (Baseline)	(2)
Urban Knowledge Stock	0.21***	0.212***
	(0.071)	(0.071)
Rural Knowledge Stock	-0.12	-0.12
	(0.088)	(0.088)
Own Knowledge Stock	-0.03*	-0.03*
	(0.018)	(0.0179)
Education	-0.0003	-0.0003
	(0.032)	(0.032)
Level of Automation in the U.S.	-	-0.000159***
		(1.23e-05)
Number of Lags of DV	2	2
Year Dummies	Yes	Yes
County Dummies	-	-
AB Test AR(1)	0.00	0.00
AB Test AR(2)	0.31	0.31
CD Test	0.46	0.46
Observations	1,180	1,180

Note: Robust standard errors are in parenthesis. *, ** and *** are significant at 10%, 5% and 1% levels, respectively. The dependent variable (DV) is ln (unemployment rate). Both dependent and independent variables are in logarithmic. Both estimations use Blundell-Bond estimators (BB), which include two lags of the dependent variable. AB (Arellano-Bond) test for Ho of no residual serial correlation (p-value is reported). The cross-sectional dependence (CD) test for Ho of no/weak cross-sectional dependent residual (p-value is reported).

I also assess the bias from not controlling for entrepreneurship. Following Stephens, Partridge and Faggian (2013), I use the total non-farm proprietor as a measure of entrepreneurship. The control variable is in log form and lagged by one period.[66] These results are presented in table 10.

[65] The coefficient of level of the automation is negative. Therefore, the increase in automation could improve rural job market performance. The phenomenon could be explained by "job polarization" in which automation creates jobs for high and low skill workers. See Acemoglu and Autor (2011) for details of "job polarization".
[66] The data on non-farm propriety was retrieved on October 20, 2017 from U.S. Bureau of Economic Analysis through https://www.bea.gov/itable/iTable.cfm?ReqID=70&step=1#reqid=70&step=27&isuri=1&7022=12&7023=7&7024=non-industry&7025=4&7026=xx&7001=712&7028=280&7083=levels&7029=12&7090=70&7031=xx

The results from the baseline estimation and the new estimation are almost identical. Therefore, the baseline estimation is robust to the inclusion of level of automation within the United States.

Figure 4: Share of Patents in Control Granted in the U.S.

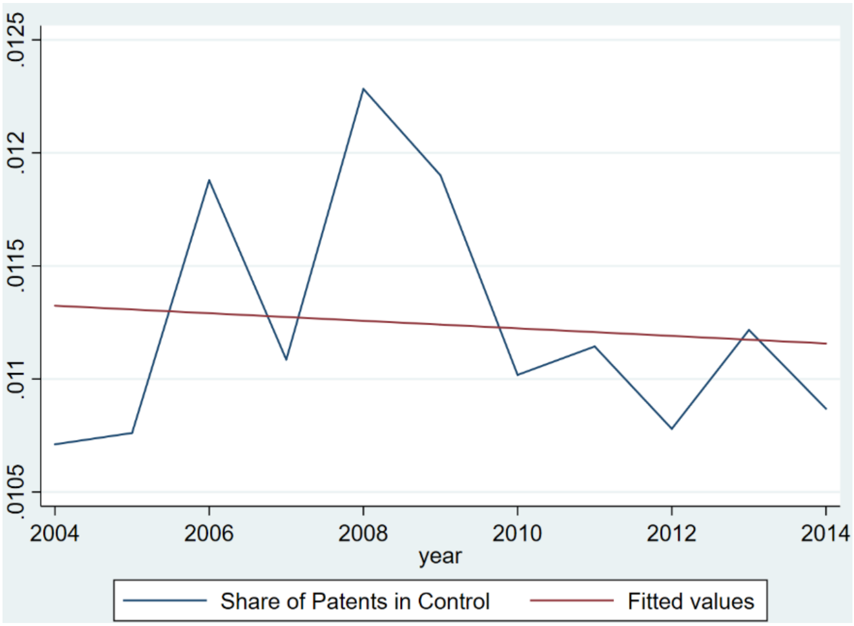

Table 10: Assessment of Entrepreneurship

	(1) (Baseline)	(2)
Urban Knowledge Stock	0.21***	0.21***
	(0.071)	(0.072)
Rural Knowledge Stock	-0.12	-0.10
	(0.088)	(0.104)
Own Knowledge Stock	-0.03*	-0.04*
	(0.018)	(0.0186)
Education	-0.0003	-0.0005
	(0.032)	(0.0327)
Entrepreneurship	-	0.0255
		(0.0805)
Number of Lags of DV	2	2
Year Dummies	Yes	Yes
County Dummies	-	-
AB Test AR(1)	0.00	0.00
AB Test AR(2)	0.31	0.28
CD Test	0.46	0.44
Observations	1,180	1,180

