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Abstract: We combine the 2005 China Inter-Census Population Survey data and the 2004 China Manufacturing Census to test whether workers, particularly rural migrants, benefit from labor market Marshallian externalities. We find that workers in general, and rural migrants in particular, benefit from labor market pooling effect (measured by total employment in a city-industry cell) and human capital externalities (measured by share of workers with a college degree or above in a city-industry cell). These findings are robust to various sorting bias tests. However, rural migrants benefit much less than do local or urban workers, possibly because rural migrants lack social networks and are discriminated doubly in terms of being both "rural" and "migrants." Our findings have policy implications on how Chinese cities can become skilled during the rapid urbanization process coupled with global competition.

Keywords: Rural migrants; labor market agglomeration economies; Marshallian externalities; labor market pooling; human capital externalities

JEL Code: J30; J61; J71; O15; O18; R23

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1. Introduction

A worker can benefit from the concentration of other workers in the same workplace; such benefits are called labor market agglomeration economies. Parallel to the concept of business agglomeration economies, benefits from the concentration of same-industry workers are called labor market Marshallian externalities, while benefits from the concentration of diverse industries and city scale are called labor market Jacobs externalities (Andini *et al.*, 2013; Fu, 2007; Groot *et al*., 2014).[1] Both types of labor market agglomeration economies can enhance workers' productivity and therefore wages if workers are paid by their marginal product revenue. This paper examines whether workers, particularly rural migrants, can benefit from labor market Marshallian externalities in manufacturing industries in Chinese cities.

Labor market agglomeration economies occur in employment clusters mainly through two channels: labor market pooling and knowledge spillovers (Moretti, 2011). A large, dense, local labor market improves matching quality between workers and firms, reduces frictional unemployment due to statistical economies (Gan and Zhang, 2006; Helsley and Strange, 1990; Overman and Puga, 2007), and facilitates job mobility (Freedman, 2008). These benefits are generally called labor market pooling effect. Knowledge spillover effects, often also dubbed human capital externalities, refer to a worker's learning from other workers in the same local market through formal and informal social interactions, such as imitating, social networking, job hopping, poaching, and learning by doing (Brunello and Gambarotto, 2007; Eriksson and Lindgren, 2009; Moretti, 2004a,c; Rosenthal and Strange, 2008). Labor market Marshallian externalities also operate through these channels.

Empirical studies on labor market agglomeration economies mainly focus on Jacobs externalities in urban labor markets in developed countries, particularly, on city size wage

[1] Traditionally, business agglomeration economies are classified into two types: localization economies resulting from the concentration of same-industry firms in a city and urbanization economies resulting from the concentration of different-industry firms in a city. In the dynamic context, the counterparts of localization and urbanization economies are dubbed Marshallian externalities and Jacobs externalities (Glaeser *et al*., 1992; Henderson, 2003; Rosenthal and Strange, 2004).

premium. For example, Glaeser and Maré (2001) find that workers receive higher wages in cities and do not experience wage loss when they leave cities, suggesting that cities help accumulate human capital through learning and knowledge spillovers. Yannow (2006) finds that one third of the city size wage premium is due to labor market agglomeration economies. Rosenthal and Strange (2008) and Fu and Ross (2013) also confirm that urban wage premium still persists after the worker endogenous sorting issue is taken into account.[2]

Only a few studies test the labor market Marshallian externalities.[3] Fu (2007) finds that workers benefit from the concentration of same-industry or same-occupation workers in the Boston metropolitan area. In the Netherlands, doubling the employment share of an industry in a city can increase a worker's wage by 2.9% (Groot *et al*., 2014). Andini *et al*. (2013) test various dimensions of labor market Marshallian externalities in Italian cities but find only weak support for both the labor market pooling and knowledge spillover effects.

Most of empirical studies on labor market agglomeration economies use data from developed countries, such as the US (Glaeser and Maré, 2001; Yannow, 2006), UK (Melo and Graham, 2009), France (Combes *et al*., 2008), Italy (Andini *et al*., 2013). Empirical studies on labor market agglomeration economies in developing countries, including China, are scant.[4] Maria and Barufi (2014) find that high employment density is associated with high wages in the Brazilian formal labor market. Woodruff and Zenteno (2007) find that in Mexico migration networks help reduce capital constraint for small business owners. Liu (2007) estimates the external returns to education in Chinese cities (measured by average schooling years in a city) using the 1988 and 1995 Chinese Household Income Projects survey data. Fu and Gabriel (2012) study how migration decisions are affected by the concentration of skilled workers in destination provinces in China. Xing and Zhang (2017) estimate a structural model using the 2005 China Inter-Census Population Survey data and find that rural migrants are willing to pay for living in big cities possibly for all kinds of agglomeration benefits that big cities offer.

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[2] Combes and Gobillon (2015) provide a thorough review on empirical studies on testing both business and labor market agglomeration economies.
[3] Many studies test Marshallian externalities in business sectors, see for example, Ellison *et al*. (2010); Henderson (2003); Jofre-Monseny *et al*. (2011); Rosenthal and Strange (2001).
[4] There are quite a few studies on business agglomeration in developing countries. For a review, see Combes and Gobillon (2015).

