Does Urban Proximity Enhance Technical Efficiency in Agriculture? Evidence from China

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Résumé / abstract

This paper assesses whether cities produce spread or backwash effects on the agriculture of counties in China by allowing for heterogeneous urban effects both by regions and by city type. Cities are found to produce very significant spread effects on counties in Coastal provinces. Yet, spread effects are less significant in Central regions and not significant at all in the less developed regions of Western China. In addition, urban effects also vary across the urban hierarchy as we found that provincial-level cities have a deteriorating impact on counties, while lower-level cities produce spread effect in most regions. Implications of these findings in terms of urban and regional planning are discussed.

Mots clés /Key words : Agriculture, technical efficiency, urban proximity, stochastic frontier model, China
Codes JEL / JEL codes : O13, O18, Q10, R11

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1. INTRODUCTION

Since the beginning of the economic reforms, China has benefited from an average annual growth rate of 10%, which has allowed more than 500 million people to get out of poverty (World Bank, 2009). However, many rural people remain poor and a striking fact is that remote rural areas suffer the most from poverty (World Bank, 1992; Jalan and Ravallion, 2002). Other studies, both on developed (Pardridge and Rickman, 2008) and developing countries (Bird and Shepherd, 2003), also highlight that poverty increases with remoteness. One primary explanation of such a phenomenon may that, contrary to rural areas surrounding cities, remote ones do not benefit from urban spread effects[1].

In China, the higher level of poverty in remote areas could also arise, at least in part, from the attenuation of spillover effects when one moves further away from the city. Indeed, it has been shown recently that cities produce diverse spillover effects on rural counties in China[2]. Ke and Feser (2010), estimate that prefectoral and higher-level cities enhance both GDP and employment growth of neighboring rural counties in Central China. Chen and Partridge (2011) highlight that different tiers of the urban hierarchy (mega-cities, provincial capitals and prefecture cities) produce heterogeneous effects on both counties and county-level cities. Interestingly, the authors also distinguish between spillover effects on rural and on urban employment and find heterogeneous impacts. While provincial capitals produce net spread effects on urban employment growth, they produce backwash effects on rural employment. In spite of this distinction, the two aforementioned studies mainly analyze the effect of cities either on the non-agricultural sector (Ke and Feser, 2010) or on the whole economy of counties (Chen and Partridge, 2011). However, cities are likely to exert very different effects on counties, depending on whether we con-

[1] In the United States, poverty is estimated to be higher in remote areas because of lower urban agglomeration effects and incomplete labor supply responses (Pardridge and Rickman, 2008). In Zimbabwe, by fostering the development of the rural non-agricultural sector and thus, household income diversification, urban proximity helps rural households to get out of poverty (Bird and Shepherd, 2003).

[2] The county corresponds to the third level of administrative divisions in China. There are three types of units at the county level: counties (*xiàn*), which are mainly rural, county-level cities (*xiànjishì*) and urban districts (*shìxiaqu*) under prefecture or provincial-level cities.

sider a county's agricultural or non-agricultural sector. Specifically, if urban growth often produces spread effects on a county's non-agricultural sector, it is likely to produce backwash effects on agriculture (Peng, Zucker and Darby, 1997). For example, urban growth often fosters industrialization in neighboring counties, i.e. stimulates non-agricultural growth (Naughton, 2007) which, in turn, produces backwash effects on a county's agriculture. Indeed, industrialization leads to the conversion of agricultural lands and thus, results both in a decrease in farm lands, which reduces agricultural production capacities, and in a fragmentation of farm lands, which increases the costs of production (Gardner, 1994). In addition, close to cities, the higher risk of conversion of farm lands can lead to the "impermanence syndrome"[3], reducing agricultural production capacities even further.

However, the effect of urban growth on the agriculture of counties remains an open question, as other authors argue that cities are engines of growth for agriculture. Thus, cities may enhance agricultural modernization, as it is easier for farmers close to cities to buy modern inputs (Ma *et al.*, 2007). In addition, urban growth can boost agricultural production in neighboring counties by providing new opportunities for selling high-value agricultural commodities to better off urban consumers. Other authors also underline that factor markets are more efficient close to cities[4], which leads to a better functioning of the labor market, more easily reducing surplus labor (Nicholls, 1961).

Thus, until now, there has been no consensus on the effect of cities on the agriculture of counties and very scarce evidence for the specific case of China. However, understanding urban effects on the agriculture of counties is a key issue, especially in the Chinese context. Indeed, in terms of regional planning, it is of primary importance to understand whether cities produce spread or backwash effects on neighboring rural areas. If urban growth fosters rural and agricultural development, an optimal policy could consist in fostering urban growth and in reducing restrictions between rural and urban areas[5]. On the con-

[3] This syndrome is defined as "the lack of confidence in the stability and long-run profitability of farming in urbanized areas, leading to disinvestment of human and capital resources" (Heimlich, 1989).

[4] "Retardation hypothesis" (Schultz, 1951).

[5] Restrictions between urban and rural areas are still very strong in China. They mainly take the form of administrative barriers with the Household Registration System, or *hukou*, but the lack of infrastructure

trary, if cities produce backwash effects on the agricultural sector of counties, this would demonstrate that favoring cities as growth poles cannot achieve agricultural development and inequality reductions, considered as priority issues by the Chinese Government in its project to build a "harmonious society". This issue is of particular interest in China given that the government has implemented a strong urban bias policy. In addition, agriculture remains a major source of income for rural households today. Therefore, if we find evidence that cities produce spread effects on the agriculture of counties, this could shed some additional light on the geographic repartition of poverty in rural China.

The present paper provides a comprehensive study on the effect of cities on the agricultural sector of counties in China. We make two contributions to the literature on urban spillover effects. First, this study focuses on the impact of urban spillover effects on the agricultural sector of counties and so, is complementary to previous studies which analyze the effects of cities on the whole economy of counties or on their non-agricultural sector. Specifically, we first propose a theoretical framework in which we disentangle the different channels by which urban proximity can produce spread or backwash effects on agriculture. After that, we empirically assess whether cities produce net spread or backwash effects on the agricultural sector of rural areas by using county-level data over the period of 2005-2009. To our knowledge, the present study provides the most comprehensive study of urban effects on the agriculture of counties in China.

Second, we investigate whether urban effects can vary across Chinese regions. Specifically, we separate China into seven macro-regions (Northeast, East, South, Central, North, Northwest and Southwest) differing both in terms of natural conditions and economic development, and we allow urban spillover effects to vary across regions. We show that, on average, cities exert significant spread effects on rural counties in Northeast, North and East China whereas their effects are less significant in Central China and insignificant in less developed Western China. To our knowledge, this study is the first to highlight that urban effects are considerably heterogeneous across Chinese regions.

The remainder of this paper proceeds as follows. In Section 2 we identify the main

also plays a significant role.

channels by which urban proximity can affect the agriculture of counties and we highlight that urban spillovers are likely to be heterogeneous across regions and urban tiers. Section 3 describes the methodology and the data. Econometric results are analyzed in Section 4. Section 5 concludes and discusses the implications of these findings in terms of urban and regional planning.

2. THEORETICAL ANALYSIS: URBAN PROXIMITY AND AGRICULTURAL EFFICIENCY

This section is divided into four subsections. First, we briefly describe the determinants of agricultural growth to emphasize that technical efficiency is the appropriate economic outcome to study whether or not cities affect agriculture. Second, we disentangle the channels by which cities can enhance or hinder agriculture in neighboring counties. Finally, in the third and fourth subsections, we explain why urban effects are likely to vary across regions and urban tiers.

Measuring the performance of the agricultural sector

Agricultural output growth results from two major factors: inputs growth and total factor productivity (TFP) growth. Given the growing shortage of arable land[6] and the diminishing marginal products of fertilizers in some regions (Chen, Huffman and Rozelle, 2009), productivity growth is the key to increase agricultural production in China.

Changes in TFP can be further broken down into technical change and efficiency change (Coelli et al., 2005). On the one hand, technical change measures the change in production technology over time. In the case of technical progress, technology improves and consequently, the maximum output that can be produced with a given quantity of inputs increases, leading to productivity gains. In Appendix A, the production frontier F represents the maximum output that can be produced given the technology and the inputs. As shown in Figure A.1., graphically technical progress corresponds to an upward shift in

[6]Between 2001 and 2008, although population increased by 4% and per capita income doubled, cultivated area fell by nearly 6.5%. Moreover, prior to 2001, the arable land area in China was already far below the world average as it was only 0.11 hectare per capita in 2000 (Tan et al., 2005).

the production frontier F between year t and year $t+1$. In year $t+1$, the production unit can produce more ($Y_{t+1} > Y_t$) using the same quantity of inputs ($X_{t+1} = X_t$) because technology has improved.

However, on the other hand, producers often do not adopt the best practice methods of application of technology and as a result, they do not realize the full potential of the technology. Thus, technical inefficiency refers to the gap between the effective production level of a producer and the maximum production level he could produce, given the existing technology and the inputs used. Graphically, producers lie below the existing production frontier as represented by E_t in Figure A.2. of Appendix A. Technically, producers could increase their output without raising the quantity of inputs employed, only by adopting better practice methods, i.e. by reducing their level of technical inefficiency. Graphically, this is represented by the shift from E_t (the producer is inefficient) to E_{t+1} (the producer is fully efficient).