Note: Robust standard errors are in parenthesis. *, ** and *** are significant at the 10%, 5% and 1% levels, respectively. The dependent variable (DV) is ln (unemployment rate). Both dependent and independent variables are in logarithmic. Both estimations use Blundell-Bond estimators (BB), which include two lags of the dependent variable. AB (Arellano-Bond) test for Ho of no residual serial correlation (p-value is reported). The cross-sectional dependence (CD) test for Ho of no/weak cross-sectional dependent residual (p-value is reported).

6.2. Econometric Sensitivity Analyses

There might be a concern that one period lagged of independent variables are not sufficient to reduce simultaneity relation between dependent and independent variables. Table 11 shows the estimation results when the independent variables are lagged by 2 periods. The negative coefficient of urban knowledge stock remains statically significant, and its magnitude is similar to the baseline result.

Table 11: Assessment of Lagged Independent Variables

	(1) (Baseline)	(2)
Urban Knowledge Stock	0.21***	0.19***
	(0.071)	(0.072)
Rural Knowledge Stock	-0.12	-0.078
	(0.088)	(0.091)
Own Knowledge Stock	-0.03*	-0.02
	(0.018)	(0.018)
Education	-0.0003	-0.0137
	(0.032)	(0.0294)
Number of Lags of DV	2	2
Year Dummies	Yes	Yes
County Dummies	-	-
AB Test AR(1)	0.00	0.00
AB Test AR(2)	0.31	0.35
CD Test	0.46	0.67
Observations	1,180	1,180

Note: Robust standard errors are in parenthesis. *, ** and *** are significant at the 10%, 5% and 1% levels, respectively. The dependent variable (DV) is ln (unemployment rate). Both dependent and independent variables are in logarithmic. Both estimations use Blundell-Bond estimators (BB), which include two lags of the dependent variable. AB (Arellano-Bond) test for Ho of no residual serial correlation (p-value is reported). The cross-sectional dependence (CD) test for Ho of no/weak cross-sectional dependent residual (p-value is reported).

There might also be a concern that the spillover effect of the urban knowledge stock is partialling out when one includes all of the knowledge stock variables in the same regression.[67] Table 12 addresses this concern by performing various estimations using the preferred Blundell-Bond estimator.[68]

[67] This is an application of Frishch-Waugh-Lowell theorem. For more details, see Greene (2003).
[68] In a separate analysis, I also include deeper lags of independent variables, but the result are almost identical to those presented here.

The analyses are carried out by examining the estimated coefficients of the urban knowledge stock when we drop either the rural knowledge stock or the own knowledge stock variables. However, it is important to know that we might also add a downward bias to the estimated coefficient of the urban knowledge stock when we drop any of the previously mentioned knowledge stock variables. Therefore, the baseline estimation, which is presented in column 4 of table 8, might result from removing the effects of the spillovers and the omitted variable bias. Nevertheless, as shown in table 12, all the coefficients of urban technological stock remain strongly positive.

Table 12: Reassessment of the Knowledge Spillovers of Urban Technology

	(1)	(2)	(3)	(4) (Baseline)
Urban Knowledge Stock	0.18***	0.17***	0.25***	0.21***
	(0.065)	(0.058)	(0.072)	(0.0713)
Rural Knowledge Stock	-	-	-0.18*	-0.12
			(0.092)	(0.0878)
Own Knowledge Stock	-	-0.04**	-	-0.03*
		(0.0168)		(0.0178)
Education	-0.01	-0.006	-0.01	-0.0003
	(0.032)	(0.032)	(0.032)	(0.032)
Number of Lags of DV	2	2	2	2
Year Dummies	Yes	Yes	Yes	Yes
AB Test AR(1)	0.00	0.00	0.00	0.00
AB Test AR(2)	0.43	0.34	0.35	0.31
CD Test	0.84	0.83	0.44	0.57
Observations	1,180	1,180	1,180	1,180

Note: Robust standard errors are in parenthesis. *, ** and *** are significant at the 10%, 5% and 1% levels, respectively. The estimators are that of Blundell and Bond (1998). The dependent variable (DV) is unemployment rate. All Blundell-Bond estimators (BB) include two lags of the dependent variable. All lags and independent variable are assumed to be strictly exogenous. AB (Arellano-Bond) test for Ho of no residual serial correlation (p-value is reported). The cross-sectional dependence (CD) for Ho of no/weak cross-sectional dependent residual (p-value is reported).