We focus on testing labor market Marshallian externalities in China and pay special attention to rural migrants. China is having a rapid urbanization and many cities have been growing persistently due to large inflows of low-skilled rural migrants each year. According to the National Bureau of Statistics of China, the total number of rural migrants in 2015 is estimated to be 277 million, about one fifth of the country's total population, and 77.4% of them have received less than high school education.[5] Given that there are still institutional barriers to migration (Au and Henderson, 2006; Zhao, 2016), such as the residential registration (*hukou*) system restricting farmers from moving into cities freely and depriving them of employee benefits in cities and a high degree of local government intervention to cities (for example, growth control), it is natural to ask such questions: Do labor market agglomeration economies exist in Chinese cities? And if so, how large is the magnitude? Do rural migrants also benefit from labor market agglomeration economies given mobility barriers and their low educational attainment?

Using data from the 2005 China Inter-Census Population Survey and the 2004 Manufacturing Census and following the standard wage model specifications in the agglomeration economies literature, we find that workers in general benefit from labor market Marshallian externalities in Chinese cities: the labor market pooling effect, measured by total employment in a two-digit industry in a city, and human capital externalities, measured by the share of workers who have a college degree or above in a two-digit industry in a city.

The classical identification issue in the agglomeration economies literature is that workers may sort into different cities and industries based on unobserved city, industry, and individual characteristics. We define agglomeration variables at the city-industry cell and are able to control for city and industry fixed effects. This identification strategy also motivates our focus on Marshallian externalities. To deal with the issue of workers' sorting based on unobserved individual ability, we follow the literature on using occupation attributes as a proxy for skills (Bacolod *et al*., 2009, 2010) and add worker occupation dummies as a proxy for unobserved worker ability. To test the robustness of our estimates,

[5] Source (in Chinese): http://www.stats.gov.cn/tjsj/zxfb/201604/t20160428_1349713.html.

we split the sample by local residents who never moved and migrants, by young and old workers. Reassuringly, for subsamples of workers who are less likely to sort across cities and industries, our agglomeration estimates are very robust, particularly, for human capital externalities.

Furthermore, we find that rural migrants also benefit from labor market agglomeration economies but benefit much less than do workers with an urban *hukou* or local workers who never moved. This is neither because most of rural migrants are low-skilled preventing them from reaping fully the benefits from agglomeration, nor because most of rural migrants work in informal sectors that generate few spillovers. We find that even in the sample of high-skilled workers, rural migrants receive much fewer benefits from agglomeration. Based on other empirical evidence, we conjecture that this may be because rural migrants lack local social networks or they suffer from "double discrimination" in urban labor markets for being "rural" and being "migrants."

That rural migrants benefit from labor market agglomeration but benefit much less than do urban workers and local workers has important policy implications. The growth of urban population in China is mainly driven by rural-urban migration. Migrants have provided massive, low-cost labor force for growing manufacturing industries. But the low labor cost advantage of Chinese manufacturing industries is waning and the new trend of manufacturing industry development requires skilled labor. Furthermore, skilled workers are crucial for city growth because cities with a high share of skilled workers tend to grow persistently in terms of population, employment, and college graduates (Glaeser and Saiz, 2004; Glaeser, 2005; Simon and Nardinelli, 2002). Such cities also generate high productivity, high quality of life (Shapiro, 2006), and more employment opportunities for low-skilled workers (Moretti, 2012). However, the majority of rural-urban migrants are low-skilled, and college shares in most of the Chinese cities are low.[6] How can Chinese cities make their unskilled workers become skilled?

[6] In the US the average college share among adults (25 years old or above) in metropolitan areas is 32% in 2010, and 41 metropolitan areas have college share above 30% (data source: http://www.nytimes.com/interactive/2012/05/31/us/education-in-metro-areas.html). College share among adults (25 years old or above) is 8.9% in China and 20.4% in urban China in 2010; only one city has college share above 30% (Beijing, 32.2%) (Calculated by authors based on the 2010 Census data).

Skills can be acquired through formal school education, or through formal or informal social interactions such as meetings, peer effect, imitating, social networking, etc. Although on-the-job training and adult continuation education are feasible, they are limited in scale. In addition, if poaching and free riding is a serious problem in a dense local labor market, employers may have less incentives to provide on-the-job training (Brunello and Gambarotto, 2006; Muehlemann and Wolter, 2011). However, employment agglomeration provides a feasible channel for social interactions to occur on a daily base and this can promote matching, knowledge spillovers, and learning. If rural migrants indeed benefit from urban labor market agglomeration, this may be one of the ways through which Chinese cities can become more skilled. Local governments therefore can design and implement labor and urban development policies to help rural migrants gain from urban labor market agglomeration to improve their skills and accumulate human capital (for example, removing the *hukou* system). These implications echo the findings that African Americans benefit less from labor market agglomeration economies in the US cities (Ananat *et al*., 2013).

The rest of the paper is organized as follows: Section 2 introduces the data; Section 3 discusses the model specification and identification issues; Section 4 presents the empirical results and Section 5 concludes.

2. Data

We use two datasets to test labor market agglomeration economies in Chinese cities. The first dataset is based on the 2005 Inter-Decennial Census (1%) Population Survey conducted by the National Bureau of Statistics of China. We obtained a one-fifth random sample of this census dataset. The population census data contains information on individual and household characteristics and labor market performance. The second dataset is the 2004 manufacturing census, which surveyed all firms in manufacturing industries by the National Bureau of Statistics of China. It includes firm location, total employment by education categories, accounting and financial, and other firm characteristics variables and enables us to calculate precisely total employment by city, industry, and education. We merge the two datasets by city-industry cell, where industry is defined at the two-digit level and a district of a large municipality is treated as a "city."[7] We then construct a set of agglomeration variables at the city-industry level for each worker based on where and in which industry she or he worked. Our approach is very similar to Moretti (2004b) where he merges the US firm census data with the US decennial population census data by metropolitan area-industry cell to estimate the effect of human capital externalities on firm productivity because education information is not available in the firm census data but available in the population census data. Using city-industry cell link also enables us to test labor market Marshallian externalities without worrying about worker sorting across cities and across industries since we can control for city and industry fixed effects and our identification comes from variations across city-industry cells.