Previous studies have shown that in China, technical progress is high whereas technical efficiency is often found to be decreasing (Kalirajan, Obwona and Zhao, 1996; Mao and Koo, 1997; Yao and Liu, 1998; Wu et al., 2001; Chen et al., 2008). As a result, while technical progress positively contributes to TFP growth in China, the decline in technical efficiency negatively affects TFP growth. Thus, understanding the determinants of agricultural efficiency is a primary concern to enhance agricultural growth. As a consequence, we use agricultural efficiency as economic outcome[7]. A few studies on agricultural efficiency in China have introduced proxies for urban influence in their analysis. For example, Yao and Liu (1998) and Monchuk, Chen and Bonaparte (2010) find that counties with a higher share of rural population are relatively less efficient. Moreover, Wang, Cramer and Wailes (1996) estimate that farmers living in mountainous areas are less efficient.

[7]According to Tian and Wan (2000) agricultural efficiency is high in China and so there is little potential to increase output by efficiency improvements. However, other studies consider that efficiency is not so high and above all declining (Yao and Liu, 1998; Chen et al., 2008) so that there is room to further improve efficiency. Studying the determinants of efficiency is of primary importance given that, while the policies to stimulate technical progress are well known, there is much less consensus on what determines technical efficiency (Monchuk, Chen and Bonaparte, 2010).

However, the present study provides a much more comprehensive study of urban effects on the agriculture of counties by proposing a theoretical analysis, by using a much more direct measure of urban influence and by allowing for heterogeneity both across cities and regions.

How can urban proximity stimulate agricultural technical efficiency?

In this subsection, we show how cities can affect agricultural efficiency in counties, a question that, to our knowledge, no previous study has addressed.

First of all, proximity to cities provides farmers opportunities for selling their agricultural commodities which encourages them to intensify labor efforts (Benziger, 1996). Major agricultural reforms have been implemented in China since 1978. As they give the opportunity for farmers to sell their agricultural commodities and reward individual efforts, they have led to important productivity gains in agriculture (Fan, 1991; Lin, 1992). Yet, market access determines whether or not farmers can enjoy these opportunities. Indeed, farmers close to cities can sell their produce on the urban market whereas more remote households are forced into self-consumption agriculture. Moreover, the closer farmers are to the city, the lower the transport costs they have to bear and thus, the higher the sale prices are for their products. By providing these opportunities to farmers, we expect urban proximity to enhance efficiency.

Secondly, peri-urban areas suffer from losses in arable land which are converted for urban uses. For example, in Beijing, Tianjin and Hebei provinces, urban areas rose by 71% between 1990 and 2000, and among the new areas converted for urban uses, 74% were farmlands. In this context of high competition for the different uses of land, the only parcels which will not be converted for urban uses are those where agricultural yields are high (Livanis et al., 2006). Given the lack of respect for leases in rural China, there is a high risk of inefficient farmers close to cities being expropriated[8]. The fear of being

[8]In China, there is still a lack of respect for farmland leases. Indeed, farmers have leases which give them the right to use their land but the land ownership remains collective. As a result, the local authorities decide what to do with the farmland even if it is under lease. Thus, local authorities sometimes relocate farmers in order to obtain their farmland to convert it for more lucrative non-agricultural uses

relocated could force farmers close to cities to intensify their labor efforts.

In addition, as it is well-known, farmers close to cities benefit from the diffusion of knowledge and ideas which enables them to better control their environment and new technologies i.e. to become more efficient (Jacobs, 1969).

Last but not least, rural workers close to cities have a higher probability of working out of agriculture (Knight and Song, 2003), either in rural industries which are concentrated around cities (Peng, Zucker and Darby, 1997), or directly in cities, through commuting. This could have two opposite effects on technical efficiency. On the one hand, areas close to cities could suffer from backwash effects if the most efficient workers, typically young and educated men, leave agriculture to work in more remunerative and socially rewarding activities (Hu, 1997). However, this would also enable China to reduce its huge surplus of agricultural labor, which could lead to an increase in labor efficiency (Lewis effect). This "Lewis effect" is likely to be (one of) the most important mechanisms by which cities affect counties in China. Indeed, labor surplus remains considerable in Chinese rural areas (Golley and Meng, 2011). The rising trend in real wages in urban areas could induce one to conclude that China has reached the Lewisian turning point and is no longer a surplus labor economy (Zhang, Yang and Wang, 2011). However, because of the very specific institutional context in China, the country is actually in a situation where a huge rural labor surplus coexists with rising wages in rural areas (Knight, Deng and Li, 2011). In addition, it has been shown that a rural labor surplus is highly detrimental for agricultural efficiency (Munchuk, Chen and Bonaparte, 2010; Yao and Liu, 1998). Thus, cities are likely to affect agriculture in counties primarily by reducing labor surplus.

All the transmission channels through which cities can affect the agricultural technical efficiency of neighboring rural areas are summarized in the top panel of Table 1. *A priori*, the effect of urban proximity on agricultural efficiency is ambiguous.

[Table 1 here]

(Naughton, 2007). Given the very high competition for non-agricultural jobs in rural China and the low skills of most farmers, there is a high risk of them becoming under or unemployed after having lost their land (Kamal-Chaoui, Leman and Rufei, 2009).

Heterogeneous urban effects across regions

Chinese provinces are traditionally grouped into three regions (East, Central and West) according to their level of economic development. Eastern (or Coastal) China is by far the most developed and urbanized part of the country. In Coastal provinces, counties benefit from transporation infrastructure. Moreover, congestion effects are higher and services are growing faster in these cities. We show in this subsection how differences in characteristics of rural and urban areas across regions can modify urban spillover[9]. Specifically, urban spread effects may be more likely to occur near the coast.

First of all, urban proximity enhances the development of industries in counties, but this phenomenon mainly takes place in Coastal provinces (Naughton, 2007). Thus, proximity to cities is likely to have a much higher impact in reducing surplus labor in Coastal provinces. Indeed, in these provinces, infrastructures have been constructed to link cities with rural areas, as these rural areas benefit from strong economic potential given their location advantages. On the contrary, in the less developed interior provinces, infrastructure construction has been mostly directed to cities and thus, transportation from cities to counties is quite costly and difficult. This is why, counties in interior provinces, even those close to cities, do not benefit from a developed non-agricultural sector which would reduce surplus labor.

Secondly, in Coastal provinces some congestion effects have appeared in large cities over the last few years. Thus, some industries have relocated to interior provinces or to neighboring counties because of the high land value and wages in Coastal cities. In this context, in Coastal provinces, cities are likely to produce spread effects on agricultural efficiency by increasing non-agricultural employment in counties, i.e. by reducing surplus labor. On the contrary, in interior and western provinces, congestion effects are much less significant so that industry prefers to remain in cities than to relocate to counties which, moreover, lack good access to the urban market.

In addition, urban effects could also be heterogeneous because the economic structure

[9] Partridge et al. (2007) emphasize that differences in characteristics of rural and urban areas in Canada modified urban spillover effects.

of cities varies greatly across regions. Services are growing faster in the largest Chinese cities and especially in the three Eastern provincial cities (Beijing, Tianjin and Shanghai). As the service sector develops, industry is relocating to smaller cities and counties (Chan, Henderson and Tsui, 2008). Thus, counties in Coastal provinces are likely to benefit from higher non-agricultural employment growth, leading to a higher reduction in surplus labor.

Finally, Northeastern cities also differ in terms of economic structure. Indeed, Northeast China has been the traditional industrial base of China, specializing in heavy industry. As industrial activities generate a high level of pollution, which has a detrimental effect on agricultural efficiency (Monchuk, Chen and Bonaparte, 2010), cities in Northeast China could produce backwash effects on agriculture, contrary to cities in other regions.

Heterogeneous urban effects across urban tiers

As the Central Place Theory points out, different urban tiers differ in terms of economic size, structure and services provided and thus, they are expected to produce diverse impacts on counties. Empirical studies on China have confirmed that different cities in the urban hierarchy produced different spillover effects on counties (Benziger, 1996; Ke and Feser, 2010; Chen and Partridge, 2011). Specifically, Chinese cities can be divided into three types according to their administrative rank. The higher the administrative rank of the city, the higher the political and administrative powers and the more favorable the policies in terms of fiscal resources, FDI and infrastructure (Chan, Henderson and Tsui, 2008). First, at the top there are provincial cities (Beijing, Tianjin, Shanghai and Chongqing) which are by far the biggest and most economically developed in China[10], followed by prefecture-level cities (including provincial capitals and sub-provincial cities). At the bottom of the hierarchy are county-level cities which are the smallest ones and which still rely heavily on agriculture so that their economic structure is quite similar to that of counties.

Given these differences, distinguishing urban spillover effects according to the administrative rank of the cities is very consistent in the Chinese context. First of all, provincial cities benefit from a higher growth rate (see Appendix B) and thus, could draw more

[10]See Table B in the Appendix for descriptive statistics on these three types of cities.

resources from counties, resulting in backwash effects (Chen and Partridge, 2011). However, provincial and prefecture cities are expected to lead to a higher decrease in counties' surplus labor than county-level cities, producing more spread effects. Indeed, on the one hand, rural workers often prefer to migrate to big cities rather than to county-level cities (Chan, Henderson and Tsui, 2008). On the other hand, both provincial and prefecture cities have a very different economic structure compared with counties. Thus, growth in these cities stimulates growth in non-agricultural employment and GDP[11] (Ke and Feser, 2010). On the contrary, county-level cities, whose production structure is very similar to that of counties, compete with them, reducing both growth in non-agricultural employment and in county GDP. Thus, they could produce backwash effects by limiting the reduction of surplus labor in counties.