Next, I replace the assumption of strict exogeneity with the predetermination of the independent variables. The exercise is conducted with the Blundell-Bond estimator, and the results of the estimation are tabulated in table 13. The qualitative results of the main finding are maintained such that urban technological progress could have an adverse effect on the rural labor market.

Unfortunately, due to strong multicollinearity, it becomes technically difficult to obtain robust standard errors for this estimation. Therefore, most coefficients reported here are statistically significant might be due to the use of GMM two-steps standard errors.[69]

Table 13: Exogenous versus Predetermined Independent Variables

	(1) Baseline	(2)
Urban Knowledge Stock	0.21***	0.12***
	(0.0713)	(0.004)
Rural Knowledge Stock	-0.12	-0.08***
	(0.088)	(0.006)
Own Knowledge Stock	-0.03*	-0.005***
	(0.018)	(0.001)
Education	-0.0003	-0.008*
	(0.032)	(0.004)
Number of lags of DV	2	2
Time dummies	Yes	Yes
Number of Instruments	66	172
AB test AR(1)	0.00	0.00
AB test AR(2)	0.31	0.45
CD test	0.34	0.56
Sargan test	0.46	0.87
Observations	1,180	1,180

Note: GMM two-step standard errors are in parenthesis. *, ** and *** are significant at the 10%, 5% and 1% levels, respectively. The estimators are that of Blundell and Bond (1998). The dependent variable (DV) is unemployment rate. All variables are in logarithmic. The independent variables are assumed to be predetermined and not strictly exogenous. AB (Arellano-Bond) test for Ho of no residual serial correlation (p-value is reported). The cross-sectional dependence (CD) for Ho of no/weak cross-sectional dependent residual (p-value is reported). The Sargan test of overidentification restrictions (p-value is reported)

Finally, another concern regarding the panel data analysis is cross-sectional dependence (that is, $E\left[u_{it}u_{jt}\right] \neq 0$). As a robust check, I implement the static common correlation effect pooled (SCCEP) estimator of Peseran (2006). To reiterate, due to the short time span, multicollinearity and the unbalanced panel data, we cannot implement the dynamic version of the common correlation effect pooled (CCEP) or the common correlation effect mean group (CCEMG) estimators.

[69] It is important to mention that the Sargan test yield a very high p-value when the independent variables are assumed to be predetermined. This could be a warning sign of proliferation of instruments which could indicate that the Sargan test is weak.

Table 14 shows the result of this estimation. First, the correlation dependence (CD) test of no cross-sectional dependence cannot be rejected. Therefore, SCCEP can effectively deal with the cross-sectional dependence issue. However, compared to the results of the Blundell-Bond estimator, the coefficients estimated using SCCEP are biased upward. This might be caused by the omitted lagged variables. Therefore, the benchmark result is more conservative.

Table 14: Static Common Correlation Effect Pooled (SCCEP) Estimator

	BB	SCCEP
Urban Knowledge Stock	0.21***	0.28***
	(0.071)	(0.066)
Rural Knowledge Stock	-0.12	-0.06
	(0.088)	(0.100)
Own Knowledge Stock	-0.03*	-0.03***
	(0.018)	(0.012)
Education	-0.0003	-0.045
	(0.032)	(0.033)
Number of Lags of DV	2	0
Year Dummies	Yes	Yes
CD Test	0.46	0.58
Observations	1,180	1,494

Note: Robust standard errors are used for the BB estimator, and the jackknife biased correction is used for SCCEP. Standard errors are in parentheses. *, ** and *** are significant at the 10%, 5% and 1% levels, respectively. The dependent variable is unemployment rate. All variables are in logarithmic. The cross-sectional dependence (CD) test for Ho of no/weak cross-sectional dependent residual (p-value is reported).

7. Rural Welfare Analysis: Basic Assessments

To assess the welfare loss of rural areas due to the progress in urban technology, I use average wage and average income deflated by CPI (consumer price index) as coarse measures of welfare. This simple assessment of welfare is merely suggestive and might not be conclusive.