Wage is defined by annual labor income or salary divided by months worked, so our wage variable is monthly wage. To remove the influence of outliers, we winsorize the wage data at the top and bottom 0.25 percentile. We select only workers of primary working age (between 18 and 60). To ensure there are enough number of workers in each city-industry cell, we require at least 20 (unweighted) workers in a city-industry cell. Increasing the cutoff improves our estimation since this reduces measurement errors of our agglomeration variables. After dropping observations with missing values of required variables, we finally obtain a sample of 172,002 workers. This sample contains 35 industries, 71 occupations, 345 cities, 7,832 city-industry cells. On average there are 33 two-digit manufacturing industries in a Chinese city.

Following the wage- and productivity-agglomeration literature (Andini *et al.*, 2013; Fu and Ross, 2013; Moretti, 2004b), we construct two agglomeration variables for each city-industry cell. The total employment in a city-industry cell measures intra-industry labor market pooling effect in a city, or how a worker benefits from the concentration of the same-industry workers in a city. College share is calculated by the number of employees with an associate degree or above in a city-industry cell divided by the total employment in that city-industry cell, measuring intra-industry human capital externalities or knowledge spillover

[7] A few studies find that agglomeration economies are localized and decay with distance rapidly over space (Duranton and Overman, 2005; Fu, 2007; Rosenthal and Strange, 2008). Therefore, we treat a district of a large municipality as a city in this study. It would not be appropriate to treat a giant city such as Beijing as a single one for localized Marshallian externalities since Beijing has a population of over 15 million in 2005.

effects in a city.[8] Table 1 provides the summary statistics for our key variables. The variations in total employment and college share across city-industry cells are very large.

(Insert Table 1 here)

3. Model Specification and Identification

Following the literature on labor market agglomeration economies, we specify the following baseline model:

$$\ln W_{ijk} = \alpha_k + \beta_1 X_i + \beta_2 \ln(Employment)_{jk} + \beta_3 CollegeShare_{jk} + I_j + \varepsilon_{ijk}, \quad (1)$$

where $\ln W_{ijk}$ is the natural logarithm of monthly wage of worker *i* working in industry *j* in city *k*. Independent variables are defined as follows.

α_k : city fixed effect, used to control for unobserved city attributes based on which workers may sort across cities.

X_i : a vector of individual characteristics, containing a set of standard variables in a wage equation: age, age squared, gender, marital status, years of migration, education attainment (less than high school, high school, associate, college, and master degree or above), minority identity, and institutional variables that may affect individual wage, including whether a worker has an urban *hukou*, types of employers, and types of labor contract.[9]

$\ln(Employment)_{jk}$: the natural logarithm of total employment in manufacturing industry *j* in city *k*. This measures labor market pooling effect within an industry in a city: how a worker benefits from the concentration of the same-industry workers in a city. [10]

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[8] An associate degree refers to graduation from a two or three year college.

[9] Minority dummy is set to 0 if a worker belongs to *Han* and 1 if a worker belongs to non-*Han* ethnicity. Employer types include social organizations and public sector, state-owned enterprises, collectively-owned enterprises, proprietary, private enterprises, and others. Labor contract types include fixed-term contract, long term contract, and no contract.

[10] Alternatively, we can use total employment. But if we assume the production function is of Cobb-Douglas type and wage equals the marginal product of labor, then the logarithm of total employment is a preferred specification.

$CollegeShare_{jk}$: the share of employees with an associate degree or above in industry *j* in city *k*. It measures human capital externalities or knowledge spillover effects within an industry in a city.

I_j: denotes industry fixed effect, controlling for unobserved, industry-specific attributes that affect employment agglomeration.

ε_{ijk}: error term, may not be independent and identically distributed. We cluster the standard errors at the city-industry cell level.

A few identification issues arise in estimating the coefficients of the two agglomeration variables: total employment and college share in a city-industry cell. The key concern is that workers may sort into different workplaces or industries based on some unobserved factors. We discuss them in turn.

First, workers may sort into different cities based on unobservable city attributes. For example, rural migrants may prefer cities not far away from their home villages (Zhang and Zhao, 2013). Also cities may have different productive and consumption amenities that affect workers' productivity and residential location choices. We include city fixed effects α_k to control for this.

Second, agglomeration economies may be specific to industries. For example, high-tech industries tend to generate stronger knowledge spillover effects (Henderson, 2003) while informal sectors are less likely to generate spillovers. We include industry fixed effects I_j to control for this.

After city and industry fixed effects are controlled, sorting across industries in a given city is less likely simply because there are not many industries available in a given city. This reasoning is similar to Bayer *et al*. (2008) in that conditional on a block group residents are less likely to sort across residential locations at the block level simply because housing markets at the block level are thin. The thought experiment of our identification strategy can be summarized as follows: two identical workers, W1 and W2, work in the same industry j in two identical cities, C1 and C2; the only thing different is that in city C1 the industry has more workers and a larger share of college-educated workers. In this case, does worker W1 have a higher productivity and therefore receive a higher wage than worker W2?