All the transmission channels highlighted in this section are summarized in Table 1.

3. METHODOLOGY AND DATA

The theoretical analysis consisted in disentangling the transmission channels by which urban effects can occur. This was particularly relevant given that, as we have said, no one has explicitly reviewed how cities can affect the agriculture of counties. The empirical investigation consists in testing whether cities produce *net* spread or *net* backwash effects on the agricultural efficiency of counties. To our knowledge, until now there has been no study which explicitly tests whether or not cities produce net backwash or spread effects on the agriculture of counties in China and whether urban effects are heterogeneous across urban tiers and regions. Thus, if testing the transmission channels by which cities can affect the efficiency of counties is an important area that requires further research, it is well beyond the scope of this paper and would require additional data which is not available to us. To test for the net impact of cities on efficiency of counties, we estimate a stochastic production frontier model.

[11] This arises because growth in high-level cities leads both to a relocation of non-agricultural activities to neighboring counties and to an increase in the demand for raw materials produced by counties.

Stochastic production frontier

Two broad types of methodologies exist to study technical efficiency: Data Envelopment Analysis (DEA) and stochastic frontiers. If both methods have their own merits, the stochastic frontier method is usually considered as the best one to study agriculture[12].

Unlike the standard production function, the stochastic production frontier relaxes the assumption that all producers are fully efficient. The stochastic production frontier model (Aigner, Lovell and Schmidt, 1977; Meeusen and van den Broeck, 1977) takes the following form:

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k \cdot \ln x_{kit} + \varepsilon_{it}$$

The error term ε_{it} is composed of two parts:

$$\varepsilon_{it} = v_{it} - u_{it}$$

where i refers to the county and t to the year. The dependant variable, y_{it}, is the output which is a function of a vector of K inputs (x_{kit}) and of a vector of unknown parameters to be estimated (β_k). The error term ε_{it} is composed of two parts: a traditional symmetric error component (v_{it}) and an inefficiency term (u_{it}). On the one hand, v_{it} is assumed to be independent and identically distributed and to follow a normal distribution centered at zero $[N(0, \sigma_v^2)]$. It is also assumed to be independent of the inefficiency term. On the other hand, u_{it} is a non-negative random variable. This component reflects the lack of ability of the producer to reach the maximum output it could produce (technical inefficiency). Indeed, the production frontier represents the maximum output that can be produced given the inputs and the technology. Thus, if $u_{it} = 0$, county i is fully efficient and its effective level of production equals the maximum potential output. However, if u_{it} is positive, then, county i is technically inefficient as its effective level of production is inferior to the maximum output it could produce. The technical efficiency score of county

[12] The DEA method does not account for noise and shocks (such as climatic shocks) and considers them as inefficiency (Coelli et al., 2005). The inherent stochastic nature of agriculture leads us to use the stochastic production frontier model.

i at year t is obtained as:

$$TE_{it} = e(-\hat{u}_{it})$$

Technical efficiency corresponds to the ratio of the effective output of county i relative to the output that would be produced by a fully efficient county. Therefore, technical efficiency scores take a value between zero and one.

In this study, we do not only seek to estimate the inefficiency component but are also interested in explaining it. More specifically, we want to assess whether urban proximity affects technical efficiency. To do that, we estimate the model for inefficiency effects in a stochastic frontier production function (Battese and Coelli, 1995)[13]. This model is composed of the following two equations:

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k \cdot \ln x_{kit} + v_{it} - u_{it} \tag{1}$$

$$u_{it} = \delta_0 + \sum_{m=1}^{M} \delta_m \cdot \ln z_{mit} + w_{it} \tag{2}$$

Equation 1 is the production frontier and Equation 2 is the inefficiency effects equation. The inefficiency effects (u_{it}) are independently distributed and are obtained by truncation at zero of the normal distribution with mean $z_{it}\delta$ and variance σ_u^2. They are is assumed to have a deterministic and a random component. On the one hand, the inefficiency effects are assumed to be a function of a set of explanatory variables (z_{mit}) and of a vector of unknown parameters (δ_m) to be estimated (deterministic component). Thus, the Equation 2 enables us to identify the factors which can explain differences in technical efficiency across rural areas. On the other hand, w_{it} is a random variable which includes the effect of the unobserved factors. It is defined by the truncation of the normal distribution with zero mean and variance σ_u^2 such that the point of truncation is $-z_{it}\delta$. This is consistent with the assumption that u_{it} is a non-negative truncation of the normal distribution with mean $z_{it}\delta$ and variance σ_u^2.

[13] Khumbakar, Ghosh and McGuckin (1991), Reifschneider and Stevenson (1991) and Huang and Liu (1994) propose this model for cross-sectional data.

Under the assumption that v_{it} is independant of u_{it}, x_{kit} and z_{mit}, the parameters of Equations 1 and 2 are consistently estimated in one-step by the maximum likelihood. The likelihood function is expressed in terms of the variance parameters $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\gamma = \sigma_u^2/\sigma^2$. Note that σ^2 is positive and γ, which represents the share of inefficiency term in the variance of the composed error term, lies between 0 and 1. Finally, equations 1 and 2 are simultaneously estimated; this approach is much more preferable than the two-step one which leads to severe estimation bias[14].

Empirical model and data

To explicitly test whether cities produce spillover effects on counties, we estimate the model for inefficiency effects in a stochastic frontier production function using county-level data. The limited availability of indicators at the county level for agricultural production leads us to carry out the analysis for 910 counties belonging to 19 provinces for the period of 2005 to 2009[15]. Specifically, we have data for the following 19 provinces, listed

[14]Indeed, the two-stage approach first estimates a standard stochastic production frontier in order to predict the inefficiency effects, assuming that these effects are not influenced by other variables. In a second stage, the predicted inefficiency effects are regressed on a set of explanatory variables, which contradicts the assumption made in the first stage. Thus, in the two-step approach, the model estimated in the first step is misspecified leading to estimations bias. Caudill and Ford (1993) provide evidence on the bias in the estimated technology parameters. Wang and Schmidt (2002) provide evidence on the bias at all stages of the procedures (both in the estimation of technology parameters, of the estimated efficiency scores and of the estimated determinants of efficiency) due to the two-step approach.

[15]A number of indicators at the county level are available in the China Statistical Yearbooks for Regional Economy as well as in the Provincial Yearbooks. Yet information on agriculture at the county level is relatively scarce. For example, gross agricultural output has only been published in the China Statistical Yearbooks for Regional Economy since 2005 and only some provinces published such information in their Yearbook before 2005. Moreover, information on fertilizers is not published in the China Statistical Yearbooks for Regional Economy but in the Provincial Yearbooks so that its availability greatly varies across time and provinces. For this reason, few studies analyze Chinese agriculture considering all counties. The only studies with data on all counties use the cross-sectional data of 1999 from the county-level socio-economic survey (Cho et al. 2007; Chen and Song, 2008; Cho, Chen and Poudyal, 2010; Monchuk, Chen and Bonaparte; 2010). After reviewing every Provincial Yearbook from 2002 to 2009, we restrict the analysis for the period from 2005 to 2009 in order to keep the highest possible number of provinces in

in alphabetical order: Anhui, Beijing, Chongqing, Gansu, Hainan, Hebei, Heilongjiang, Henan, Inner Mongolia, Jiangsu, Jiangxi, Jilin, Ningxia, Qinghai, Shaanxi, Shanghai, Sichuan, Tianjin and Xinjiang. As there were a total of 1636 counties in China over the period of 2005-2009, we carry out the analysis for more than half of the Chinese counties. Thus, our dataset covers a very large part of China, spanning from the North to the South (with Heilongjiang and Hainan Island) and from the West to the East (with Xinjiang and Jiangsu provinces) of the country.

Previous analyses on agricultural productivity have stressed that there are seven macro-regions in China, differing both in terms of economic development, institutions and agro-climatic conditions (Fan, 1991; Bhattacharyya and Parker, 1999; Cho et al., 2007; Cho, Chen and Poudyal, 2010). Specifically, the country is broken down into the following seven zones: Central, East, North, Northeast, Northwest, Southwest and South as shown in Figure 1.[16]. Such differences in economic and geographic conditions lead agricultural production technology to differ across Chinese regions (Cho et al., 2007; Chen, Huffman and Rozelle, 2009; Cho, Chen and Poudyal, 2010; Zhou, Li and Li, 2011). Thus, as each region has its own frontier production, it is necessary to estimate a separate frontier production for each of the seven macro-regions in order to obtain unbiased estimates of efficiency scores[17] (Chen and Song, 2008). Given that efficiency scores are the outcome of interest in the present study, this point is of primary importance.

[Figure 1 here]

our sample. Nevertheless, 12 provinces are not included because they did not publish data on all the necessary indicators (mainly fertilizers).

[16]Provinces are grouped into the seven zones as follows: Central (Henan, Hubei, Hunan); East (Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi and Shandong); North (Beijing, Tianjin, Hebei, Shanxi and Inner Mongolia); Northeast (Liaoning, Jilin, Heilongjiang); Northwest (Shaanxi, Gansu, Qinghai, Nongxia and Xinjiang); Southwest (Guangxi, Guizhou, Sichuan, Chongqing, Tibet, Yunnan) and South (Fujian, Guangdong and Hainan). See Cho et al. (2007) for a description of the climatic characteristics of each area.