Average wage is defined as the total wages and salaries divided by the total number of employment. Average incomes of a region is the total income which is made up of wage, salaries, transfers and other forms of income, divided by the total population living in that region.[70] Both wage and income have been deflated to prices in year 2000.[71]

Table 15: Assessment of Wage and Income

	(1) Wage	(2) Income
Urban Knowledge Stock	-0.069***	-0.03
	(0.022)	(0.028)
Rural Knowledge Stock	0.21***	0.145*
	(0.067)	(0.082)
Own Knowledge Stock	0.0005	0.0125
	(0.0065)	(0.00788)
Education	0.00187	0.0138
	(0.00918)	(0.0127)
Industry Mixed Employment Growth	0.236***	0.292***
	(0.0503)	(0.0505)
State GDP	0.162***	0.203***
	(0.0499)	(0.0542)
Number of Lags of DV	2	2
Year Dummies	Yes	Yes
County Dummies	Yes	Yes
CD Test	0.43	0.25
Observations	1,494	1,494

Note: Robust standard errors are in parenthesis. *, ** and *** are significant at 10%, 5% and 1% levels, respectively. The dependent variable (DV) is ln (unemployment rate). Both dependent and independent variables are in logarithmic. Both estimations use two-way fixed effect, which include year and county fixed effects. The regional technological stock variables and education are lagged by one year. The cross-sectional dependence (CD) test for Ho of no/weak cross-sectional dependent residual (p-value is reported).

I estimate the effect of urban technology on rural wages and income by controlling for industry composition and gross domestic product at the state level. While the industry composition variable captures labor demand shock, the GDP variable could control for several economic conditions that affect wage and income. Both estimations also control for year and county fixed effects, and all variables are in logarithmic form. The results of the estimations are shown in table 15.[72]

[70] Wages and Income (CA1) data are from the U.S. Bureau of Economic Analysis through https://www.bea.gov/itable/iTable.cfm?ReqID=70&step=1#reqid=70&step=1&isuri=1

[71] The base years used to calculate the consumer price index are 1982-1984. The index is retrieved November, 6th 2017 from the Federal Reserve Bank of Minneapolis: https://www.minneapolisfed.org/community/teaching-aids/cpi-calculator-information/consumer-price-index-and-inflation-rates-1913.

[72] I also estimate the effects of urban technology on rural wages and income using the Blundell-Bond estimator using one lag and first-difference. Using the Blundell-Bond estimator and for the wage estimation, the coefficient of the urban stock variable is -0.40 and significant at 5 percent level. For the income estimation, the Blundell-Bond estimator yields the coefficient of the urban technological stock of -0.23 and insignificant at any conventional level. On the other hand, for both of the wage and income estimations, the first-difference estimator reports similar coefficients of the urban technological stock to those estimated by the fixed effects estimator.

The results show that urban technology can significantly reduce wages offered in rural areas. However, the coefficient of urban technology is insignificant but negative when wage is replaced by income. These findings suggest that employed workers might be adversely affected by the progress in urban technology, although government transfers might help alleviate some of the welfare loss. Perhaps, to keep the welfare of rural regions intact, the assessment also suggests that a future increase in urban research and development funding should be accompanied with a higher transfer to rural areas. Yet the best solution requires more rigorous analyses.

A caution to this analysis is the use of the average income because it ignores the redistribution effect. Consider a situation where the government only transfers a lump-sum tax toward the unemployed agents living in the rural region. The welfare loss of the unemployed agents could be compensated by the transfer, yet the employed workers are not compensated. These findings could be cursory and therefore future studies are needed to give a definite conclusion on the impact of urban technological progress on rural welfare.

8. Conclusion

While urban technological progress has positive impacts on rural labor market performance through knowledge spillovers, urban technology also exerts the product market competition effect on the rural labor market. On the other hand, brain drain has an ambiguous effect on rural labor performance. Unfortunately, these facts have not yet received full attention in academic and political arenas. Without taking these negative effects into full account, any place-based policy aiming at increasing local and regional jobs by an improvement of technology might have unintended consequences. Furthermore, one cannot ignore the effects of technology on the regional labor market within any country because the interregional flow of labor is prominent.

Motivated by a basic model and with an empirical analysis of patent counts at the county level, I have found that a 1 percent growth in urban technological stock increases the rural unemployment rate by 0.1-0.2 percent in a short or medium run. To establish a robust finding, I conduct several sensitivity analyses which includes examining other competing hypothesis and performing several econometric tests. The results of the analyses indicate that the main finding is satisfactory in terms of robustness. Last but not least, I also find suggestive evidence that urban technology reduce wages of rural workers, although government transfer might alleviate some of this welfare loss.

This finding might not be decisive; however, I hope this paper can motivate scholars and policy makers to put more effort into further studying of the effects of urban technology on rural labor market performance and other economic indicators, such as GDP and productivity. While the current study focuses on the impact of technology on urban-rural dependence, the implications of this study could be applicable to other interregional studies.

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