Third, conditional on city and industry, sorting could still occur due to unobserved individual ability. For example, workers with better local social networks are more likely to work in industries where firm performance is more stable and employee fringe benefits are generous. Existing studies have used different approaches to deal with this issue. For example, Glaeser and Maré (2001) use individual panel data and control for individual fixed effects; Rosenthal and Strange (2008) use geographic features as instrumental variables (IV) for agglomeration variables to break the correlation between unobserved individual attributes and agglomeration; Moretti (2004c) uses a city's historical demographic structure and the presence of a land-grant college as IVs; Fu and Ross (2013) use residential location at the census tract level as proxy for unobserved ability.[11] Due to data constraint, we cannot employ any of them.

However, an emerging literature uses occupation attributes to proxy for skills (Ingram and Neumann, 2006; Bacolod *et al*., 2009, 2010). The rationale is that in a competitive, frictionless labor market, if workers perfectly match their skills with job requirements, we can infer that a worker taking a certain job (occupation) should possess the required skills, and therefore, observed occupation (attribute) serves as a good proxy for ability (or a particular skill). We follow this reasoning and use a worker's occupation to proxy for the worker's unobserved ability. Occupation choice is endogenous in a wage model; but in our setting, the inclusion of occupation can help reduce the correlation between error term and the two agglomeration variables. A rule of thumb to test this method is to see whether the coefficients of education category variables become attenuated after the inclusion of occupation fixed effects since in general unobserved ability should be positively correlated with observed ability such as education attainment (Oster, 2017).

Fourth, even if we include city, industry, and occupation fixed effects, these controls may still not be perfect, and it is still possible that workers sort into different city-industry cells based on unobservables. Since workers with a high degree of mobility are more likely

[11] Recent studies have used randomized experiments (Afridi *et al*., 2015).

to sort across cities and industries than those with a low degree of mobility, we split the sample into migrants and local residents who never moved. If both types of workers benefit similarly from agglomeration, then sorting bias is not a serious problem.

Fifth, China has transitioned from a planned economy to a market economy. Older workers who experienced the centrally planned economy and the transition period face more stringent mobility constraints: they are more likely to be affiliated with state-owned enterprises, having more family dependents, and with different human capital and skills that may not be easily transferable or adapted to market economy. That is, old workers tend to have low mobility, while young workers tend to have high mobility. Sorting bias should be stronger in the young worker subsample. We also estimate the models for the young and old worker subsamples separately to gauge the seriousness of sorting bias issue.

Because our wage data is in 2005 and the agglomeration variables are measured in 2004 from the manufacturing census data, it is the lagged labor market agglomeration that generates current wage premium. This data structure also to some degree mitigates the endogeneity concern that agglomeration and worker wage are simultaneously determined due to sorting.

Model (1) is estimated for the full sample but also for a subsample of rural migrants. Complementary to the sample splits, we also interact rural and migrant dummies with agglomeration variables to check the robustness of results. The next section reports and discusses the empirical results.

4. Results

4.1 Existence of labor market agglomeration economies

To test whether labor market agglomeration economies exist in Chinese cities, we estimate different versions of Model (1). Table 2 presents the estimation results. Column 1 reports the result of a simple wage model with individual attributes, agglomeration variables, and city fixed effects. The coefficients of the individual characteristics variables have expected signs and reasonable magnitudes. Both the coefficients of total employment and college share in a city-industry cell are positive and statistically significant, suggesting the existence of Marshallian externalities in urban labor markets. But this result may be driven by industry specific attributes or individual sorting based on unobserved ability.

(Insert Table 2 here)

We add industry fixed effects to Column 1 and the coefficients of individual characteristics variables remain almost identical (Column 2), suggesting that there is little sorting across industries based on unobserved individual attributes. However, the coefficient of logarithmic total employment attenuates from 0.0052 to 0.0015 and becomes insignificant, suggesting that agglomeration benefit from same-industry peers in a city may be mainly industry-specific. The human capital externalities effect remains highly significant albeit attenuated by about 30% (from 0.5044 to 0.3431). These results suggest that conditional on industry-specific factors, substantial agglomeration economies, particularly, human capital externalities, still exist.

To test whether workers sort across industries in a given city based on unobserved ability biasing the estimates of agglomeration variables, we add occupation fixed effects to Column 1, aiming to capture unobserved worker ability. Column 3 presents the result. As discussed in the previous section, if occupation fixed effects can absorb part of unobserved ability and since observed and unobserved ability should be positively correlated, then, the coefficients of education variables should attenuate significantly. Column 3 indeed shows that the coefficients of education variables do attenuate by between 15% and 24%. For example, the coefficient of college degree dummy decreases by 20%, from 0.7560 to 0.6032. This pattern is consistent with the findings in Fu and Ross (2013) where residential fixed effects are used to proxy for unobserved worker ability. After controlling for unobserved ability, we still find substantial human capital externalities (coefficient of college share is 0.4621 and statistically significant).