[17]Remember that efficiency scores are obtained by comparing the effective level of production with the maximum output that can be produced (represented by the frontier production). Thus, if the frontier production is not consistently estimated, this will lead to biased efficiency scores.

Table 2 gives the name of the provinces and the number of counties, for each of the seven zones, in our sample along with some descriptive statistics. Given our dataset, we are able to estimate a production frontier for each region except for the South. Indeed, Hainan is the only Southern province for which we have data and it only contains 10 counties.

[Table 2 here]

Estimating the model for inefficiency effects in a stochastic frontier production function separately for each of the six zones enables us (1) to obtain unbiased efficiency scores and (2) to account for heterogeneity of urban effects across the six regions. Alternative groupings of provinces exist and could have been used to analyze heterogeneity of urban effects across regions. The most common grouping divides Chinese provinces into Coastal, Central and Western China. However, this grouping is likely to be inappropriate for taking into account all the regional heterogeneity of urban effects. For example, such a grouping would not enable us to account for the heterogeneity of urban effects that is likely to arise due to the particular economic structure of Northeastern cities, as explained in Section 2. Furthermore, as highlighted in Table 2, there is considerable variation in the level of economic development and urbanization among Coastal provinces and among Central provinces. For example, South provinces lag behind other Coastal provinces in terms of GDP per capita. Moreover, Northeast provinces are much more urbanized than other Central provinces. As a result, grouping provinces into Coastal, Central and Western would not be consistent to capture regional heterogeneity of urban effects. To summarize, breaking China down into seven areas was primarely due to the necessity of matching differences in production technology in order to obtain unbiased efficiency scores. However, this classification seems fully appropriate for accounting for regional heterogeneity of urban effects, as these seven areas also differ in terms of economic and urban development.

We estimate simultaneously the following two equations for China as a whole and separately for each of the Chinese macro-regions[18]:

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{4} \beta_k \cdot \ln x_{kit} + \beta_5 \cdot trend + \sum_{p=1}^{P} \alpha_p \cdot prov_p + v_{it} - u_{it} \tag{3}$$

$$u_{it} = \delta_0 + \delta_1 \cdot \ln prox_{it} + \sum_{m=2}^{4} \delta_m \cdot \ln z_{mit} + \delta_5 \cdot trend + \sum_{p=1}^{P} \lambda_p \cdot prov_p + w_{it} \tag{4}$$

where i refers to the county, p to the province, k to the input and t to the year.

In the estimated model, we identify two different categories of variables: the production frontier variables (Equation 3) and the inefficiency variables (Equation 4). First, with regard to the production frontier variables, the dependent variable, y_{it}, and the inputs, x_{it}, are the variables currently introduced in the literature on agricultural productivity. We use the logarithm of the gross output value of agriculture in constant prices as dependent variable[19]. We consider two traditional inputs (labor and land) and two modern inputs (chemical fertilizers and machinery). We also introduce provincial fixed-effects ($prov_p$) to control for agro-climatic conditions in each region and a time trend to take into account technical change. The stochastic approach forces us to choose a specification for the production frontier. Although it imposes restrictions on the technology, we estimate a Cobb-Douglas function which does not suffer from multicolinearity problems, contrary to flexible functional forms, such as the translog function (Hassine and Kandil, 2009; Mayen, Balagtas and Alexander, 2010).

Second, regarding the inefficiency effects equation, to test whether urban proximity affects technical efficiency, we follow Nehring et al. (2006) by introducing a measure of urban proximity ($prox_{it}$) among the determinants of technical inefficiency. As explained, the goal of the empirical analysis consists in estimating whether cities produce *net* spread or *net* backwash effects on the agriculture of counties in China. To test for this, we

[18]Estimations are made with the maximum likelihood using *Frontier 4.1*.

[19]Fan and Zhang (2002) underline that using constant prices for aggregate output cannot account for changes in relative prices which can lead to a bias in the estimation of productivity. The authors propose a method to minimize this potential bias. However, such a method cannot be implemented with county-level data due to data unavailability.

follow Chen and Partridge (2011) by constructing a set of measures of market potential (Harris, 1954) to account for urban proximity. First, we construct an aggregated measure of market potential as follows:

$$Prox_i = \sum_{j=1}^{J} \frac{GDP_j}{DIST_{ij}}$$

where i refers to the county and j to the city. $DIST_{ij}$ is the number of kilometers from the centroid of county i to the centroid of city j[20] and GDP_j is the gross domestic product of city j in 2005. We use GDP of city j at the initial period to minimize the potential endogeneity problem which could arise from common shocks affecting both counties and cities. We will further discuss the problem of endogeneity in the discussion part of Section 5. This market potential variable captures all the potential effects outlined in Section 2, i.e. opportunities for selling agricultural commodities, risk for farmers to be relocated, diffusion of ideas and non-agricultural job opportunities provided by urban proximity. To construct this aggregated market potential variable, we consider all kinds of cities: provincial, prefecture and county-level cities. Second, to take into account potential heterogeneity across the urban hierarchy, we create different market potential variables according to the administrative rank of the city (provincial, prefecture and county-level). By using similar indicators of market potential to those of Chen and Partridge (2011) who study urban effects on counties's GDP and employment growth, we are able to clearly compare whether cities produce varying impacts on the agriculture and the other sectors of counties.

Finally, following Liu and Zhang (2000) and Chen and Song (2008), we assume that inefficiency depends on the level of education, health and loan (z_{mit}) of the county. We also introduce provincial dummies ($prov_p$) and allow inefficiency to vary over time by introducing a time trend. Data is taken from the 2006-2010 China Statistical Yearbooks for Regional Economy and from the 2006-2010 Provincial Yearbooks. The precise definitions and descriptive statistics of all the variables are provided in Appendices C and D.

[20] Data on cities' GDP is from the 2006 China City Statistical Yearbook. Distance is calculated using the latitude and longitude of each county and city using data available on the U.S. Geological Survey website.

4. RESULTS

In this section, we begin by estimating whether cities produce net spread or backwash effects on the agriculture of counties in each of the six macro-regions. In a second step, we test for urban hierarchy effects in each region by substituting the aggregated market potential variable for the desaggregated variables.

Does urban proximity enhance technical efficiency in each Chinese region?

[Table 3 here]

First of all, we investigate whether proximity to cities enhances agricultural efficiency by estimating the model for China as a whole and for each of the six macro-regions, using the aggregated market potential variable. Table 3 presents estimates of the inefficiency effects in the production frontier model. The estimates of the production frontier are reported in the first part of the table. On the one hand, estimated elasticities for inputs significantly vary across regions, confirming that estimating a different production frontier is necessary in order to obtain unbiased efficiency scores. Thus, results for China as a whole (Column 1) are likely to be biased. On the other hand, overall estimated elasticities are consistent. Thus, the coefficient associated with machinery is insignificant in nearly all regressions, which is not surprising, as in China labor is abundant and so, we expect mechanical technologies (or labor-saving technologies) to be insignificant. We also find decreasing returns to scale in each region[21]. Finally, the coefficient associated to the time trend is positive, high and very significant for all regions except Central China. This confirms that technical progress is a strong component of total factor productivity growth in China.

The second part of Table 3 is of particular interest, as it gives the results of the estimation of the inefficiency model. First, inefficiency does exist in Chinese agriculture. Indeed, the estimated variance parameters are significant and the parameter γ lies between 0 and

[21] As we estimate a Cobb-Douglas function, returns to scale are calculated as the sum of the estimated input elasticities. As the sum is inferior to one, we conclude that returns to scale are decreasing.

1 and is close to one. More importantly, the likelihood ratio test of the null hypothesis that there are no technical inefficiency effects is strongly rejected at the 1% level in every case[22]. Average technical efficiency ranges from about 55% in the Southwest to 79% in the North. Efficiency estimates are close to those found by Wang, Cramer and Wailes (1996) and Yao and Liu (1998) but lower than those found by Tian and Wan (2000). Second, several studies warn that agricultural efficiency has been deteriorating in China since the 1980s (Kalirajan, Obwona and Zhao, 1996; Mao and Koo, 1997; Chen et al., 2008). Our result confirms that most regions suffer from a decrease in their technical efficiency level given that the coefficient associated to the time trend is positive[23] and significant for most regions. Regarding the determinants of technical efficiency, counties with better health infrastructures are consistently significantly more efficient. One surprising result is that education increases inefficiency in most regions whereas we expected better educated farmers to be more able to utilize existing technologies. Although this result is unexpected, it is not new in the literature (Chen et al., 2008; Chen and Song, 2008). This is most likely due to the fact that education variables at the county level are no longer appropriate indicators of the level of education of farmers because most educated rural workers are involved in non-agricultural activities. "Loan" is also found to be a significant determinant of efficiency but its impact varies across regions. This arises because loan exerts two opposite impacts on technical efficiency. On the one hand, farmers benefiting from better access to credit often use better quality inputs, leading to higher technical efficiency (Carter, 1989). On the other hand, credit also raises investment in new technologies. Yet a high rate of technical change can lead to deterioration in efficiency when farmers do not have the time to assimilate new technologies (Mao and Koo, 1997).

When it comes to our variable of interest, it appears that cities either produce net spread effects or no effect on the agriculture of counties. Thus, cities enhance agricultural efficiency probably by providing opportunities for selling agricultural commodities,

[22] The likelihood ratio statistic has a a mixed Chi-square distribution (Coelli, 1995). The critical values, which are reported in the Table, can be found in Kodde and Palm (1986).

[23] A positive sign in the inefficiency model means that the associated variable increases technical inefficiency (and so, reduces efficiency).

increasing the competition for the use of land, facilitating transmission of ideas and/or reducing surplus labor. In addition, we find considerable heterogeneity across regions: urban proximity significantly enhances efficiency in the Northeast, North and East regions, while its effect is less significant and lower for the Central region and not significant at all for the Southwest and the Northwest. As predicted in Section 2, cities are much more likely to enhance non-agricultural employment growth in counties close to the coast (which includes both the North, East and to some extent the Northeast region). Indeed, in cities of such provinces, (i) the growth in wages and in land prices and (ii) the development of the tertiary sector lead to relocation of manufactures to adjacent counties. Moreover, in such provinces counties benefit from a higher level of development in infrastructure and industry, which facilitates relocation of industry to rural areas. To our knowledge, this study is the first to emphasize that cities produce heterogeneous spillover effects across Chinese regions. Last, we find that cities have no impact on the agriculture of counties in the West. However, until now we do not know whether this is the result of compensation between spread and backwash effects or of the absence of ties between cities and counties in the West. The next subsection sheds light on this issue.

Do all cities exert the same impact?

As explained in the theoretical analysis of Section 2, different urban tiers are expected to produce different impacts on the agriculture of counties. In this subsection, we further analyze urban spillover effects by investigating the net spillover effects produced by each type of city. To do so, we substitute the aggregated market potential variable for the disaggregated ones. Table 4 presents the estimates of the model when allowing urban effects to vary both across regions and across the urban hierarchy.

First of all, provincial cities have a detrimental impact on counties. This probably arises because provincial cities are growing fast so that they pull resources from counties. This result is very consistent with the estimations of Chen and Partridge (2011) and, as the authors highlight, this tends to invalidate the expectations of the government according to which the provincial cities produce spread effects on the rest of the country. Consistently, provincial-level cities have an impact in the North, because of the proximity to Beijing and Tianjin, in the East, because of Shanghai, and in the West, because of Chongqing. Conversely, counties located in the Northeast and Central regions are not affected by provincial cities which are located too far away.

Second, contrary to provincial cities, prefecture-level cities produce net spread effects on the agriculture of counties in most regions. Our results are complementary to previous studies (Ke and Feser, 2010; Chen and Partridge, 2011) which find that high-level cities produce spread effects on counties' (non-agricultural) GDP growth. Thus, prefecture-level cities appear to constitute engines of growth for counties both for their agricultural and non-agricultural sectors. In addition, it is interesting to note that Northeast China is the only region in which prefecture cities produce backwash effects. As highlighted in Section 2, Northeast cities could produce backwash on agriculture given their specialization in heavily polluting industries.

Turning to county-level cities, we find that their impact varies a great deal across regions. While they produce net spread effects in the Southwest, Northwest and Northeast, they have no net impact in the East and Center and they produce backwash effects in the North. Such a geographic patterns probably arises for two reasons. On the one hand, county-level cities are likely to enhance efficiency in the West where they probably lead to a higher reduction in counties' surplus labor than in other regions. Indeed, in the West, where the urbanization rate, the number of large cities and the level of infrastructure development are low, many county-level cities are remote. In this context, county-level cities constitute attractive destinations for rural workers so that they lead to a significant decrease in rural surplus labor in these regions. Conversely, in the more developed and urbanized parts of the country, almost every county-level city is near to a bigger city. In this context, rural workers are much more likely to migrate to large cities (see Section 2) so that county-level cities do not lead to a reduction in surplus labor of counties. On the other hand, many small (county-level) cities have benefited from high growth rates. This is particularly true in Coastal provinces, where export processing jobs have developed, and close to large cities, which stimulate smaller cities' economic development (Chan, Henderson and Tsui, 1998). Thus, county-level cities could benefit from higher growth rates in the Eastern and the Northern regions. As underlined in Section 2, given their similar economic structure, county-level cities and counties compete so that growth in county-level cities can produce backwash effects on counties in these regions.

Finally, using disaggregated market potential variables, we are able to conclude that the absence of impact of cities on counties in the West, as estimated in Table 3, arises from the compensation of spread and backwash effects. In Table 3, the aggregated market potential variable has no significant impact on the agriculture of Western counties. Thus, the use of an aggregated indicator for urban proximity can be misleading, as one could conclude that counties and cities in Western China are two separated worlds. On the contrary, Table 4 highlights that cities and counties in Western China are interconnected. Indeed, the coefficient associated to the disaggregated market potential variables are statistically significant both in the Northwest and Southwest regions. However, cities produce both spread and backwash effects on counties, resulting in a net impact equal to zero. This issue has important policy implications. Indeed, if Western counties and cities did not interact, an optimal policy would be a local one, targeting only rural areas. However, as counties and cities are interconnected, the optimal policy should be a regional one, including both rural and urban areas (Roberts, 2000).

[Table 4 here]

Discussion

To our knowledge, this study is the first to estimate the effect of urban proximity on agricultural technical efficiency in China. We find that on average, i.e. when using the aggregated market potential variable, being close to a city increases technical efficiency in the Northeast, North, East and Central regions. For other regions, we find that cities, at the aggregated level, have no impact on counties. This is very interesting to note that our conclusion differs from that of Nehring et al. (2006) according to which urban proximity negatively affects farmers' technical efficiency level in the US. However, their study is carried out on a sample of farmers in the Corn Belt, the production context of which is very different from the Chinese context. Therefore, we do not expect urban proximity to impact technical efficiency by the same transmission channels. For example, if urban proximity most likely enhances efficiency in China giving farmers more opportunities to access market to sell their produce, in the Corn Belt, this transmission channel should not be at work, as even farmers in remote areas have easy access to markets.

One possible shortcoming of this study however, is that we assume that remote counties and counties close to cities produce the same agricultural products, which could be misleading. Indeed, we assume that counties close to cities are more efficient thanks to the mechanisms highlighted in Section 2 (urban market access, knowledge spillovers, land use competition, the Lewis effect). Nevertheless, their higher level of efficiency could also be explained by the fact that the agricultural output they produce is less complicated to yield than those of remote counties. To relax the assumption that all counties produce the same type of agricultural output, we could estimate a production frontier, either with several outputs or with only one type of output (for example grain or vegetables). Yet the lack of disaggregated output data at the county level prevents us from estimating these models.

Another objection could be made regarding the direction of causality. It could indeed be argued that farmers sort across rural areas according to their individual characteristics which could be one major source of endogeneity. For example, the most talented and enterprising farmers may move close to cities in order to benefit from the urban market. In this case, the higher level of technical efficiency would not stem from urban proximity but from differences in farmers' characteristics (omitted variable problem). However, in China, it is very likely that the causality runs from urban proximity to agricultural productivity. Indeed, farmlands are allocated to farmers by the authorities, according to birth place, and nothing indicates that the most enterprising farmers are given land close to urban centers. Moreover in China, the land market is under-developed and migration from one rural area to another area is very low[24]. As a result, spatial sorting of farmers across rural areas is not likely to lead to estimation bias and thus, the location of Chinese farmers should be exogeneous to their ability to produce.

[24] According to the 2007 Chinese Household Income Project data, more than 90% of migrant rural laborers leave their local countryside to work in towns or cities.

5. CONCLUSION

Some recent studies have shown that in China, cities produce a diverse range of spread and backwash effects on the non-agricultural sector or whole economy of counties. The present study focuses on the effect of urban proximity on the agricultural sector of counties. Indeed, as some scholars argue, cities are likely to produce very diverse effects on neighboring rural areas, depending on whether we consider their agricultural or non-agricultural sector. Studying urban effects on agriculture is particularly relevant given the importance of China's agriculture, both in terms of alimentary self-sufficiency and poverty-inequality reduction (Liu and Zhang, 2000).

Specifically, we investigate the effect of cities on agricultural efficiency, which is one of the most crucial determinants of potential agricultural growth in China. First, in a theoretical analysis we disentangle the transmission channels by which cities can affect efficiency in neighboring counties and we emphasize that urban effects are probably heterogeneous both across regions and across the urban hierarchy. Second, we carry out an empirical investigation to estimate whether cities produce *net* spread or backwash effects on counties.

Using an aggregated indicator of market potential, we find no evidence that cities produce net backwash effects on the agriculture of counties. Conversely, cities can be engines of growth for the agriculture of counties. However, urban effects are very heterogeneous across regions. In Coastal provinces, we found that cities produce significant net spread effects and this probably arises from the fact that firms relocate more from cities to counties. In less developed provinces, spread effects are much less significant or even not significant at all. In the Western and Central regions, counties probably benefit from lower spread effects because of a lack of infrastructure which results in costly and difficult transportation between cities and counties, limiting the relocation of firms to counties. Thus, enhancing infrastructure development could result in stronger spread effects in these regions.

Second, spillover effects not only appear to vary across regions but also across the urban hierarchy. Provincial-level cities are found to produce significant backwash effects on counties, as already estimated by Chen and Partridge (2011). Thus, the current policies that favour provincial-level cities are unable to enhance agricultural and rural development. On the contrary, prefecture-level cities, and to some extent county-level ones, produce spread effects on counties in almost every region. In terms of urban-planning, favouring the development of a network of medium-sized cities, scattered across the territory, is much more likely to enhance rural development and achieve balanced growth than the development of a few huge cities.