Column 4 adds both industry and occupation fixed effects. This baseline model specification is preferred since we have controlled for city- and industry-specific attributes and unobserved ability. The result suggests that although not statistically significant, doubling the employment size of an industry in a city increases the wage of a worker in that industry by 0.29%. This is a very conservative estimate since industry employment is very likely to have measurement errors and individual sorting may not be perfectly controlled for.[12] On the other hand, human capital externalities remain important and significant: a one percentage point increase in college share of an industry-city cell raises a worker's wage by about 0.36% (or a one standard deviation increase in college share in an industry-city cell raises wage by about 3.06%). Interestingly, this magnitude is in line with other estimates in the literature. Moretti (2004c) uses the US census data and finds that a one percentage point increase in college share (in a city) raises average wages by 0.6–1.2%. Using the 2007 American Community Survey data, Winters (2011) finds that a one percentage point increase in college share (in a city) raises average wages by 0.41–0.48%.

To check the robustness of our preferred specification, we estimate the baseline model by a set of sample splits: local residents who never moved versus migrants, migrants with below or above median migrating years (2.5 years), and workers with below or above median ages (33 years old). Compared with migrants, inexperienced migrants, and young workers, local residents, experienced migrants, and old workers should have less sorting due to stronger social network and more attachment to family and housing. The results presented in Table 3 confirm this conjecture. Column 1 replicates the baseline model result (Column 4 of Table 2). Columns 2 and 3 show that compared with migrants, local workers benefit more from both labor market pooling and human capital externalities, suggesting that the existence of labor market agglomeration economies cannot be due to worker sorting. Columns 4 and 5 show that compared with new migrants, experienced migrants benefit more from both labor market pooling and human capital externalities, suggesting that working in cities longer helps develop social network and accumulate human capital through learning from peers. This is consistent with the idea of learning in cities by Glaeser and Maré (2001). Similar patterns hold for young versus old workers as indicated in Columns 6 and 7.

(Insert Table 3 here)

[12] When we select city-industry employment greater than 300 workers to reduce measurement errors, the coefficient of ln(Employment) is 0.0068 and significant at the 10% level, and the coefficient of college share remains similar (0.3969 significant at the 1% level).

Taking together the results from Tables 2 and 3, we conclude that there exist economically important labor market Marshallian externalities in manufacturing industries in Chinese cities. Specifically, there is weak evidence for labor market pooling effect but strong and robust evidence for human capital externalities effect in Chinese urban labor markets.

4.2 Rural migrants benefit from labor market agglomeration economies

Given the massive migration from rural areas to cities during the past decades in China and that many rural migrants work in manufacturing industries, it is natural and important to test whether rural migrants benefit from agglomeration economies in urban labor markets. We estimate the baseline model for the subsample of rural migrants.[13] Column 1 of Table 4 shows that rural migrants benefit significantly from labor market Marshallian externalities. Specifically, for rural migrants working in a two-digit manufacturing industry in a city, doubling the industry employment size in that city increases the wage by 1.23%; a ten percentage point increase in college share in that industry located in that city increases the wage by 2.1%. These findings are robust to subsamples of rural migrants with less or more migration experience (Columns 2 and 3) and to subsamples of young or old workers (Columns 4 and 5), except that human capital externalities effect is not statistically significant for experienced rural migrants.[14] To summarize, rural migrants in general also benefit from labor market agglomeration economies in Chinese cities.

(Insert Table 4 here)

This finding is consistent with some existing evidence that low-skilled workers also benefit from human capital externalities. Using the 1980 and 1990 US Census data, Moretti (2004c) finds that a one percentage point increase in college share in a city raises high school drop-outs' wages by 1.9% and high school graduates' wages by 1.6%. Using the 2000 Census data, Rosenthal and Strange (2008) and Winters (2014) also find that workers with less than a college degree benefit from the concentration of college graduates in cities. Our

[13] A worker is a rural-urban migrant if he or she has a rural *hukou* and stayed in a city for more than six months.
[14] Peri (2002) finds that young workers tend to learn more in dense labor market while old workers decrease learning.

finding is also consistent with a recent study by Yu *et al*. (2017). They use the 2007 China Household Income Project data and find that rural migrants who have worked in other provinces are more likely to become entrepreneurs when they return home, suggesting that rural migrants have accumulated human capital in cities.

4.3 Rural migrants benefit less than do local, urban workers

A careful comparison reveals that although rural migrants benefit from labor market agglomeration economies in Chinese cities, they benefit much less than do workers with an urban *hukou* or workers who are local. Table 5 presents a set of such results. To facilitate comparison, Columns 1 and 2 replicate the baseline results for the full sample (Column 4 of Table 2) and for the rural migrants sample (Column 1 of Table 4). It is striking that rural migrants benefit 42% less than the full sample in terms of human capital externalities. Such an under-compensation pattern persists compared with workers with an urban *hukou* (Column 3), workers who are local residents in a city regardless of *hukou* (Column 4), workers who are local urban residents (Column 5), and urban workers moving across cities (who are in general skilled) (Column 6). These results imply that rural workers benefit much less from human capital externalities in two dimensions—being "rural" and being "migrants."

(Insert Table 5 here)

In terms of labor market pooling effect, although it is not informative to compare the rural migrants subsample with the full sample, it is straightforward to see that rural migrants benefit 30% to 40% less compared with workers with an urban *hukou* (Column 3), workers who are local urban residents (Column 5), and urban workers moving across cities (Column 6). Again, this pattern hints that rural workers benefit much less from labor market pooling in an industry in a city in two dimensions—being "rural" and being "migrants."