Finally, cities appear to interact with their adjacent counties in every region of China. Indeed, close to the Coast and in Central China, counties benefit from net spread effects. Moreover, in the West, we found that the absence of significant urban effects at the aggregated level arises as a result of compensation of equal spread and backwash effects and not as a result of a lack of ties between counties and cities. Thus, given that cities interact with their adjacent counties, regional policies, including both cities and neighboring counties, should be given preference over more local policies which would focus only on rural areas. However, urban effects are attenuated as one moves further away from the city. Thus, remote counties are likely not to benefit from urban effects and their economies are probably less dependant on those of cities. Thus, if the urban growth strategy has some merits (as cities produce net spread effects on counties in Coastal provinces) it also raises concerns, as it is likely to increase inequalities between counties close to cities and remote counties, which do not benefit from urban spillovers. As highlighted in the introduction, remote counties suffer from a higher level of poverty. Thus, the attenuation of spread effects by the distance to urban areas could be one potential explanation of such a phenomenon, at least in the North-East, North, East and Central regions.

Aigner, D., C. A. K. Lovell, and P. Schmidt, 1977: Formulation and Estimation of Stochastic Frontier Production Function models. *Journal of Econometrics*, **6 (1)**, 21–37.

Battese, G. E. and T. J. Coelli, 1995: A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics*, **20 (2)**, 325–32.

Benziger, V., 1996: Urban Access and Rural Productivity Growth in Post-Mao China. *Economic Development and Cultural Change*, **44 (3)**, 539–570.

Bhattacharyya, A. and E. Parker, 1999: Labor Productivity and Migration in Chinese Agriculture: A Stochastic Frontier Approach. *China Economic Review*, **10 (1)**, 59–74.

Bird, K. and A. Shepherd, 2003: Livelihoods and Chronic Poverty in Semi-Arid Zimbabwe. *World Development*, **31 (3)**, 591–610.

Carter, M. R., 1989: The Impact of Credit on Peasant Productivity and Differentiation in Nicaragua. *Journal of Development Economics*, **31 (1)**, 13–36.

Caudill, S. B. and J. M. Ford, 1993: Biases in Frontier Estimation due to Heteroscedasticity. *Economics Letters*, **41 (1)**, 17–20.

Chan, K. W., J. V. Henderson, and K. Y. Tsui, 2008: *Spatial Dimensions of Chinese Economic Development*. in: Loren Brandt and Thomas G. Rawski (Eds) China's Great Economic Transformation, chp.19 pp. 776-828, Cambridge University Press.

Chen, A. and M. D. Partridge, 2011: When are Cities Engines of Growth in China? Spread and Backwash Effects across the Urban Hierarchy. *Regional Studies*, 1–19, doi: 10.1080/00343404.2011.589831.

Chen, P.-C., M.-M. Yu, C.-C. Chang, and S.-H. Hsu, 2008: Total Factor Productivity Growth in China's Agricultural Sector. *China Economic Review*, **19 (4)**, 580–593.

Chen, Z., W. E. Huffman, and S. Rozelle, 2009: Farm Technology and Technical Efficiency: Evidence from Four Regions in China. *China Economic Review*, **20 (2)**, 153–161.

Chen, Z. and S. Song, 2008: Efficiency and Technology Gap in China's Agriculture: A Regional Meta-frontier Analysis. *China Economic Review*, **19 (2)**, 287–296.

Cho, S.-H., Z. Chen, and N. Poudyal, 2010: Spatial Structure of Agricultural Production in China. *Applied Economics*, **42 (16)**, 2031–2040.

Cho, S.-H., Z. Chen, S. T. Yen, and B. C. English, 2007: Spatial Variation of Output-Input Elasticities: Evidence from Chinese County-level Agricultural Production Data. *Papers in Regional Science*, **86 (1)**, 139–157.

Coelli, T., 1995: Estimators and Hypothesis Tests for a Stochastic Frontier Function: A Monte Carlo Analysis. *Journal of Productivity Analysis*, **6**, 247–268.

Coelli, T. J., D. Rao, C. J. O'Donnell, and G. Battese, 2005: *An Introduction to Efficiency and Productivity Analysis*. Kluwer Academic Publishers, Inc., Boston.

Fan, S., 1991: Effects of Technological Change and Institutional Reform on Production Growth in Chinese Agriculture. *American Journal of Agricultural Economics*, **73 (2)**, 266–275.

Fan, S. and X. Zhang, 2002: Production and Productivity Growth in Chinese Agriculture: New National and Regional Measures. *Economic Development and Cultural Change*, **50 (4)**, 819–838.

Gardner, B. L., 1994: Commercial Agriculture In Metropolitan Areas: Economics And Regulatory Issues. *Agricultural and Resource Economics Review*, **23 (1)**, 100–109.

Golley, J. and X. Meng, 2011: Has China run out of surplus labour? *China Economic Review*, **22 (4)**, 555–572.

Harris, C. D., 1954: The Market as a Factor in the Localization of Industry in the United States. *Annals of the Association of American Geographers*, **44 (4)**, 315–348.

Hassine, N. B. and M. Kandil, 2009: Trade Liberalisation, Agricultural Productivity and Poverty in the Mediterranean Region. *European Review of Agricultural Economics*, **36 (1)**, 1–29.

Heimlich, R. E., 1989: Metropolitan Agriculture: Farming in the City's Shadow. *Journal of the American Planning Association*, **55 (4)**, 457–466.

Hu, W., 1997: Household Land Tenure Reform in China: Its Impact on Farming Land Use and Agro-environment. *Land Use Policy*, **14 (3)**, 175–186.

Huang, C. J. and J.-T. Liu, 1994: Estimation of a Non-neutral Stochastic Frontier Production Function. *Journal of Productivity Analysis*, **5**, 171–180.

Jacobs, J., 1969: *The Economy of Cities*. New-York: Vintage.

Jalan, J. and M. Ravallion, 2002: Geographic Poverty Traps? A Micro Model of Consumption Growth in Rural China. *Journal of Applied Econometrics*, **17 (4)**, 329–346.

Kalirajan, K. P., M. B. Obwona, and S. Zhao, 1996: A Decomposition of Total Factor Productivity Growth: The Case of Chinese Agricultural Growth before and after Reforms. *American Journal of Agricultural Economics*, **78 (2)**, 331–338.

Kamal-Chaoui, L., E. Leeman, and Z. Rufei, 2009: Urban Trends and Policy in China. OECD Regional Development Working Papers 2009/1, OECD Publishing.

Ke, S. and E. Feser, 2010: Count on the Growth Pole Strategy for Regional Economic Growth? Spread-Backwash Effects in Greater Central China. *Regional Studies*, **44 (9)**, 1131–1147.

Knight, J., Q. Deng, and S. Li, 2011: The Puzzle of Migrant Labour Shortage and Rural Labour Surplus in China. *China Economic Review*, **22 (4)**, 585 – 600.

Knight, J. and L. Song, 2003: Chinese Peasant Choices: Migration, Rural Industry or Farming. *Oxford Development Studies*, **31 (2)**, 123–148.

Kodde, D. A. and F. C. Palm, 1986: Wald Criteria for Jointly Testing Equality and Inequality Restrictions. *Econometrica*, **54 (5)**, 1243–48.

Kumbhakar, S. C., S. Ghosh, and J. T. McGuckin, 1991: A Generalized Production Frontier Approach for Estimating Determinants of Inefficiency in U.S. Dairy Farms. *Journal of Business and Economic Statistics*, **9 (3)**, 279–86.

Lin, J. Y., 1992: Rural Reforms and Agricultural Growth in China. *American Economic Review*, **82 (1)**, 34–51.

Liu, Z. and J. Zhang, 2000: Determinants of Technical Efficiency in Post-Collective Chinese Agriculture: Evidence from Farm-Level Data. *Journal of Comparative Economics*, **28 (3)**, 545–564.

Livanis, G., C. B. Moss, V. E. Breneman, and R. F. Nehring, 2006: Urban Sprawl and Farmland Prices. *American Journal of Agricultural Economics*, **88 (4)**, 915–929.

Ma, H., A. N. Rae, J. Huang, and S. Rozelle, 2007: Enhancing Productivity on Suburban Dairy Farms in China. *Agricultural Economics*, **37 (1)**, 29–42.

Mao, W. and W. W. Koo, 1997: Productivity Growth, Technological Progress, and Efficiency Change in Chinese Agriculture after Rural Economic Reforms: A DEA Approach. *China Economic Review*, **8 (2)**, 157–174.

Mayen, C. D., C. D. Balagtas, and C. E. Alexander, 2010: Technology Adoption and Technical Efficiency: Organic and Conventional Dairy Farms in the United States. *American Journal of Agricultural Economics*, **92 (1)**, 181–195.

Meeusen, W. and J. van den Broeck, 1977: Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review*, **18 (2)**, 435–44.

Monchuk, D. C., Z. Chen, and Y. Bonaparte, 2010: Explaining Production Inefficiency in China's Agriculture using Data Envelopment Analysis and Semi-parametric Bootstrapping. *China Economic Review*, **21 (2)**, 346–354.

Naughton, B., 2007: *The Chinese Economy: Transitions and Growth.* The MIT Press.

Nehring, R., C. Barnard, D. Banker, and V. Breneman, 2006: Urban Influence on Costs of Production in the Corn Belt. *American Journal of Agricultural Economics*, **88 (4)**, 930–946.

Nicholls, W. H., 1961: Industrialization, Factor Markets, and Agricultural Development. *Journal of Political Economy*, **69 (4)**, 319–340.

Partridge, M., R. D. Bollman, M. R. Olfert, and A. Alasia, 2007: Riding the Wave of Urban Growth in the Countryside: Spread, Backwash, or Stagnation? *Land Economics*, **83 (2)**, 128–152.

Partridge, M. D. and D. S. Rickman, 2008: Distance from Urban Agglomeration Economies and Rural Poverty. *Journal of Regional Science*, **48 (2)**, 285–310.

Peng, Y., L. G. Zucker, and M. R. Darby, 1997: Chinese Rural Industrial Productivity and Urban Spillovers. NBER Working Papers 6202, National Bureau of Economic Research, Cambridge MA.

Reifschneider, D. and R. Stevenson, 1991: Systematic Departures from the Frontier: A Framework for the Analysis of Firm Inefficiency. *International Economic Review*, **32 (3)**, 715–23.

Roberts, D., 2000: The Spatial Diffusion of Secondary Impacts: Rural-Urban Spillovers in Grampian, Scotland. *Land Economics*, **76 (3)**, 395–412.

Schultz, T. W., 1951: A Framework for Land Economics - The Long View. *Journal of Farm Economics*, **33 (2)**, 204–215.

Tan, M., X. Li, H. Xie, and C. Lu, 2005: Urban Land Expansion and Arable Land Loss in China-A Case Study of Beijing-Tianjin-Hebei Region. *Land Use Policy*, **22 (3)**, 187 – 196.

Tian, W. and G. H. Wan, 2000: Technical Efficiency and Its Determinants in China's Grain Production. *Journal of Productivity Analysis*, **13**, 159–174.

Wang, H.-j. and P. Schmidt, 2002: One-Step and Two-Step Estimation of the Effects of Exogenous Variables on Technical Efficiency Levels. *Journal of Productivity Analysis*, **18**, 129–144.

Wang, J., G. L. Cramer, and E. J. Wailes, 1996: Production Efficiency of Chinese Agriculture: Evidence from Rural Household Survey Data. *Agricultural Economics*, **15 (1)**, 17–28.

World Bank, 1992: Strategies for Reducing Poverty in the 1990s, Washington DC: The World Bank.

World Bank, 2009: From Poor Areas to Poor People: China's Evolving Poverty Reduction Agenda, An Assessment of Poverty and Inequality in China, Beijing Office: Poverty Reduction and Economic Management Department, East Asia and Pacific Region.

Wu, S., D. Walker, S. Devadoss, and Y.-C. Lu, 2001: Productivity Growth and Its Components in Chinese Agriculture after Reforms. *Review of Development Economics*, **5 (3)**, 375–91.

Yao, S. and Z. Liu, 1998: Determinants of Grain Production and Technical Efficiency in China. *Journal of Agricultural Economics*, **49 (2)**, 171–184.

Zhang, X., J. Yang, and S. Wang, 2011: China Has Reached the Lewis Turning Point. *China Economic Review*, **22 (4)**, 542 – 554.

Zhou, X., K.-W. Li, and Q. Li, 2011: An Analysis on Technical Efficiency in post-reform China. *China Economic Review*, **22 (3)**, 357–372.

Appendix A. Technical progress and improvement in technical efficiency

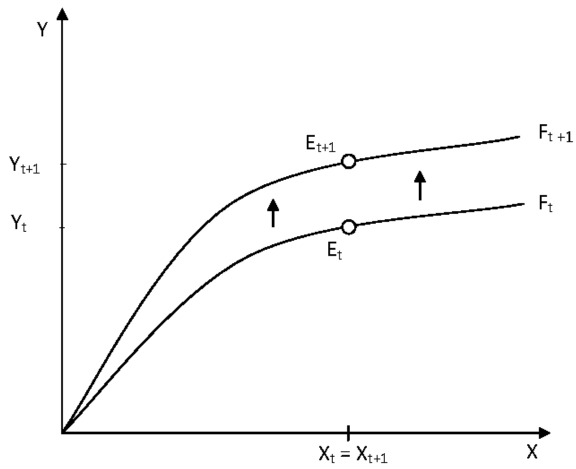

Figure A.1. : Technical progress

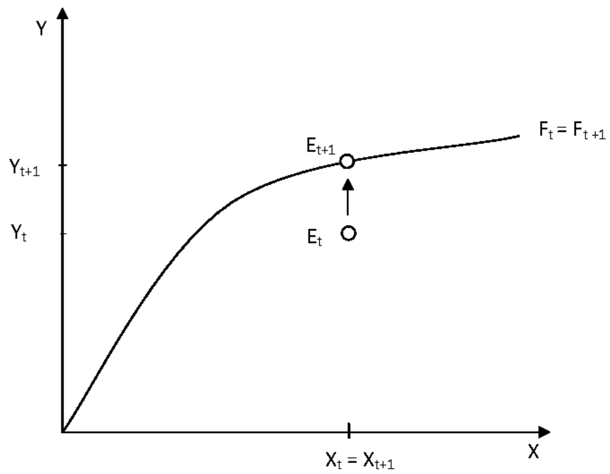

Figure A.2. : Technical efficiency change

Appendix B. Provincial, prefecture and county-level cities

	Population (10,000 persons)	Primary sector (% GDP)	Secondary sector (% GDP)	Tertiairy sector (% GDP)	Population growth
Provincial cities	1196.17	2.53	43.80	53.67	3.87
Prefecture-level cities	115.75	7.78	50.82	41.41	1.57
County-level cities	66.82	17.01	47.89	34.99	0.70

Appendix C. Definition of the variables

Variable	Definition	Unit
	Frontier variables	
Output	Gross output value of agriculture	100 million yuan (constant prices)
Land	Cultivated area	100 hectares
Labor	Agricultural labor	10,000 persons
Machinery	Total power of agricultural machinery	10,000 kW
Fertilizer	Consumption of chemical fertilizer	100 tons
	Inefficiency variables	
Aggregated market potential	Sum of GDP in cities weighted by the inverse of the distance between each city and county	
Market potential: provincial cities	Sum of GDP in provincial cities weighted by the inverse of the distance between each city and county	
Market potential: prefecture-level cities	Sum of GDP in prefecture cities weighted by the inverse of the distance between each city and county	
Market potential: county-level cities	Sum of GDP in county-level cities weighted by the inverse of the distance between each city and county	
Education	Share of students enrolled in regular secondary schools in population	%
Health	Number of beds in hospitals and sanitation agencies	10,000 beds
Loan	Outstanding loan of financial institutes at year-end	100 million yuan

Appendix D. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Frontier Variables					
Agricultural output	4417	16.71	14.53	0.16	102.08
Land	4317	482.80	484.84	0.02	4699.26
Labor	4512	11.94	10.03	0.04	59.51
Machinery	4369	33.69	34.94	0.17	290.00
Fertilizer	4452	248.14	293.91	0.02	2597.57
Inefficiency variables					
Aggregated Market Potential	4550	294.29	68.25	135.11	688.39
Market potential: provincial cities	4550	6544.97	1577.28	2021.85	11939.75
Market potential: prefecture-level cities	4550	391.04	84.26	184.84	731.81
Market potential: county-level cities	4550	136.82	32.65	53.23	303.29
Education	4518	6.07	1.85	0.29	27.00
Health	4496	0.07	0.05	0.01	0.38
Loan	4511	16.48	17.62	0.03	341.06

Table D.1: Urban spillover effects on agricultural technical efficiency

Transmission channels	Expected effect
(1) Urban proximity and agricultural efficiency	
1. Opportunities for selling agricultural commodities: incentive to intensify labor efforts	Spread
2. Competition for the use of land and risk of being relocated	Spread
3. Knowledge diffusion : better control on the environment	Spread
4. Job opportunities out of agriculture. Two effects:	
4.1. Departure of the most efficient workers	Backwash
4.2. Reduce surplus labor (Lewis effect)	Spread
(2) Heterogeneous effects across regions	
1. Counties are better linked to cities in Coastal provinces: firm relocations to counties easier in these provinces	More spread effects in Coastal provinces
2. Congestion effects in large Coastal cities: more firm relocations to counties in these provinces	More spread effects in Coastal provinces
3. Growth of services in the largest cities (mainly Coastal cities): more firm relocations to counties in Coastal provinces	More spread effects in Coastal provinces
4. Polluting cities in North-Eastern China	Backwash effects in North-East China
(3) Heterogeneous effects across urban tiers	
1. Provincial cities are growing faster	Provincial cities: backwash effects
2. Migrants prefer to migrate to high-level cities	High-level cities: more spread effects
3. County-level cities and counties have a similar economic structure	County-level cities: backwash effects

Table D.2: Data on the seven zones of China

	China	**NE**	**N**	**E**	**C**	**NW**	**SW**	**S**
(1) Data in the sample:								
	19 provinces	Heilongjiang	Beijing	Anhui	Henan	Gansu	Chongqing	Hainan
Provinces		Jilin	Hebei	Jiangsu		Ningxia	Sichuan	
in the			Inner Mongolia	Jiangxi		Qinghai		
sample			Tianjin	Shanghai		Shaanxi		
						Xinjiang		
Nb. counties	910	66	188	152	88	261	145	10
(2) Descriptive statistics on the seven regions*:								
GDP per capita	22,479	21,708	34,453	31,783	15,989	14,712	12,183	24,710
Urbanization rate	45	56	59	54	40	39	34	53
Nb. Cities	654	89	77	165	103	60	84	75
Nb. provincial cities	4	0	2	1	0	0	1	0
Nb. prefecture cities	283	34	31	69	42	30	44	32
Nb. county-level cities	367	55	44	95	61	30	39	43

Note: NE=Northeast, N=North, E=East, C=Central, NW=Northwest, SW=Southwest, S=South.