To make use of the full sample information, we create four dummy variables for these four worker categories: urban migrants, rural migrants, local urban, and local rural workers. We choose local urban workers as the default category and interact the other three category dummies with the two agglomeration variables while keeping their main effects. Column 7 of Table 5 presents the results. For labor market pooling effects, local urban workers benefit significantly: doubling industrial employment size increases their wage by 1.18%; workers with an urban *hukou* and moving across cities (urban migrants) enjoy additional benefit of 0.93%. However, local rural workers suffer a penalty of 1.38% less compared with local urban workers; more strikingly, rural migrants suffer a penalty of 2.40% less compared with local urban workers. A similar pattern holds for human capital externalities: a ten percentage point increase in college share in a city-industry cell increases the wage of local urban workers by 5.5%; urban migrants enjoy similar benefit. However, both local rural workers and rural migrants suffer 6% less compared with local urban workers. All these results again suggest that rural migrants benefit less from labor market agglomeration economies because of their being "non-urban" and "non-local." [15]

4.4 Why do rural migrants benefit less?

Why do rural migrants benefit much less from labor market agglomeration economies compared with local, urban residents? We cannot fully answer this question in this study but it seems there are at least three possible explanations. First, most of rural migrants are low-skilled with less education attainment (98.56% of rural migrants finished only high school or less education in our sample) and work in low-tech industries, which may prevent them from learning from other workers in the same industry.[16] Second, rural migrants lack social networks in cities preventing them finding better jobs and learning from spillovers. Third, rural migrants are discriminated in the urban labor markets because they are non-urban and non-local. We are unable to test the second and the third but can rule out the first.

To test whether low education attainment hinders rural migrants reaping fully the benefit from labor market agglomeration economies, we estimate the baseline model for subsamples of low-skilled (high school diploma or below) and high-skilled (associate degree or above) workers. Table 6 reports the results. Column 1 shows that although the benefit from labor market pooling is not statistically significant, low-skilled workers do benefit significantly

[15] These findings are in contrast to some empirical evidence based on the US data. Moretti (2004c) finds that workers with high school or less education benefit more from human capital externalities than do college graduates. Rosenthal and Strange (2008) find that both college and non-college educated workers can benefit from urbanization economies (measured by total employment) and human capital externalities and the difference is minor.

[16] Many rural migrants work in informal sectors and those sectors generally generate little knowledge spillovers. Our model specifications have included industry fixed effects and can rule out this interpretation.

from human capital externalities (coefficient is 0.3112), more so than rural migrants (coefficient is 0.2095). Column 2 shows that for low-skilled worker sample, being "rural" deprives them of almost all the benefit from both types of agglomeration economies. Column 3 further shows that being "migrant" (being "nonlocal") wipes out all benefit from labor market pooling, possibly due to their lack of local social networks. Columns 4-6 present the same set of results for high-skilled workers. Although for high-skilled workers, being "migrant" does not affect their ability to reap agglomeration benefit, being "rural" is very harmful, making the benefit from agglomeration economies almost disappear.

(Insert Table 6 here)

As a robustness check, we also report the interactive model results in Table 7, using local urban workers as the default category. Column 1 replicates the interactive model for the full sample (Column 7 of Table 5). Columns 2 and 3 reveal the same pattern as in Table 6 that rural migrants, whether they are low-skilled or high-skilled, receive much less benefit from agglomeration economies.[17] Taking together, we can infer that it is not education disparity, but the disparity in terms of rural and urban *hukou*, nonlocal and local residence that prevent rural migrants reaping the full benefit from urban labor market agglomeration economies.

(Insert Table 7 here)

Rural migrants generally lack local social networks compared with local urban residents; they may be discriminated by urban residents and employers. Either or both can explain why rural migrants benefit much less from labor market agglomeration economies than do local urban workers. Lack of social networks may be partially due to discrimination. We cannot distinguish or test these two hypotheses in the current study, but many existing studies based on micro data tend to support both hypotheses.

Using the 2010 population census data from Shanghai, Liu *et al*. (2016) find that residential neighborhoods in Shanghai are highly segregated by *hukou* and migration status: local urban residents concentrate in the central city (with rich urban amenities and high-

[17] The only exception is that the coefficient of college share interacting with rural migrant dummy for high-skilled workers (Column 3 of Table 7) is marginally significant (at the 15% level).

quality public services), rural migrants in the outer suburban areas, and urban migrants in the between. They also find that living in a neighborhood with a high concentration of rural migrants can significantly increase a rural migrant's likelihood of being employed, suggesting that rural migrants' social networks are very localized and limited. Using the 2007 Rural-Urban Migration in China and Indonesia (RUMiCI) data, Chen *et al*. (2015) find that two thirds of rural migrants in China search jobs through informal social networks but they receive much lower wage if they find jobs through social networks.[18] Zax (2016) explores extensive micro datasets (multiple waves of China Income Project data) and finds that returns to education of urban workers vary substantially and persistently across provinces and years, implying strong barriers (such as *hukou*) preventing workers moving freely across regions in China. Recent field experiments also document discrimination against rural *hukou* migrants (Afridi *et al*., 2015).