* Indicators calculated using data on every provinces of each region i.e. we do not just consider provinces in our sample. Urbanization rate corresponds to the share of urban population in total population in 2009. GDP per capita refers to the annual regional gross domestic product per capita in yuan in 2009. Data is from the 2010 China Statistical Yearbook.

Figure D.1: Seven areas of China

Table D.3: Urban effects across Chinese regions

	(1) China	(2) Northeast	(3) North	(4) East	(5) Central	(6) Northwest	(7) Southwest
Production Frontier Model							
Constant	8.060***	10.736***	5.876***	6.553***	7.805***	4.892***	8.441***
	(0.081)	(0.503)	(0.315)	(0.215)	(0.805)	(0.219)	(0.204)
Land	0.047***	0.009	0.006	0.350***	0.344***	0.115***	0.019**
	(0.006)	(0.006)	(0.021)	(0.027)	(0.057)	(0.017)	(0.007)
Labor	0.397***	0.337***	0.232***	0.223***	0.240***	0.193***	0.729***
	(0.016)	(0.059)	(0.025)	(0.029)	(0.052)	(0.020)	(0.030)
Machinery	0.009**	-0.056	0.447***	-0.006	0.047	0.278***	-0.001
	(0.004)	(0.055)	(0.023)	(0.012)	(0.032)	(0.021)	(0.003)
Fertilizer	0.230***	0.115***	0.056***	0.162***	0.021	0.187***	0.121***
	(0.009)	(0.044)	(0.018)	(0.020)	(0.031)	(0.012)	(0.015)
Trend	0.127***	0.130***	0.039***	0.125***	-0.043	0.039***	0.154***
	(0.006)	(0.020)	(0.012)	(0.005)	(0.138)	(0.008)	(0.037)
Provincial dummies	Yes	Yes	Yes	Yes	No†	Yes	Yes
Inefficiency effects model							
Constant	-26.248***	-1.973	26.146***	4.482***	4.809**	-5.472*	3.229
	1.364	(4.483)	(2.516)	(0.830)	(1.872)	(2.803)	(2.195)
Urban Proximity	-0.137	-3.695***	-6.801***	-0.729***	-0.682**	0.582	-0.386
	0.249	(0.730)	(0.510)	(0.153)	(0.319)	(0.533)	(0.409)
Education	0.501***	3.977***	1.754***	0.111**	0.161**	-0.231***	0.581***
	0.153	(0.578)	(0.195)	(0.044)	(0.082)	(0.073)	(0.058)
Health	-0.182**	-4.985***	-2.013***	-0.137***	-0.208***	-0.116***	-0.136***
	0.089	(0.304)	(0.181)	(0.036)	(0.069)	(0.042)	(0.024)
Loan	0.044	1.102***	1.608***	-0.107***	-0.184***	0.091***	-0.031*
	0.062	(0.212)	(0.103)	(0.028)	(0.043)	(0.030)	(0.018)
Trend	2.856***	0.857***	0.239**	0.086***	-0.087	-0.142***	0.116***
	0.033	(0.173)	(0.119)	(0.011)	(0.139)	(0.018)	(0.040)
Provincial dummies	Yes	Yes	Yes	Yes	No†	Yes	Yes
Average efficiency level	0.674	0.664	0.785	0.614	0.624	0.703	0.545
σ^2	9.216***	4.973***	2.575***	0.043***	0.062***	0.204***	0.101***
	(0.124)	(0.613)	(0.187)	(0.003)	(0.006)	(0.013)	(0.007)
γ	0.991***	0.985***	0.965***	0.999***	0.527	0.659***	0.590***
	(0.004)	(0.003)	(0.004)	(0.005)	(0.549)	(0.039)	(0.137)
Likelihood ratio test statistic	7339.66	359.99	755.58	64.47	51.52	207.67	198.54
Critical value of LR test	43.696	19.384	22.525	20.972	17.755	24.049	19.384
N	881‡	65	186	151	88	242	139
$N * T$	4317	325	930	755	352	1210	695

Note : *, **, *** indicate significance at the 10%, 5% and 1% levels respectively. Standard-errors in parenthesis. A negative sign in the inefficiency model means that the associated variable reduces technical inefficiency (and so, enhances efficiency).
† No provincial dummies are introduced given that Henan is the only province included in the Central region.
‡ The total number of counties for China is higher than the sum of the counties belonging to each region. This difference is due to Hainan province (10 counties) which is included in the regression for China and which belongs to the South region. Remember that we do do not run estimation for the South region because of the lack of sufficient observations.

Table D.4: Urban effects across regions and urban tiers

	(1) China	(2) Northeast	(3) North	(4) East	(5) Central	(6) Northwest	(7) Southwest
Production Frontier Model							
Constant	8.085***	10.840***	5.236***	6.628***	7.569***	4.730***	8.100***
	(0.082)	(0.530)	(0.282)	(0.195)	(0.760)	(0.210)	(0.178)
Land	0.044***	0.008	0.032	0.367***	0.316***	0.132***	0.016**
	(0.005)	(0.006)	(0.023)	(0.026)	(0.060)	(0.018)	(0.007)
Labor	0.388***	0.349***	0.208***	0.193***	0.226***	0.189***	0.703***
	(0.013)	(0.055)	(0.027)	(0.027)	(0.054)	(0.021)	(0.035)
Machinery	0.010***	-0.065	0.415***	-0.014	0.102**	0.287***	0.001
	(0.003)	(0.059)	(0.026)	(0.013)	(0.040)	(0.023)	(0.003)
Fertilizer	0.231***	0.115***	0.072***	0.152***	0.016	0.176***	0.120***
	(0.008)	(0.043)	(0.020)	(0.019)	(0.030)	(0.012)	(0.015)
Trend	0.127***	0.129***	0.036***	0.126***	-0.069	0.035***	0.138***
	(0.006)	(0.024)	(0.009)	(0.009)	(0.133)	(0.009)	(0.032)
Provincial dummies	Yes	Yes	Yes	Yes	No†	Yes	Yes
Inefficiency effects model							
Constant	-30.508***	-0.296	16.731***	-0.744	7.591*	-13.245***	4.421
	(2.050)	(1.012)	(2.107)	(1.305)	(4.298)	(1.551)	(3.170)
Provincial cities	1.343**	-0.999	3.584***	0.768**	-0.049	4.164***	0.425*
	(0.589)	(2.353)	(0.775)	(0.310)	(0.678)	(0.326)	(0.236)
Prefecture cities	-0.016	9.536***	-19.717***	-0.663***	-1.364***	-2.118***	-0.107
	(0.798)	(1.366)	(0.782)	(0.112)	(0.352)	(0.471)	(0.236)
County-level cities	-0.945	-15.977***	12.133***	-0.300	0.368	-2.634***	-1.311**
	(0.953)	(4.210)	(0.905)	(0.411)	(0.489)	(0.427)	(0.665)
Education	1.395***	1.902***	2.720***	0.109*	0.150*	-0.344***	0.597***
	(0.263)	(0.326)	(0.121)	(0.062)	(0.078)	(0.083)	(0.064)
Health	-0.569***	-5.147***	-0.833***	-0.122***	-0.228***	-0.060	-0.151***
	(0.184)	(0.907)	(0.191)	(0.039)	(0.065)	(0.048)	(0.026)
Loan	0.103	1.349**	0.845***	-0.159***	-0.192***	0.031	-0.033*
	(0.092)	(0.530)	(0.100)	(0.036)	(0.038)	(0.029)	(0.018)
Trend	2.635***	0.656***	0.105***	0.095***	-0.106	-0.144***	0.218**
	(0.061)	(0.156)	(0.049)	(0.016)	(0.133)	(0.020)	(0.093)
Provincial dummies	Yes	Yes	Yes	Yes	No†	Yes	Yes
Average efficiency level	0.668	0.666	0.774	0.617	0.597	0.709	0.559
σ^2	8.604***	4.035***	2.945***	0.041***	0.059***	0.156***	0.104***
	(0.191)	(0.671)	(0.164)	(0.004)	(0.005)	(0.008)	(0.008)
γ	0.991***	0.981***	0.971***	0.999***	0.519	0.558***	0.642***
	(0.001)	(0.005)	(0.003)	(0.016)	(0.462)	(0.033)	(0.094)
Likelihood ratio test statistic	7512.563	366.232	776.889	240.444	64.466	345.745	271.783
Critical value of LR test	46.349	22.525	25.549	24.049	20.972	27.026	22.525
N	881‡	65	186	151	88	242	139
$N * T$	4317	325	930	755	352	1210	695

Note : *, **, *** indicate significance at the 10%, 5% and 1% levels respectively. Standard-errors in parenthesis. A negative sign in the inefficiency model means that the associated variable reduces technical inefficiency (and so, enhances efficiency).

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