5. Conclusion

Agglomeration economies in urban labor markets have attracted much attention in developed countries. This paper offers a complementary evidence for labor market agglomeration economies in Chinese cities. We find that in general workers benefit from Marshallian externalities, including intra-industry labor market pooling effect and human capital externalities in cities. These findings are robust to various sorting bias tests. We also find that although rural migrants benefit from labor market agglomeration economies, they benefit much less than do workers who have an urban *hukou* or who are local. We provide evidence to show that this is not because rural migrants are generally low-skilled preventing them from reaping fully the benefit from labor market agglomeration economies. The two alternative interpretations could be that rural migrants lack local social networks and that they are discriminated by local urban residents and employers. Testing these two hypotheses warrants future studies.

[18] In other developing countries low-skilled workers also tend to find jobs through social networks (see for example, Wahba and Zenou, 2005).

That rural migrants cannot benefit fully from urban labor market agglomeration economies has important policy ramifications. The growth of population and employment in Chinese cities is mainly driven by massive rural-urban migration, implying that the skill intensity in many Chinese cities becomes diluted. Globalization and outsourcing of manufacturing firms from China to other developing countries has strongly motivated Chinese cities to become "skilled" to gain competitive advantage. Although some cities start to subsidize rural migrants for attending vocational schools (for example, Chengdu), it is unlikely to send most rural migrants back to school to receive formal education. However, social interactions in cities, especially in dense urban labor markets, provide another channel of learning and human capital accumulation. Designing policies to help rural migrants gain fully the benefit from urban labor market agglomeration to improve their productivity is a pressing task. Such policies should help develop an open, tolerant urban social milieu. An immediate policy suggestion would be to remove the *hukou* barrier and allow rural migrants to enjoy the same employee benefits and public services as do local urban residents. This can facilitate rural migrants to settle down in cities and to be integrated into urban society and urban culture. Fortunately, the Chinese government policies are moving toward this direction.[19]

[19] Xiaobo Wu, Hukou reform under way in 29 regions across China. Web link: http://www.chinadaily.com.cn/business/2016-04/29/content_24966027.htm.

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Table 1: Summary statistics of key variables

	Mean	Standard deviation	Min	Max
Wage (monthly, yuan)	956	707	100	10000
Male	0.544	0.498	0	1
Age	33.310	9.980	18	60
Single	0.263	0.440	0	1
Minority	0.042	0.201	0	1
High school	0.235	0.424	0	1
Associate	0.063	0.243	0	1
College	0.027	0.163	0	1
Graduate	0.002	0.047	0	1
Urban *hukou*	0.389	0.487	0	1
Migrating year	1.211	1.922	0	6
Employment (of a city-industry)	81,805	123,834	20	773,914
College share (of a city-industry)	0.113	0.085	0	1
Sample size	172,002			

Table 2: Labor market agglomeration economies

	1	2	3	4
Male	0.2189***	0.2135***	0.2080***	0.2060***
	(30.23)	(35.78)	(36.82)	(37.85)
Age	0.0124***	0.0120***	0.0117***	0.0114***
	(9.49)	(9.78)	(10.27)	(10.04)
Age squared	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(-11.17)	(-11.65)	(-12.55)	(-12.29)
Single	-0.0651***	-0.0641***	-0.0555***	-0.0554***
	(-10.17)	(-10.08)	(-10.04)	(-10.12)
Minority	-0.0562***	-0.0531***	-0.0492***	-0.0477***
	(-7.31)	(-7.11)	(-6.56)	(-6.42)
High school	0.1330***	0.1322***	0.1008***	0.1004***
	(23.57)	(22.47)	(26.64)	(26.91)
Associate	0.4284***	0.4250***	0.3226***	0.3200***
	(31.01)	(31.02)	(33.12)	(33.56)
College	0.7560***	0.7522***	0.6032***	0.6005***
	(26.67)	(26.81)	(28.84)	(29.53)
Graduate	1.3198***	1.3097***	1.1195***	1.1132***
	(29.55)	(29.48)	(31.21)	(31.45)
Urban *hukou*	0.0297***	0.0375***	0.0166**	0.0217***
	(2.51)	(3.49)	(2.20)	(2.93)
Migrating year	0.0113***	0.0114***	0.0107***	0.0107***
	(8.64)	(9.51)	(8.79)	(8.91)
ln(Employment)	0.0052*	0.0015	0.0019	0.0029
	(1.72)	(0.36)	(0.66)	(0.74)
College share	0.5044***	0.3431***	0.4621***	0.3598***
	(9.97)	(5.36)	(10.03)	(6.10)
Industry fixed effects	N	Y	N	Y
Occupation fixed effects	N	N	Y	Y
Adj. R^2	0.39	0.41	0.43	0.44

Note: City fixed effects, employee type, and work contract type dummies are included. Standard errors are clustered at the city-industry cell level. *t* statistics are in parentheses. "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels. Sample size: 172,002.

Table 3: Labor market agglomeration economies: robustness checks

	1 Baseline	2 Local	3 Migrants	4 <2.5 years	5 ≥2.5 years	6 Below median age	7 Above median age
ln(Employment)	0.0029	0.0111**	0.0015	-0.0018	0.0147***	0.0018	0.0071
	(0.74)	(1.91)	(0.47)	(-0.51)	(3.40)	(0.50)	(1.49)
College share	0.3598***	0.3473***	0.2812***	0.2285***	0.3454***	0.3228***	0.3847***
	(6.10)	(5.06)	(3.87)	()3.05	(3.22)	(5.26)	(5.63)
Adj. R^2	0.44	0.44	0.43	0.39	0.46	0.44	0.45
Sample size	172,002	97,478	74,524	34,975	39,549	91,426	80,576

Note: All models include the same set of independent variables as those in Column 4 of Table 2 except that Column 2 excludes migrating years. Median migrating year is 2.5. Median age is 33 in the full sample. Standard errors are clustered at the city-industry cell level. *t* statistics are in parentheses. "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels.

Table 4: Rural migrants benefit from labor market agglomeration economies

	1 Rural migrants sample	2 Below median migrating years	3 Above median migrating years	4 Below median age	5 Above median age
ln(Employment)	0.0123***	0.0128**	0.0115**	0.0181***	0.0104**
	(2.70)	(2.20)	(2.26)	(3.02)	(2.19)
College share	0.2095**	0.3551***	0.1119	0.2209*	0.2381**
	(1.93)	(2.64)	(0.93)	(1.67)	(2.07)
Adj. R^2	0.30	0.25	0.33	0.26	0.35
Sample size	49,916	23,302	266,14	25,260	24,656

Note: All models include the same set of independent variables as those in Column 4 of Table 2. Columns 2 and 3 use subsamples below or above median migrating years (cutoff is 2.5 years); Columns 4 and 5 use subsamples below or above median age (cutoff is 26). Standard errors are clustered at the city-industry cell level. *t* statistics are in parentheses. "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels.

Table 5: Rural migrants benefit less than do local, urban workers

	1 Full sample	2 Rural migrants	3 Urban	4 Local	5 Local urban	6 Urban migrants	7 Interactive model
ln(Employment)	0.0029	0.0123***	0.0178***	0.0111**	0.0197***	0.0181**	0.0118**
	(0.74)	(2.70)	(5.23)	(1.91)	(5.60)	(2.27)	(1.97)
ln(Employment)× Urban×Migrant							0.0093**
							(1.94)
ln(Employment)× Local×Rural							-0.0138***
							(-2.79)
ln(Employment) × Rural×Migrant							-0.0240***
							(-3.21)
College share	0.3598***	0.2095**	0.3483***	0.3473***	0.3287***	0.5133***	0.5539***
	(6.10)	(1.93)	(6.10)	(5.06)	(5.39)	(3.71)	(8.81)
College share× Urban×Migrant							0.0366
							(0.49)
College share× Local×Rural							-0.6150***
							(-8.03)
College share× Rural×Migrant							-0.5883***
							(-4.76)
Adj. R^2	0.44	0.30	0.53	0.44	0.50	0.55	0.44
Sample size	172,002	49,916	66,827	97,478	57,431	9,396	172,002

Note: All models include the same set of independent variables as those in Column 4 of Table 2. Column 7 also includes dummies for urban migrant, local rural, and rural migrant categories. Standard errors are clustered at the city-industry cell level. *t* statistics are in parentheses. "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels.

Table 6: Low-skilled versus high-skilled worker samples

	1 Low skilled	2 Low skilled	3 Low skilled	4 High skilled	5 High skilled	6 High skilled
ln(Employment)	0.0029	0.0100*	0.0052	0.0140**	0.0174***	0.0167**
	(0.72)	(1.86)	(1.18)	(2.37)	(2.89)	(2.40)
ln(Employment) × Rural		-0.0128***			-0.0382**	
		(-3.21)			(-3.45)	
ln(Employment) × Migrant			-0.0094**			-0.0102
			(-2.02)			(-0.77)
College share	0.3112***	0.5365***	0.3220***	0.5037***	0.5168***	0.4992***
	(5.48)	(8.30)	(5.37)	(6.42)	(6.66)	(6.26)
College share× Rural		-0.5555***			-0.5765***	
		(-7.89)			(-2.49)	
College share× Migrant			-0.0740			0.0353
			(-0.81)			(0.25)
Adj. R^2	0.34	0.35	0.34	0.52	0.52	0.52
Sample size	156,034	156,034	156,034	15,968	15,968	15,968

Note: All models include individual attributes variables, city, industry, and occupation fixed effects. Standard errors are clustered at the city-industry cell level. *t* statistics are in parentheses. "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels.

Table 7: Interactive models by skill

	1	2	3
	Full sample	Low-skilled workers	High-skilled workers
ln(Employment)	0.0118**	0.0077	0.0178***
	(1.97)	(1.32)	(2.53)
ln(Employment) ×Urban ×Migrant	0.0093**	0.0002	-0.0038
	(1.94)	(0.03)	(-0.30)
ln(Employment) ×Local ×Rural	-0.0138***	-0.0072*	-0.0188
	(-2.79)	(-1.64)	(-1.20)
ln(Employment) ×Rural ×Migrant	-0.0240***	-0.0139**	-0.0458***
	(-3.21)	(-2.38)	(-2.62)
College share	0.5539***	0.5379***	0.5086***
	(8.81)	(8.26)	(6.38)
College share ×Urban ×Migrant	0.0366	-0.0928	0.0528
	(0.49)	(-1.12)	(0.39)
College share ×Local ×Rural	-0.6150***	-0.5798***	-0.5835**
	(-8.03)	(-7.55)	(-2.00)
College share ×Rural ×Migrant	-0.5883***	-0.4996***	-0.5028
	(-4.76)	(-4.35)	(-1.49)
Adj. R^2	0.44	0.35	0.52
Sample size	172,002	156,034	15,968

Note: All models include individual attributes variables, city, industry, occupation fixed effects, and dummies for urban migrant, local rural, and rural migrant categories. Standard errors are clustered at the city-industry cell level. *t* statistics are in parentheses. "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels.