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THREE ESSAYS ON URBANIZATION IN CHINA

Thèse nouveau Régime
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"Quelque soit la durée de la nuit, le soleil finit toujours par se lever"

— Les proverbes de l'Afrique (1992)

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Résumé

L'augmentation constante des températures combinée à la multiplication des catastrophes naturelles changent tous les jours un peu plus la donne en terme d'immigration. Pourtant, leurs effets sur la migration au sein d'un même pays ne sont que trop peu connu. La Chine, avec ses zones climatiques diverses, ses nombreuses catastrophes naturelles et son faible taux d'urbanisation, est un lieu propice à l'étude de ce phénomène. Cette thèse offre trois études empiriques qui, dans un premier temps, dresse un état des lieux des déterminants de l'urbanisation chinoise, pour ensuite évaluer l'influence des variations climatiques mais aussi d'une catastrophe naturelle sur les flux de migration entre les campagnes et les villes.

Le chapitre 2 repense l'étude des déterminants de l'urbanisation en incluant les possibles interactions spatiales entre provinces chinoises voisines, et ce, entre 1980 et 2015. Ce travail contribue à la littérature économique en apportant des éléments nouveaux pour expliquer le développement urbain très inégal présent en Chine. Il contribue également aux travaux d'économie régionale puisque j'utilise un modèle Spatial Durbin Error (SDEM) pour tester l'existence d'interactions spatiales entre provinces. Ce faisant, je peux estime quels sont les déterminants de l'urbanisation d'une province chinoise, tout en prenant en compte l'influence que pourrait avoir sa proximité avec d'autres villes. Les résultats montrent l'existence d'un effet de synergie entre provinces voisines. Être géographiquement proche d'une province attractive -caractérisée par un fort PIB par habitant, une population dense et un système de transport efficient- entraîne bel et bien une augmentation du taux d'urbanisation d'une province donnée. Cependant, cette relation n'est pas monotone. La croissance des villes peut engendrer de la compétition entre voisins lorsque la province voisine atteint un certain niveau de richesse économique, et donc d'attractivité.

Le chapitre 3 met en lumière le lien entre les variations climatiques et la migration rural-urbaine, entre 1992 et 2012, en China. On fait l'hypothèse implicite que les anomalies météorologiques affectent la production agricole, et de ce fait, le revenu des agriculteurs. Par conséquent, cela impacte leurs incitations mais aussi leurs moyens financiers nécessaires pour migrer vers les villes. Ce qui, par suite, influe sur la taille des villes. Ce travail contribue à la littérature en utilisant une mesure inhabituelle de l'urbanisation, qui ne dépend ni de données récoltées lors de recensement, ni d'une définition de la ville basée sur ses frontières administratives. J'utilise ainsi la luminosité des villes la nuit pour estimer la taille de celles-ci, et ce sur des données de panel à l'échelle de grids. Ce faisant, les résultats montrent l'existence d'un impact significatif des variations météorologiques tout autour d'une ville, sur la taille de celle-ci. Cet impact diffère selon la nature de l'intempérie. Un déficit de précipitations a plus de chances d'avoir des répercus-

sions sur les flux migratoires que les surplus précipitations. Ce premier engendre un flux de migration vers les villes l'année même où la sécheresse affecte la récolte des agriculteurs, mais les résultats tendent à montrer que cette migration est temporaire et ne sert qu'à maintenir un revenu stable pour le ménage sur le court-terme. Les inondations, qui sont elles plus semblables à des catastrophes naturelles brutales, qu'un changement météorologique graduel, ont plutôt un effet négatif sur la migration. Cette différence entre les deux types de catastrophes naturelles est étudiée plus en détail dans le chapitre suivant.

Le chapitre 4 utilise le tremblement de terre de Wenchuan comme une expérience naturelle pour évaluer l'impact d'une catastrophe naturelle soudaine sur la taille des villes voisines, mais aussi l'efficacité de la réponse du gouvernement chinois pour la reconstruction. Ce chapitre fait avancer la littérature en étant le seul à avoir étudier les flux migratoires hors des campagnes du Sichuan, suite à ce tremblement de terre. J'ai utilisé une Synthetic Control Method pour générer un contrefactuel convaincant pour la province du Sichuan. Les résultats mettent en évidence les effets négatifs qu'a eu le tremblement de terre de Wenchuan sur la taille des villes du Sichuan. Cela fait écho aux résultats obtenus dans le chapitre précédent, les catastrophes naturelles affectent les flux migratoires en empêchant ou au moins retardant le départ vers les villes. En effet, les villes, aussi impactées par celles-ci, n'apparaissent plus comme des sources d'opportunités économiques, et n'attirent donc plus les migrants potentiels. Dans un second temps, on voit aussi que trois ans après le choc, l'effet sur l'attractivité des villes, et donc sur les flux migratoires, est à nouveau nul. Un retour à la tendance pré-choc a lieu, suggérant que les catastrophes naturelles soudaines n'ont aucun impact permanent sur la migration. Le timing de ce retour à la tendance coïncide parfaitement avec la fin du plan de reconstruction du gouvernement chinoise, échelonné sur trois ans. Ce chapitre fait donc le constat de l'efficacité de l'intervention chinoise.

Mots clés : Economie du développement, Migration Interne, Chine, Urbanisation, Changement Climatique, Anomalies Météorologiques, Catastrophes Naturelles.
Codes JEL : R19, O15, O53, Q15, Q54

Summary

Increasing weather variations along more frequent natural disasters set new living conditions worldwide. Yet, their impacts on internal migration are still not fully understood. China, characterized by diverse climate zones, frequent natural disasters and a still low urbanization rate, is a great field experiment to analyze this potential link. The present thesis provides three empirical studies that first give an insight on Chinese urban determinants to later investigate the implications of both weather variations and natural disasters on rural-urban migration.

Chapter 2 revisits the study of urbanization driving forces by looking at spatial interactions among Chinese provinces over the 1980-2015 period. This work contributes to the literature by bringing new elements to explain the great diversity in China urban development. It also contributes to the regional science literature by using the Spatial Durbin Error Model to explore the presence of spatial spillovers. Using this method, I test the determinants of urbanization, controlling for the influence of close proximity to other cities. I find evidence of a synergy effect between neighboring provinces. Being close to an attractive province -characterized by a high GDP per-capita, dense population or an efficient transportation system-triggers one province urbanization. Yet, the relation is not monotonous, the urban process becomes competitive between neighboring provinces when one province reaches a certain threshold of economic wealth.

Chapter 3 highlights the link between weather variations and rural-urban migration, between 1992 and 2012, in China. The implied hypothesis is that weather anomalies affect crop productivity as well as farmers' income. It later changes their incentives and financial means to migrate toward cities, impacting cities size. The main contribution lies on the use of an original measure of urbanization that does not rely on either census data or any urban definition based on administrative borders. Indeed, I test this assumption using a grid-level panel dataset and nighttime light intensity as a proxy for city size. I find a significant link between weather variations in surrounding areas and cities' size. Yet, the effects differ according to the type of weather variation. Rainfall shortages are more likely to affect migratory behaviors than rainfall surpluses. Results suggest that these former trigger short-term migration to cities when the latter.

Chapter 4 uses Wenchuan earthquake as a natural experiment for investigating the impact of a sudden natural hazard on city size nearby, along with the efficiency of Chinese government plan to reconstruct. I contribute to the literature by being the first to analyze out-migration from rural areas following Wenchuan earthquake. Using the Synthetic Control Method, results show negative effects of Wenchuan earthquake on Sichuan city size. In accordance with the results in this thesis previous chapter, natural hazards prevent migration from happening. Cities, also

damaged by the event, no longer attract migrants. In addition, I find evidence that, three years after the shock, in 2011, the effects on city size are null. Sichuan experiences a "back to trend" migratory flows, suggesting that rapid-onset naturals disasters have no permanent impact on migration patterns. The timing of this return-to-trend exactly coincides with the end of the three-year reconstruction plan led by Chinese government, suggesting the effiency of the latter.
Keywords: Development economics, Internal Migration, China, Urbanization, Climate Change, Weather Anomalies, Natural Disasters.
JEL codes: R19, O15, O53, Q15, Q54

List of acronyms

CERDI:	Centre d'Études et de Recherches sur le Développement International
CRED:	Centre for Research on the Epidemiology of Disasters
CRU ts:	Climate Research Unit Time Series
DC:	Developed Countries
DMSP-OLS:	Defense Meteorological Program Operational Line-Scan System
EM-DAT:	Emergency Events Database
FAO:	Food and Agriculture Organization
FE:	Fixed Effects
GDP:	Gross Domestic Product
IPCC:	Intergovernmental Panel on Climate Change
Km:	Kilometers
LDC:	Less Developed Countries
NASA:	National Aeronautics and Space Administration
NDRC:	National Development and Reform Committee
NBSC:	National Bureau of Statistics in China
NOAA:	National Oceanic and Atmospheric Administration
NTL:	Night Time Lights
PWT:	Penn World Table
SDEM:	Spatial Durbin Error Model
SPEI:	Standardized Precipitation and Evaporation Index
UCA:	University Clermont Auvergne
UN:	United Nations
UNESCAP:	United Nations Economic and Social Commission for Asia and the Pacific
WB:	World Bank
WMO:	World Meteorological Organization

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Chapter 1

General Introduction

1.1 Developing countries, particularly vulnerable to adverse climatic conditions and natural disasters

To introduce this work, I highlight the increasingly changing climatic conditions and the growing number of natural disasters (Section 1.1.1). Both features have particularly high consequences on developing countries (Section 1.1.2). If no proper *ex ante* and *ex post* risk management policies are enforced to both mitigate the risk and the costs related to natural events, an adaptation behavior for local population could be migration (Section 1.1.3). Namely, it often translates into migrating to areas with better infrastructures, access to services and to a diversified economy such as cities. It is the phenomenon discussed in this thesis in the Chinese case, a relatable one for developing countries (Section 1.1.4). The structure of the current thesis is detailled in Section 1.2.

1.1.1 Emergence of a "New normal" for climatic and natural hazards

Mainly due to climate change[1], Earth average temperature has already risen by more than one degree Celsius over the previous century, and it keeps increasing[2]. Thus, daily temperatures inflate worldwide. And more importantly, the planet experiences greater climatic anomalies, that is to say "*deviations of climatic statistics over a given period of time (e.g. a month, season or year) when compared to long-term statistics for the same calendar perio*d[3]". As observed on Figure 1.1, daily temperatures widely diverge from their usual value at the same time of the year.

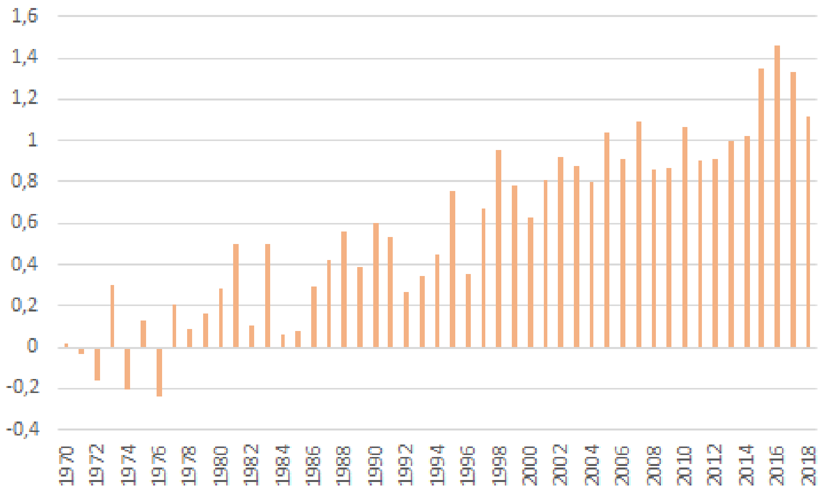
[1]Climate Change refers to a persisting change in the world overall climate for an extended period. Definition provided by the World Meteorological Organization. Retrieved from: http://www.wmo.int/pages/prog/wcp/ccl/faqs.php. Accessed 10.06.2019.

[2]Source: National Aeronautics and Space Administration (NASA). Retrieved from https://www.nasa.gov/audience/forstudents/5-8/features/nasa-knows/what-is-climate-change-58.html. Accessed 10.06.2019.

[3]Source: WMO

Namely, between 1970 and 2018, it goes from null to nearly 1.5 degree Celsius positive deviation from the historical average temperature of the period 1901-2000.

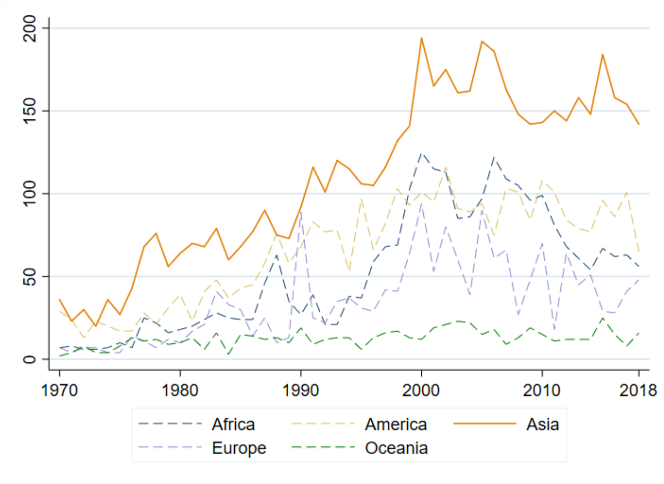
Figure 1.1: Annual Temperature Deviations from the historical trend in Degrees Celsius



Notes: The ordinate axis depicts the annual temperature deviation from its historical value (Base period: 1901-2000). Source: Author's elaboration on NOAA data.

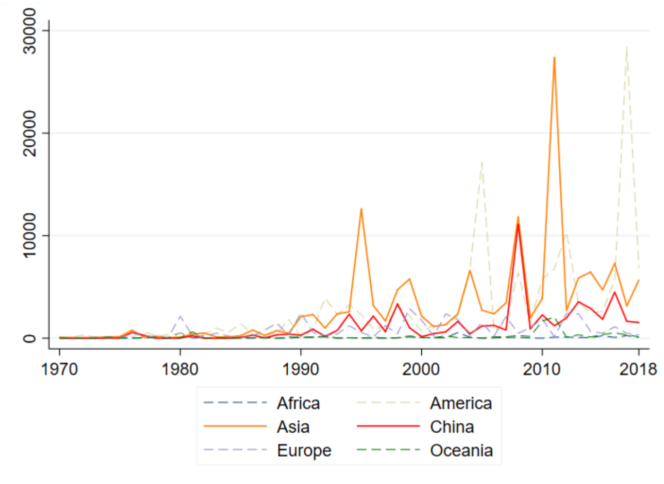
In addition, formerly rare events are becoming frequent, namely natural disasters (see Figure 1.2). Natural disasters turn a livable area into an unfit zone for habitation. Beyond being more numerous, there also are more damaging. Indeed, the Centre for Research on the Epidemiology of Disasters (CRED) estimates the cost of each natural disaster since 1970. Figure 1.3 displays estimated damage caused by natural disasters for nearly 50 years. These have skyrocketed over the years. It is most certainly due to the growing number of natural hazards but also to the global increasing wealth. With more damaging hazards and highly variable weather conditions, it becomes pretty costly for countries which economy relies on weather-sensitive sectors, such as agriculture.

Figure 1.2: Frequency of Natural Disasters by continent



Notes: Natural disasters regroup geophysical (earthquake, volcanic activity), meteorological (extreme temperature, storm), hydrological (flood, landslide), climatological (drought, wildfire) and biological (epidemic) events. An exhaustive list can be retrieved from emdat.be/classification. All disasters referenced here met at least one of the following criteria: 10 or more fatalities; 100 or more people affected; the country made a declaration of a state of emergency or a call for international assistance. Source: Author's elaboration on EM-DAT data.

Figure 1.3: Estimated damage caused by Natural Disasters by continent



Notes: The ordinate axis displays the total estimated damages related to the disaster, expressed in 10 millions US dollars (current value). These damages include all the economic losses directly or indirectly linked to the disaster. Source: Author's elaboration using EM-DAT data.

1.1.2 Developing countries, particularly affected by these changes

All parts of the globe are not equally affected by such climatic and natural events. One area is more hardly hit, Asia. Asia alone accounts for 47% of the world's natural hazards in 2015 (experiencing 160 out of the 344 occurring that year according to the UNESCAP (2017)). In terms of damages, it is not clear that Asia outweight the economic costs caused in America. But in terms of people affected, they exceed the number of casualities, injured and homeless left after a natural hazard. Figure 1.4 depicts the number of people that needed assistance following each natural hazard. Most of these people are located in Asia. Indeed, the world population got four times bigger during the past century (UN Population Division, 2007). It reached 7.7 billion people this year. Hence, mathematically, natural hazards strike more populous areas and generate more victims. It is especially true for developing countries. For now on, the population growing the fastest, live in Asia, and more particularly in China, India and the Southeast Asia. This area is predicted to be home to nearly 60% of the world population by 2050 (UN Population Division, 2007). According to the UN also, Central America and Africa are close behind in term of population growth. These densely populated areas are more vulnerable to natural hazards since they create more victims.

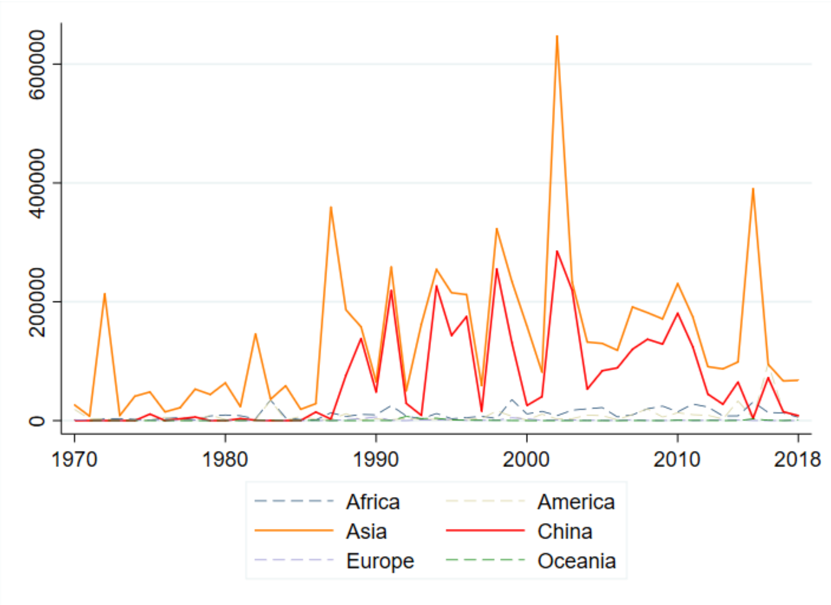
Furthermore, unusual climatic variations translate into adverse conditions for agriculture. This sector represents nearly one quarter of the economic losses due to medium and large natural disasters in developing countries (FAO, 2015). They destroy agricultural assets and infrastructure and cause damage in agricultural-dependent manufacturing subsectors such as the textile. In addition, climate variability alone explains 30 to 60% of yield variability worldwide (Ray et al., 2015). Hence, climate variability mitigates economic growth in countries where agricultural sector makes a significant contribution to national income. For this reason, Asia and the Pacific region alone concentrates 40% of global economic losses due to natural disasters [4], with China and Japan experiencing the greatest losses. Indeed, in China, the amount of natural catastrophes keep increasing (see Figure 1.5). With no surprise, the country is ranked as the third most hardly hit economically in 2017[5]. Rural areas, being home to agricultural activities, absorb major economic losses.

It all translates in numbers. Yearly, natural disasters are responsible for a 35 billion US dollars loss in damages between 1990 and 2000 (Mirza, 2003). Therefore, the developing world economic losses due to natural disasters are 20 times bigger

[4]Source: The 2017 Disaster-Report of UNESCAP (2017).

[5]Ranking by the non-profit and non-governmental organization (NGO) Germanwatch. The NGO sorts countries according to their vulnerability to the risk during the current year, it is based on losses in millions of US$ in purchasing power parity in 2017.

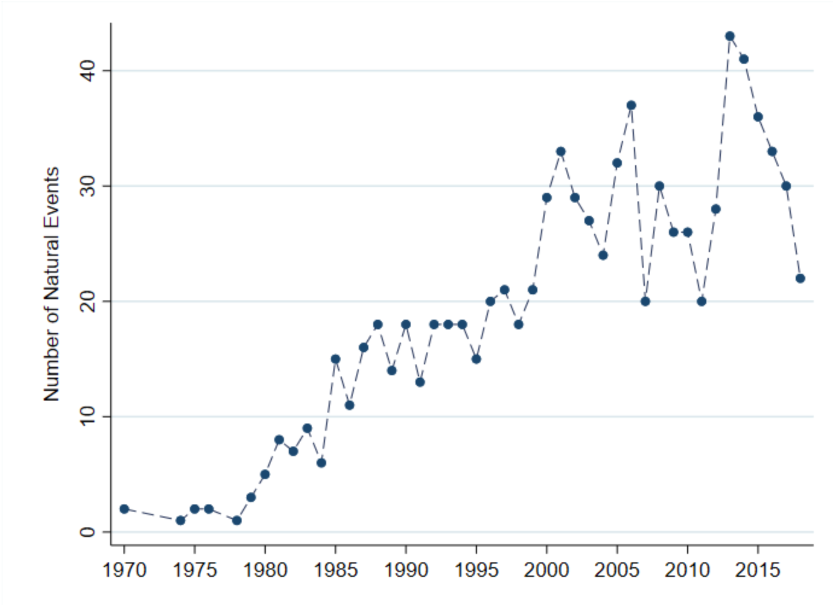
Figure 1.4: Estimated damage caused by Natural Disasters by continent



Notes: The ordinate axis displays the number of people affected by a natural hazard, either because they are injured, left homeless or only affected (individual that requires assistance during the emergency of the situation). It is expressed in thousands of people. Source: EM-DAT.

than those of the developed world (calculation in terms of gross domestic product (GDP) per capita made by Freeman (2000)). Developed countries, due to their numerous population, their localisation and their economic structure, are particularly vulnerable areas to climatic variability. An increasing option to adapt to climatic events is to use migration as a coping strategy to mitigate the risks.

Figure 1.5: Frequency of Natural Disasters in China



Notes: All disasters referenced here met at least one of the following criteria: they occurred 10 or more fatalities; 100 or more people were affected; the country made a declaration of a state of emergency or a call for international assistance. Source: Author's elaboration using EM-DAT data.

1.1.3 Migrating to adapt to the "New normal"

Indeed, the literature agrees to say that environmental conditions do affect migration, and it is particularly true in developing countries (Gray, 2009; Massey et al., 2010; Mueller et al., 2014; Kuhn, 2015). The intuition is that, when such natural hazards occur, people have three possible adaptation strategies: either they stay put, waiting for the disaster to end, accepting related costs; they stay put but have risk mitigation strategies that lower their economic losses; or they flee from the devastated areas, that is to say, home. One migrates if no other adaptation strategy is provided by either public or private sectors. Thus, very often, migration is a prime adaptation strategy in developing countries (Mirza, 2003; Reuveny, 2007; Noy, 2009). Indeed, these latter lack of financial means or technological skills to mitigate the risk *ex ante* by having for instance Early Warning Systems to inform the population, buildings made to resist to hazards, or widespread irrigation systems in case of droughts for agriculture; but also to limitate the costs *ex post* through quick interventions and efficient funding of the reconstruction. It is especially true in Asia where it gets more and more complicated to enforce adequate risk management strategies since the natural hazards are both getting more frequent and more damaging over time. Thus, curative options are preferred. Namely, risk management resources are mainly used for reconstruction and less for pro-active prevention (Amendola et al., 2008).

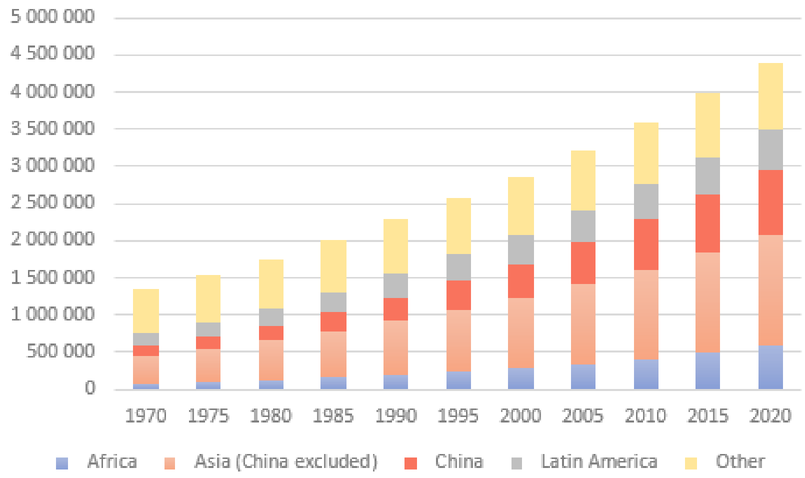
When migrating, even for environmental reasons, a migrant targets a location in order to maximize the difference in income between the origin and destination areas. Hence, cities are often prime targets. They are home to a more diversified economy, with better infrastructures and greater job opportunities, especially in developing countries (Yang, 1999; Sahn and Stifel, 2003; Nguyen et al., 2007; Hagen-Zanker, 2008). It translates into a wide gap in wages between rural and urban areas. Such a difference motivates rural dwellers to migrate. Thus, climatic variability can trigger rural-urban migration and increase the size of cities in the developing world.

Some economists provide evidence of such a link. However, most of these studies focus on developed countries. When they do not, they study Sub-Saharan countries. Problem is, the national context does matter to draw a conclusion on this link. Indeed, the impact of climatic variation on migration can be either positive (Barrios et al., 2006; Marchiori et al., 2012; Henderson et al., 2017) or negative (Hirvonen, 2016). Precisely, even though adverse climatic conditions or severe natural disasters give greater motivation to migrate and could, in turn, generate more out-migration from the affected areas; it also represents a loss of earnings in the short-run and could hinder migration by preventing the farmer to afford the cost of moving away.

Developing countries are interesting to study since there is a wide margin for urbanization. Within this context, environmental factors have room to strongly impact cities size[6]. As depicted in Figure 1.6, nowadays, most of urbanization worldwide takes place in the Asian continent. From 1970 to 2020, Asian urban population accounts for 37% to 54% of the global population (see Figure 1.7). China alone represents from 28 to 37% within the same period. For this reason, I focus my work on Chinese case since each climatic event affects a large share of people, generates wide economic losses , which, in turn, could create a massive flow of migrants looking for ways to maintain their level of income.

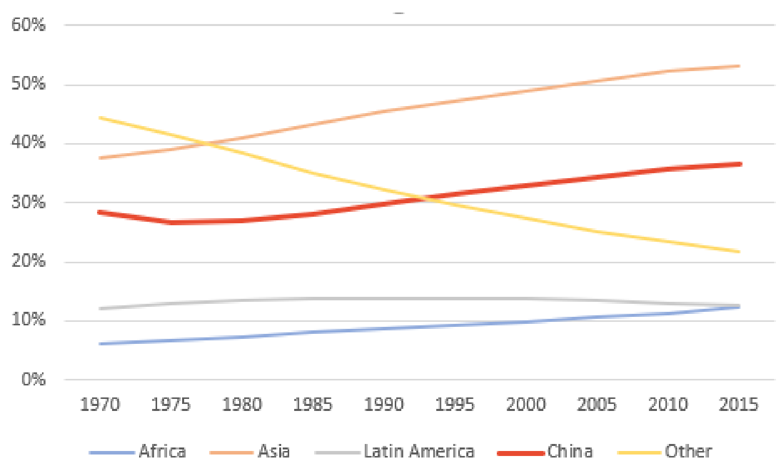
[6] Urbanization is defined by demographers as the increasing share of population living in urban areas (Poston and Bouvier, 2010)

Figure 1.6: Urban population by continent



Notes: The ordinate axis depicts the annual urban population at mid-year (in thousands). Year 2020 data are based on UN prospects. In the "Other" category belongs Oceania, Europe and Northern America. Source: Author's elaboration from the *World Urbanization Prospects: The 2018 Revision* provided by the UN.

Figure 1.7: Share of urban population out of the global one, for each region



Notes: The ordinate axis depicts the annual share of urban population for each region in the total urban population. In the "Other" category belongs Oceania, Europe and Northern America. Source: Author's elaboration from the *World Urbanization Prospects: The 2018 Revision* provided by the UN.

1.1.4 China, a relatable case study for developing countries

Even though economic studies on migration are often context-specific, many of Chinese features are characteristic of developing countries. Thus, some conclusions made in this thesis can be relatable for other developing countries, sharing some common characteristics.

For instance, studying China sheds light on migratory flows following natural events in a very populous country. Asia, Latin America and Africa all have quite densely populated countries with a high natural growth rate. Africa is even predicted to have a faster demographic growth than Asia for the years to come (UN Population Division, 2007). Namely, in relative numbers, African population growth is estimated to be 70% faster than Asian one. Hence, the lessons taught here can be helpful for African countries, when their population growth will skyrocket.

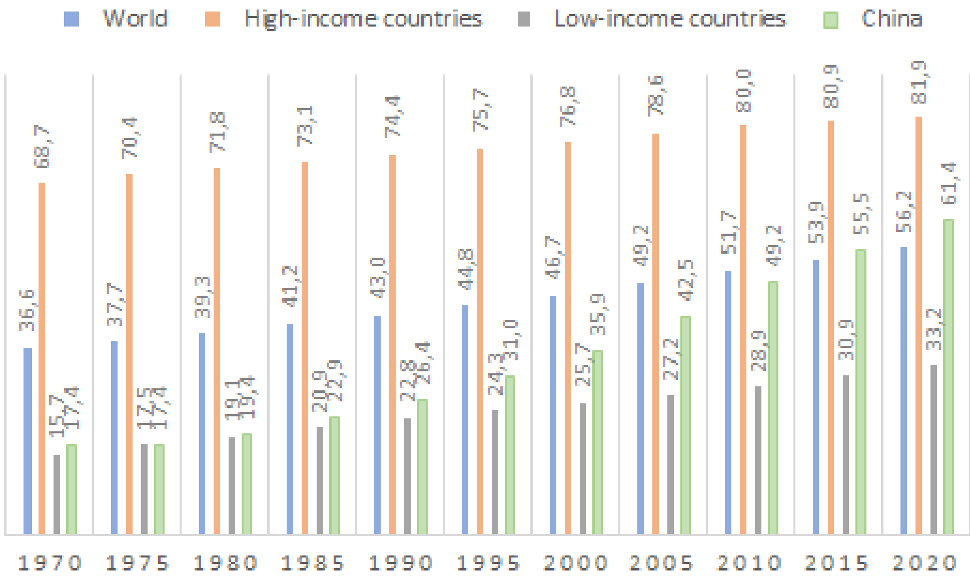
Also, as in many developing countries, migration is very costly for an individual in China. Indeed, costs of migration come from differents sources, as summarizes the work of Carrington et al. (1996). First, there is the physical cost of migration, namely the time and money spent in moving toward the destination area via any sort of transportation mean. Second is the adaptation cost to the destination area, that is to say the differences in labor and housing market but also the change in culture and sometimes in language. Last, the migrant faces uncertainty regarding housing and labor-market settings. For instance, a strong network at the destination can mitigate this cost.

In China, costs of migration are mainly institutional. The government enforces an Household Registration System *i.e.* the residence status depends on the place of birth. Namely, when migrating to a different administrative area, Chinese citizens lose access to many services such as the official housing market, educational structure, medical care, some public subsidies and so on (Wang, 2004). Thus internal migration causes the loss of many rights for a Chinese citizen, which tremendously increase costs of moving. This residence permit (the *Hukou*) is delivered by the police and can change over time. But converting a *Hukou* from a rural to an urban one is difficult, especially when targeting a large city.

Third, China, as a developing country, has an unfinished urbanization process. Namely, urbanization rate in China is rather low for its level of economic wealth. Indeed, comparing to high-income countries, China has still a small urban population as illustrated in Figure 1.8. Chinese urbanization rate was up to low-income countries level in 1970s -when its economic growth and therefore its urban process started- and increased tremendously to reach the world average in 2015. China still suffers from insufficient agglomeration of economic activity on one side, and a labor force surplus in the agricultural sector on the other side (Au and Henderson,

2006). This latter phenomenon is widespread among developing countries.
However, China is hardly comparable to countries whom urbanization only relies on urban population growth. Differently said, urbanization is the consequence of both urban population natural growth rate and net rural–urban migration. In Asia, and in China especially, urbanization is mostly the result of rural-urban migration (Tacoli et al., 2015). It comes in contrast with some developing countries, especially Sub-Sahara African ones, whom urbanization is the result of a high rate of urban population growth due to high rate of overall population growth. This contrast, in China, is the consequence of strict natality restrictions. In 1979, the Central government implemented a birth planning program, called the One Child Policy, that sets to one the number of children a family can have (Scharping, 2013). These constraints do not apply equally countrywide, parents from rural areas were allowed to have a second child if the first one was a daughter, in the beginning of the 1980s. Hence, natality restrictions particularly apply to urban areas and restrict urban population growth rate. The first supply source of new urban dwellers in China are rural migrants.
Last common feature, in China, internal migration is mainly uni-directional, that is to say, from rural to urban areas. This statement also applies to a large share of developing countries (Yang, 1999; Sahn and Stifel, 2003; Nguyen et al., 2007; Hagen-Zanker, 2008). Indeed, migration is greatly motivated by job opportunities. Yet, as Todaro (1980) declares, "The greater the difference in economic opportunities between urban and rural regions, the greater the flow of migrants from rural to urban areas". If, due to both climatic variability and natural disasters, the economic opportunities in rural areas decline, thus it will give further motivation both in China and in the rest of the developing world to migrate out of the countryside. Thus, it comes as no surprise when the Intergovernmental Panel on Climate Change (IPCC), in its report from 2014, states that climatic variations are expected to displace an increasing amount of people worldwide. This work onset is to investigate the consequences on cities size of both climatic variability and natural hazards, in a densely populated and frequently affected country. More generally, as discussed early, Asia is the region the most affected by natural disasters, but also the one producting most of the new urban population. Hence, adverse conditions for agriculture could further increase this movement toward cities. This zone, and China in particular, will serve as a lab to estimate how rural-urban migration is affected by these new climatic conditions. In this thesis, I investigate if changing climatic conditions and natural disasters do displace people as states the IPCC, and if so, if cities are considered as shelters in China. To do so, I present the structure of the thesis in the following section.

Figure 1.8: Chinese urban population ratio compared to the rest of the world



Notes: The ordinate axis depicts the annual percentage of population residing in urban areas at mid-year. The country classification as high-income or low-income one is based on 2016 GNI per capita from the World Bank. Source: Author's elaboration from the *World Urbanization Prospects: The 2018 Revision* provided by the UN.

1.2 Structure of the thesis

Between rivalry and synergy: A spatial analysis of urbanization in Chinese provinces

Motivation

Chapter 2 objective is to determine the potential causes of urbanization. Yet, as exhaustively documented by the literature, urbanization in China is greatly unequal between the east coast and the rest of the territory (Zhang and Shunfeng, 2003; Lin et al., 2015). Big cities have long been concentrated on the east part of the country, and urbanization slowly spreads westward since the economic reforms in 1970s. Furthermore, all top-destination provinces are geographically close if not adjacent, that is to say Guangdong, Zhejiang, Fujian and Jiangsu (city-municipalities excluded[7]). Some big cities start to emerge in the center of the country. More precisely, the main ones are Chongqing and Chengdu and they also are adjacent. Hence, looking at the data presented in Chapter 2, I make the assumption that a synergy effect exists between eastern cities, effect that also influence urbanization in inland China, and later on, in the western part. Though, going through the urbanization policy of the Central government, there could also be some competition between Chinese cities, according to their size and economic influence. Namely, very big cities have advantages that small and medium size ones do not, as Henderson et al. (2009) argue. The latter suffer from fewer public financial resources allocated by the Central government, less autonomy in decision making, less access to "transport corridors and rail capacity". Such hierarchy between cities could motivate local governments to expand the city size of their province to benefit from great financial resource and autonomy. Thus, this Chapter investigates whether proximity to a city triggers or rather hinders urbanization in a province. But also, what criteria dictates this relationship.

The existing literature

Why some cities are more attractive for a migrant than others? Rural-urban migration is widely studied by the literature. But pioneer work stressing the importance of geography in the urban process comes from Krugman (1991). He argues that urbanization is the result of a tension between "centripetal" forces that pull population and production to agglomerate and the "centrifugal" forces that hinder such concentration. The relative strength of centripetal and centrifugal forces determinate the urban landscape. Among theses centripetal forces, natural endowments of a particular area -proximity to a coast, to a river- increase the attractiveness of the destination for would-be migrants (Krugman, 1996). Along with these natural advantages, centripetal forces are also driven by market-size external economies (access to market: it includes the economic and opportunity cost of transport), pure external economies (knowledge). Centrifugal forces correspond to market and non-market related forces (commuting cost, urban land rent; congestion, pollution). Further than economic or geographical forces, this chapter underlying assumption relies on the role of relative distance between cities and their synergy or competitive effect on each other. Meijers (2005) has contributed to this literature by searching for synergy between administratively independent cities in the Randstad region of the Netherlands. He does so by computing complementarity ratios. He finds mixed results, meaning that the synergy keeps increasing in the

[7]A city-municipality in China is the highest level of classification for a city, meaning that a city has the same rank as a province in China administrative division. They obtain their own financial resources, independence in their expenditures and so on. Cities such as Beijing, Tianjin, Shanghai and Chongqing are municipalities.

Randstad region but some cities still have conflicting economic roles that prevent any chance of complementary.

Contribution to the literature

Chapter 2 of this dissertation identifies the determinants of urbanization in China, and takes into account the potential effect of the proximity to other cities. This work both contributes to the regional science and to the rural-urban migration literature. Indeed, it first presents a singular specification in spatial econometrics. To the best of my knowledge, it is among the first study to use a Spatial Durbin Error Model to estimate regional interactions. Second, it looks at rural-urban migration in China with a new perspective, acknowledging the influence surrounding cities have, on one province urbanization. Doing so, results show the existence of a synergy effect between neighboring provinces, when urbanizing. The factors driving urbanization in one province, also impact positively its neighbors', creating a virtuous circle of urbanization among provinces. Yet, results also show that the relationship is not monotonous. A threshold effect does exist. Up to a certain point, the neighboring province is so economically attractive - meaning great GDP per-capita, dense population, efficient transportation system- that it becomes a favorite destination. Then, the relationship between neighboring provinces becomes competitive.

Public Policy Implications

If anything, this chapter sheds additional light on the potential adverse impact on urbanization of proximity to a very attractive city such as the big eastern ones. Migrants preferences tend toward these cities rather than the neighboring ones. It echoes a great concern on Chinese urbanization. Big cities keep growing despite the restrictive regulation on migration, because they remain favorite destination for migrants. These mega-cities then become hardly manageable or breathable in the long run (World Bank and DRC, 2014). As a solution, Henderson et al. (2009) advocates that restrictions on migration could be relaxed for intra-province movement but not for inter-province one. Indeed, as documented by Zhang and Shunfeng (2003), most of migrants living in eastern cities -cities with the highest GDP *i.e.* the most attractive economically- are from inland or western China. Regulating inter-province migration only would enhance the intra-province one and reduce urban development disparities in China.

Are cities shelters for rural dwellers experiencing weather variations? Evidence from China

Motivation

As evidenced in the previous chapter, lack of job opportunities in the rural area is a main factor in the migratory decision. Yet, weather variations significantly impact these job opportunities by affecting both agricultural production and productivity (Schlenker and Roberts, 2009; Lobell et al., 2011; Ray et al., 2015; Challinor et al., 2014; Lesk et al., 2016).. As a consequence, less people are able to earn a living from agricultural activities, giving incentives to out-migrate from rural areas to reach better life conditions (Martin et al., 2014; Falco et al., 2018). Rural-urban migration becomes an adaptation strategy to secure the household income during the year, when severe weather variations occur. In developing countries, the migratory response following weather anomalies is two-sided. On one hand, in poor countries, people have fewer options to adapt to weather anomalies. They have low access to agricultural insurance and no possibility to self-insure. Migration becomes the last resort (Barrios et al., 2006; Beine and Parsons, 2015). On the other hand, farmers in poor countries have less access to credit and experience strong liquidity constraints. By further tightening their liquidity constraints, weather variations unable them to afford migration cost, prevent them from moving and trap them in the affected areas (Black et al., 2013; Mastrorillo et al., 2016; Cattaneo and Peri, 2016; Otto et al., 2017). As results mostly depend on the country specific context, I investigate Chinese particular settings.

The existing literature

Indeed, in the related literature, no consensus holds on the impact of weather variations on migratory behaviors. On one hand, it could trigger migration. Barassi et al. (2018) investigate internal migration between Chinese provinces following climate anomalies -temperature, precipitation and sunshine variations- between 1987 and 2015, on a three-dimensional panel dataset (time, sending and receiving provinces). They find that increased temperature and precipitation significantly foster migration while greater sunshine hinders migration to another province. In line with these results, Yang (2018) uses a theoretical and an empirical model on individual-level panel data on more than 30,000 Chinese rural residents, to assess the influence of peaks of temperatures on their likelihood to migrate. Evidence shows that rural dwellers are keen to out-migrate to work outside their village, if the crop yields decrease in theirs. On the other hand, others stress the absence of migraton flows following weather variations. For instance,Zheng and Byg (2014) conduct a survey on 162 household from three different villages in Lijiang, Yunnan province. They estimate that, after a drought or a hailstorm, farmers prefer to stay put.

Contribution to the literature

This work investigates the link between weather variations and rural-urban migration in China, using satellite data on a grid-level panel basis. It first contributes to the literature by the original use of nighttime lights as a proxy for city size. Indeed, the use of low-frequency census data as in the previous chapter is not suitable for a study on short-term population movement. As argued using both the chapter data and some literature on the matter (such as Zhang and Seto (2013) work), I argue that nighttime lights are a good fit to estimate the Chinese city size. Second, this work contributes to settle the on-going debate on the impact of weather variations on Chinese internal migration. It first shows evidence of an immediate migratory response toward cities following slow-onset events such as rainfall shortage. Second, results also suggest that migrants return home one year following the shock. It would further motivate the idea that Chinese farmers migrate to maintain a certain level of income for the household, in the short-run. Last, this chapter contributes to highlight the heterogeneous response in migration whether the climatic event has a slow or rapid-onset. Indeed, people move if there is a drought, but do not if a flood of equivalent intensity occurs.

Public Policy Implications

From a public policy perspective, the main result of the chapter is that, rural dwellers lack of coping strategies when facing weather anomalies. Indeed, weather variations affect farmers income, that suffer from further liquidity constraints, and are unable to migrate for financial reasons. Two solutions appear. First possibility, if institutional regulations were relaxed, migration could be a coping strategy against weather variations at last. People would not have to stay put due to migratory restrictions that inflate migration cost. Second possibility, central government should invest in rural labor and area as also suggested by Henderson et al. (2009). More qualified rural dwellers and better public infrastructures will facilitate the search for alternative income in rural areas. There will endorse the role of a coping strategy.

When does it go back to normal? A Natural Experiment on Wenchuan earthquake impact on migration to cities

Motivation

From 2000 to 2016, China has experienced in average three natural disasters a month[8]. In the economic literature, migratory response is different whether the natural disaster has a slow or rapid-onset[9]. Indeed, for instance, Koubi et al. (2016) examine five different developing countries migratory response following gradual and sudden-onset events. They find that droughts, a gradual environmental event, are less likely to trigger migratory movement whereas floods, a sudden-onset disaster enhance migration. In constrast, in this thesis previous chapter, findings show the exact opposite for China. Namely, floods trigger less movement than droughts. These contrasting results could be imputed to Chinese particular context, in particular rapid intervention led by a strong Central government, following natural hazards. Because China presents a particular setting, this chapter proposes to investigate the use of migration as an *ex post* risk management strategy when a severe sudden-onset disaster occurs.

The existing literature

The literature emphasizes two sorts of consequences following natural disasters. First, people from affected areas can benefit from the reconstruction, which can either give job opportunities and prevent migration; or increase the level and quality of local infrastructures following the reconstruction. Thus, earthquakes could be responsible for the so-called "creative destruction". Gignoux and Menéndez (2016) look into long-term effects of a series of earthquakes on economic outcomes of a set of earthquakes taking place in rural Indonesia since 1985. They find that people do not migrate out of affected areas. At the opposite, migration diminishes following an earthquake. It translates the fact that people only suffered from economic losses in the short-run. They recover in the medium-run (between two to five years after the shock) and exhibit income and welfare gains in the long-run thanks to the reconstruction of local infrastructures. Second, a sudden-onset disaster can also negatively impact people income and generate out-migration. For instance, comparing 2004-hurricanes and Katrina, Smith and McCarty (1996); Smith et al. (2006) find that Katrina created more permanent migration than the

[8] Calculated based on the data from 2000 to 2016, using Emergency Events Database (EM-DAT) thoroughly discussed in Section 4 and 5.

[9] By rapid-onset disasters, scientists refer to natural disasters that arrive rapidly and with short if not zero warning. Are part of that list floods, volcanic eruptions, earthquakes, tornadoes, wildfires, tsunamis (Bates, 2002). Slow-onset disasters are gradual. Droughts, desertification are considered as such.

2004-hurricanes that occurred in Florida, USA. The rationale for this finding is that Katrina was far more damaging economically than the 2004-hurricanes. It implied more job losses and therefore, more motivation to migrate.

Contribution to the literature

The present chapter aims at examining migratory response after a sudden-onset disaster, that is to say, Wenchuan earthquake, and check if the efficiency of public intervention in China is responsible for the low migratory impact. To do so, I use Wenchuan earthquake as a natural experiment for investigating the impact of sudden natural hazards on migration patterns, within a Chinese province. To the best of my knowledge, this work is the first to do so. I use high-frequency satellite data, that capture annual light density at night, to proxy the evolving size of cities. In China, since natural population growth rate is quite low due to the still on-going One Child Policy[10], rural-urban migration is responsable for most of the city size growth. As for the empirical technique, I match Sichuan province with a counterfactual built using the Synthetic Control Method (SCM). Results show negative effects of Wenchuan earthquake on Sichuan city size. In accordance with the results in this thesis previous chapter, natural hazards prevent migration from happening. Cities, probably also affected by the event, no longer attract migrants. Plus, results also show that, three years after the shock, in 2011, the effects on migration are null. Sichuan experiences a “back to trend” migratory behaviors, suggesting that rapid-onset naturals disasters have no permanent impact on migration patterns. The timing of this return-to-trend exactly coincides with the end of the three-year reconstruction plan led by Chinese government.

Public Policy Implications

If the results suggest the effiency of the Chinese government following Wenchuan earthquake, the private sector was complety missing from the rescue forces. Indeed, insurance companies contribution to the reconstruction following the disaster did not exceed 0.3% of the total economic losses (Wu et al., 2012). Currently, farmers still do not have a widespread access to crop insurance in China (Boyd et al., 2011). Even though crop insurance exist in theory, it is still hardly affordable for small farmers, that is to say, the most vulnerable population regarding natural hazards (Wang et al., 2012). Thus, the government has a role to play in cultivating the disaster insurance market, make its access easier and more affordable, but also by creating strong incentives for the farmers to subscribe. Hence, efficient coping

[10] Even though this policy has been relaxed in recent years, it still largely restrict the natural growth rate of the population.

strategy in rural areas will reduce the willingness to move, and above all, prevent the worsening of poverty when no coping strategy exists.

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Chapter 2

Between Rivalry and Synergy: A spatial analysis of urbanization in Chinese provinces

2.1 Introduction

Geographically large countries often suffer from a wide variety in regional development. Chinese urban process is no exception. In 2015, the east coast alone is home to nearly half of the Chinese city dweelers (44%), when western provinces[1] only host 18% of them[2]. City growth is the result of two distinct phenomena: the natural growth rate of the urban population and rural-urban migration. Since 1979, China regulates natality via the One Child Policy. It restricts to one the number of children a couple can have[3]. Some exceptions occurred among the rural population, notably for some ethnics groups. However it was thoroughly enforced in urban areas. Hence, rapid urbanization growth in China is mainly attributed to rural-urban migration[4] (Zhang and Shunfeng, 2003). Explaining the difference in attractivity of Chinese cities is the point of focus of this chapter.

The unequal development of cities between the east coast and the rest of the territory has been exhaustively documented by the literature (Zhang and Shunfeng, 2003; Lin et al., 2015). Big cities have long been concentrated on the east part of the country, and urbanization slowly spreads westward since the economic reforms in 1970s. Furthermore, all top-destination provinces are geographically close if not adjacent, that is to say Guangdong, Zhejiang, Fujian and Jiangsu

[1]The term province refers by extension to the first level of administrative division. Are part of this group: 22 provinces, 5 autonomous regions (province where a large share of the population is part of a minority ethnic group, such as Tibet, Inner Mongolia, ...) and 4 municipalities (which are cities with provincial power, such as Beijing, Shanghai, Tianjin, Chongqing). These provinces are classified in different regions (The East, The North-East, The Center, The West), as presented in Table A6.

[2]Source: National Bureau of Statistics of China (NBSC) in the 2015 China Statistical Yearbook at City-level.

[3]Tools to ensure compliance were contraception, sterilizations or abortions but also enormous fines *ex post* if some violations occurred.

[4]A detailed definition of rural-urban migration is proposed in the Appendix, in Paragraph 2.6

(city-municipalities excluded[5]). The biggest cities at the center of the territory are Chongqing and Chengdu and they also are adjacent[6]. The implied hypothesis here is that a synergy effect exists between eastern cities, effect that also influence urbanization in inland China, and later on, in the western part.

However, going through the urbanization policy of the Central government, there could also be some competition between Chinese cities, according to their size and economic influence. Namely, very big cities have advantages that small and medium size ones do not, as Henderson et al. (2009) argues. The latter suffer from fewer public financial resources allocated by the Central government, less autonomy in the decision-making, less access to "transport corridors and rail capacity". Such hierarchy between cities could motivate local governments to expand the city size of their province to benefit from great financial resource and autonomy. Thus, this chapter investigates whether proximity to a city triggers or rather hinders urbanization in a province. But also, what criteria dictates this relationship.

In this chapter, I identify the determinants of urbanization in China and bring new elements to explain its great diversity in urban development. I look into spatial spillovers among provinces to explain why would-be migrants massively head toward cities located within the same area (that is to say, the east coast). This work contributes to both regional science and rural-urban migration literature by presenting a singular specification in spatial econometrics, the Spatial Durbin Error Model (SDEM), but also by looking at rural-urban migration in China with a new perspective. To be more precise, using this method, I identify the determinants of urbanization while taking into account the potential effect of the proximity to other cities. The analysis is carried out on provincial panel data, over 1980 and 2015. Results show the existence of a synergy effect between neighboring provinces, regarding their process of urbanization[7]. Being close to an attractive province -characterized by a high GDP per-capita, dense population or an efficient transportation system- stimulates one province's urbanization rate. However this relation is not completely monotonous, a threshold effect exists. Indeed, this synergy is jeopardized when the neighboring province is too economically attractive. Then, the relationship become competitive between neighboring provinces to attract the would-be migrants.

[5]A city-municipality in China is the highest level of classification for a city, meaning that a city has the same rank as a province in China administrative division. They obtain their own financial resources, independence in their expenditures and so on. Cities such as Beijing, Tianjin, Shanghai and Chongqing are municipalities.

[6]Based on 2010 Census data provided by the NSBC.

[7]This chapter focuses on inter-province migration *i.e.* migration from people native of another province. Crossing provinces to migrate is more costly and therefore less widespread than intra-province migration. Yet, it is the fastest growing source of migration since 1990s in (Su et al., 2018) and also the main responsible for the eastern/western divide in China

Why some cities are more attractive for a migrant than others? Rural-urban migration is widely studied by the literature. Pioneer work stressing the importance of geography in the urban process comes from Krugman (1991). He argues that urbanization is the result of a tension between "centripetal" forces that pull population and production to agglomerate and the "centrifugal" forces that hinder such concentration. The relative strength of centripetal and centrifugal forces design the urban landscape. Centripetal forces include natural endowments -proximity to a coast, to a river- as attractive features for would-be migrants (Krugman, 1996). Along with these natural advantages, centripetal forces are also driven by market-size external economies (access to market: it includes the economic and opportunity cost of transport), pure external economies (knowledge). Differently, centrifugal forces correspond to market and non-market related forces (commuting cost, urban land rent; congestion, pollution). Many economists confirmed the significant impact of geographic factors in urban growth. The design of the urban landscape is greatly driven by the proximity to a coast or a mountain (Rappaport and Sachs, 2003), but also by weather conditions (Rappaport, 2007). It could explain why all top-destination provinces are geographically close (see Figure 2.2). They could all benefit from proximity to the coast for instance. However it would not explain why the urbanization process spreads westward.

The remaining explanation would be the presence of synergy effects among neighboring cities. The provinces at the center and the west of China benefit from positive spillovers due to their proximity to big coastal cities. By definition, a synergy means that when two or more actors cooperate/are part of the same group, positive externalities may be created and exploited by these actors. Meijers (2005) investigates this phenomenon among administratively independent cities in the Randstad region of the Netherlands. He computes complementary ratios to estimate whether these cities cooperate or compete. Results are mixed. He finds that cities cooperate most of the time. Yet, a reverse effect exists when focusing on the "less complementary economic roles of the cities". Similarly, it is possible to measure the degree of complementarity among different areas with a spatial econometric model such as the SDEM.

Chinese particular settings are favorable to the emergence of synergy effects between metropolises. Indeed, there could be synergy between cities even if they are administratively and politically independent, as long as they are located in close proximity and well connected through infrastructures (Meijers, 2005). Chinese massive investment in term of infrastructure could stimulate synergy between eastern and central provinces in China. According to the World Bank (1994), Chinese government spendings in infrastructures are well above the average for a developing country (6.5% of GDP in 1993 against 4% in average). By 2009, these investments reached 15% to 20% of GDP for the coastal provinces and municipal-

Figure 2.1: Chinese provinces top-destination for a migrant

Notes: The top-destination provinces were computed by Zhang and Shunfeng (2003). They excluded municipalities that are also top-destination for rural migrants (Beijing, Chongqing, Tianjin, Shanghai). Source: Author's elaboration using data from the China Labor Statistical Yearbook of 1999, issued by the National Bureau of Statistics of China (NSBC).

ities (Démurger, 2001). These investments more intense in the eastern part of the country, are prone to generate more interactions among neighboring cities. Urbanization would therefore develop westward, along with the infrastructure system. This chapter aims at testing this assumption.

Hence, the rest of the chapter is organized as follows. Section 2.2 presents the sample and discusses the chapter assumptions. Section 2.3 describes the empirical strategy. Section 2.4 exposes the main empirical results. Section 2.5 tests the robustness of the results. Section 2.6 draws the main conclusions.

2.2 Data and Descriptive Statistics

2.2.1 Sample

The sample is divided into provinces, the largest administrative area in China. Then, as stipulates the Constitution of the People's Republic of China, provinces are divided into prefectures, that are divided into smaller administrative areas i.e. the counties, then divided into townships. The data come from linked administrative data covering 28 of the 31 Chinese provinces from 1980 to 2015. To construct a balanced database (required in spatial econometrics), and considering that the dependent variable is only available in Census data, I used 5-year periods and averaged the data per variable and province within this period. Three provinces, namely Chongqing[8], Hainan and Tibet, are excluded due to a lack of data on this period. Hence, with 8 time periods and 28 provinces, it produces a balanced panel with 224 observations.

To construct the sample, I compile data from various sources. Explanatory variables data[9] come from *China Statistical Yearbooks* (extracted from the China Data Center (2017) website). Concerning the urbanization rate, it comes from Liu et al. (2003) for the period 1980-1995 and from China Data Center (2017) for the period 2000-2015. Indeed, the National Bureau of Statistics has used various kinds of definitions of urban population over time. Before 2000-Population Census, the definition of urban population was strictly administrative. This definition remains arbitrary, given that it is based on administrative borders of the city, excluding, for example, non-urban Hukou residents. Since 2000-Census, the definition of an urban area has been reshaped, using physical indicators such as proximity to urban constructions and population density. Thus, this last one becomes more relevant and reliable than the former (Chan, 2007). To stay consistent in this analysis, I use the 2000-Census definition, using Liu et al. (2003)'s adjusted data.

To take into account spatial correlation among neighboring provinces, spatially lagged variables are created. For this purpose, I construct a spatially weighted matrix, i.e. a matrix where each element $w_{i,j}$ equals the inverse of the distance $1/d$ between two provinces. Note that the distance d is approximated by the kilometers separating the capitals of i's and j's provinces. Finally, to obtain the spatially lagged variables of province i, I weight the economic variables of the neighboring provinces by the inverse distance, separating them from province i. The further the province is located, the less weight it has.

To get a clear picture, the variables used in the model are detailled in Table A5 in

[8]Data are unavailable for the city of Chongqing before 1996, date of the municipality creation. To be consistent, city of Chongqing was treated as part of Sichuan province.

[9]Summary statistics of the sample variables are available in Table 2.1.

the Appendix.

2.2.2 Descriptive Statistics

This section provides stylized facts of the variables used in this chapter. Table 2.1 presents some basic statistics of the dependent variable (urbanization rate of province i), the direct regressors (economic and infrastructure proxies for province i) and the indirect/neighbors regressors (economic and infrastructure proxies of the provinces j, k and l *i.e.* the provinces in close proximity of i).

Table 2.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Dependent Variable				
Urbanization rate	39.301	18.777	10.37	89.304
Direct Independent Variables				
GDP	12.431	18.224	0.17	98.337
GDP^2	486.65	1312.333	0.029	9670.081
Pop. Density	367.132	494.085	5.048	3780.438
Rural Employment	67.245	16.054	21.178	89.681
Income Difference	4.483	5.039	0.071	22.273
Education	29.15	39.5	0.294	192.18
Transport Quality	1000.87	755.315	77.016	4554.501
Agr. Subsidies	15.238	13.566	0	88.492
Independent Variables Spatially Lagged				
GDP	12.628	15.295	0.333	56.806
GDP^2	481.751	850.997	0.173	3510.948
Pop. Density	417.175	178.368	170.488	1259.282
Rural Employment	67.278	8.628	33.105	79.383
Income Difference	4.493	4.827	0.16	15.714
Education	30.836	32.776	1.908	128.331
Transport Quality	1016.032	602.412	192.65	3222.934
Agr. Subsidies	13.133	5.009	3.722	39.894

Notes: It is a balanced panel dataset, each variable counts 224 observations. Detailed definition of all the variables used in this chapter are proposed in Table A5, in the Appendix. Source: Data from NBSC.

Second, Figure 2.2 displays empirically, the uneven regional development of urbanization. Looking at the data, urbanization did not really start before 1990, long after the first economic reforms of 1978, responsible for China economic growth. Before 1990, the only urbanized areas (with an urbanization rate exceeding 50%) were Beijing, Tianjin and Shanghai. The first actual provinces to pass the 50%

bar were located on the east coast (namely Guangdong, Jilin and Heilongjiang), in 2000, when the country was already close to a two-digit annual GDP growth. Second, the urbanization process slowly spreads westward. Provinces around Beijing and Tianjin, on the North-East, and around Shanghai and Guangdong in the Center started to urbanize, and finished by reaching the 50% bar. It suggests the positive influence of the close proximity to large metropolises, to start the urbanization process.

To continue in that direction, I examine the urbanization rates of adjacent provinces. Figure 2.3 depicts how one province urbanization rate reacts to variations of its neighbors city size. Here is presented the evolution for 6 different provinces, from various regions[10].

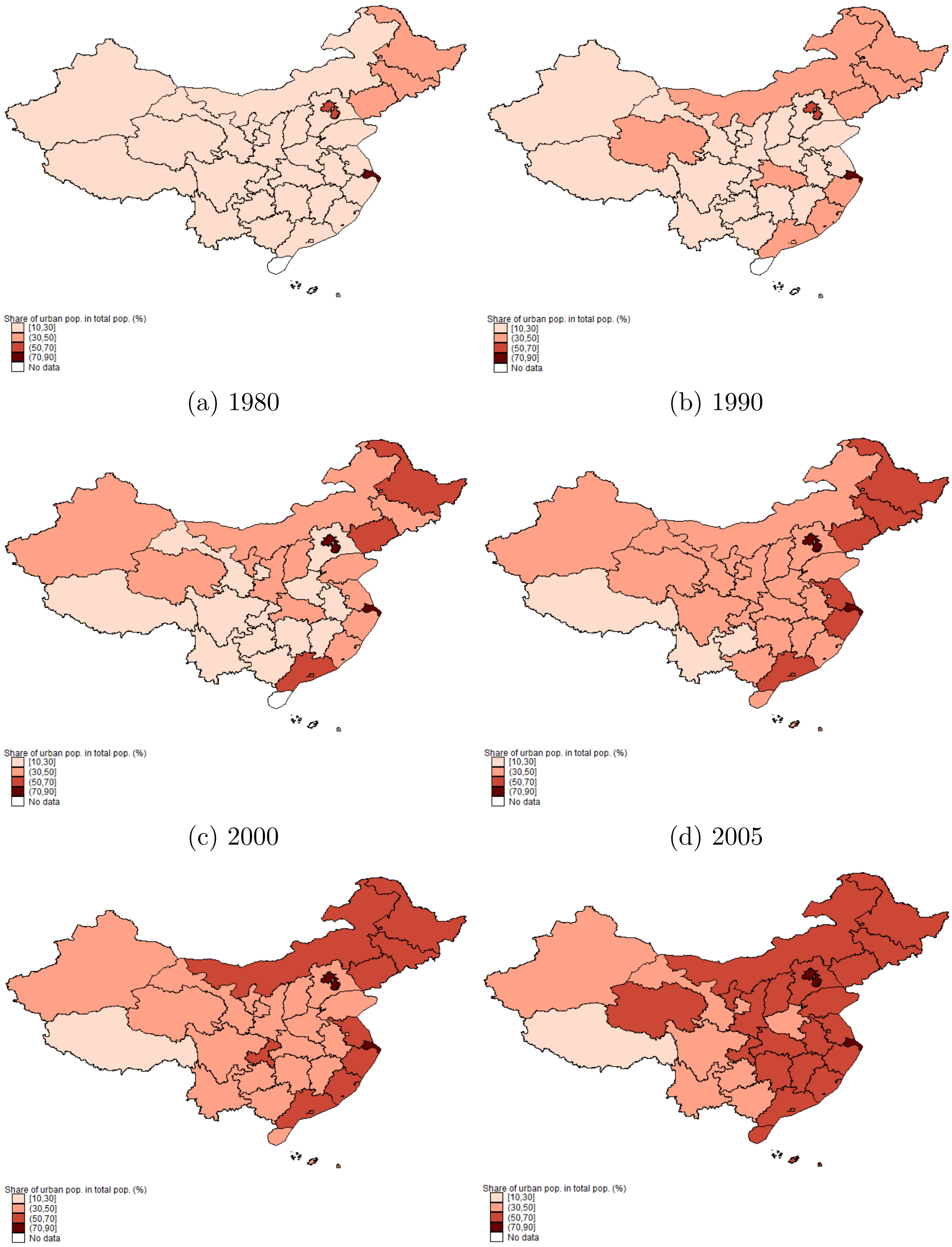
On the one hand, three of them (namely Guangxi, Ningxia and Shaanxi) present a positive and perfectly linear relationship between their urbanization process and their neighbors' over the period of analysis. This correlation supports the synergy theory among Chinese provinces, regarding urbanization.

On the other hand, three others exhibit a not so linear relationship between their urbanization rate, and their neighbors'. For Shanghai, Guangdong and Jilin, the nature of spatial interactions among neighbors is not so clear. At the end of the study period, the relationship reaches a turning point. Taking the case of Jilin province, the more neighboring cities grow, the less its urbanization rises. Hence, up to a certain point, the positive relationship between neighboring provinces vanishes.

The scale of each figure being different, this reversal happens at distinct levels of urbanization rates. No threshold level can be clearly identified yet. Also, the provinces experiencing a threshold effect all belong to the east coast. This area is particularly attractive for would-be migrants, the top-destination being in this zone (Figure 2.1). Yet, a migrant is attracted by "great centres of commerce or industry" (Ravenstein, 1885) rather than the size of the city itself. Therefore, the empirical study should focus on the GDP as the trigger of this change of relationship among provinces.

[10]Shanghai and Guangdong are from the East, Jilin The North-Est, Guangxi from the Center, Ningxia and Shaanxi from the West part of the territory (see Table A6).

Figure 2.2: The evolution over time of urbanization among Chinese provinces



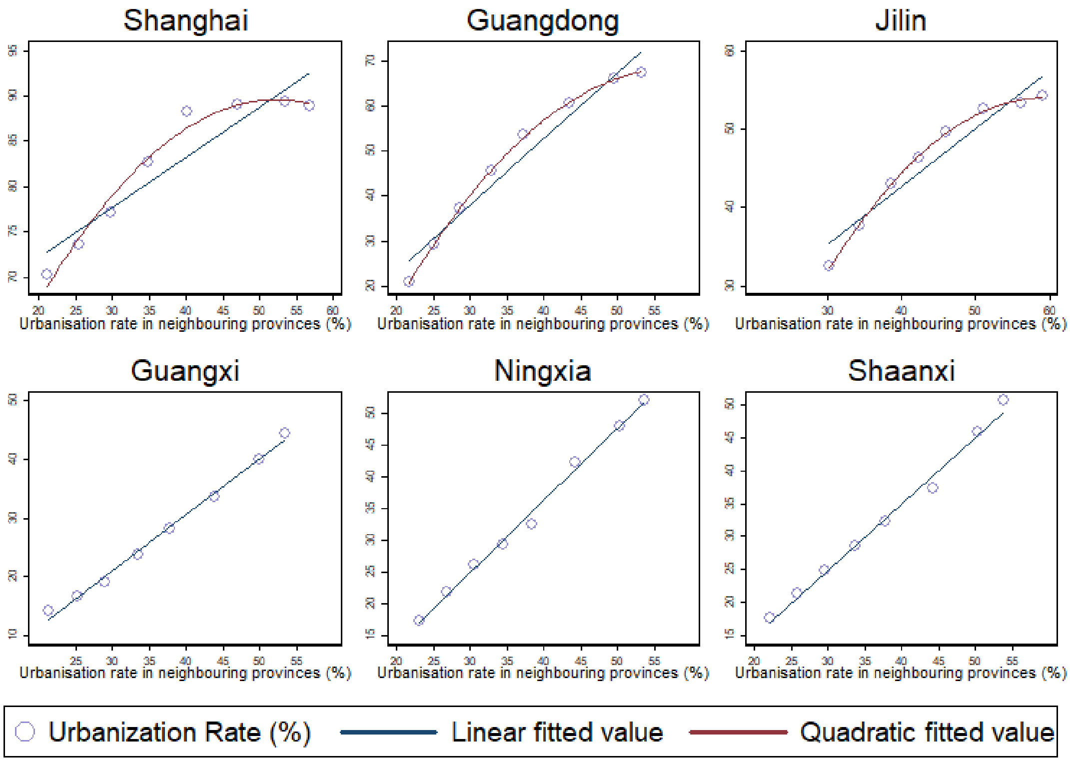
(a) 1980 (b) 1990

(c) 2000 (d) 2005

(e) 2010 (f) 2015

Notes: The proportion of urban dwellers in the total population (urbanization rate) was computed by the author using *China Census* and *Statistical Yearbooks* from 1980 to 2015. Within this time interval, urbanization rates go from 10 to 90%. The darker the color, the more urbanized is the province. Source: Author's elaboration.

Figure 2.3: Spatial correlation between neigbhoring provinces, regarding urbanization



Note: The y-axis represents the urbanization rate of a province i (that can be either Shanghai, Guangdong, Jilin, Guangxi, Ningxia or Shaanxi). It is expressed in percentage. The x-axis exposes the urbanization rate of its neighboring provinces, in average. The urbanization rate of each neighboring province has been weighted by the inverse distance that separates both provinces. Two fitted values have been computed according to the shape of the relationship between the province i and its neighbors. The data come from *China Statistical Yearbooks.*

2.3 Empirical strategy

2.3.1 Empirical specification

The core of the chapter is to identify spatial effects between neighboring provinces, in China. Two models dominate in regional science (LeSage, 2014), namely the Spatial Durbin Model (SDM) and the Spatial Durbin Error Model (SDEM). They provide a very different demonstration. The first one looks for *global* spatial spillovers. The SDM assumes that a change in province i triggers a series of adjustments so that it modifies the long term equilibrium of the whole sample, ending up impacting the province responsible for that initial change (the so called "feedback effect" and "endogenous interaction"). On the contrary, the SDEM looks for *local* spatial spillovers i.e. a change in province i impacts neighboring provinces only. There are no feedback effects or endogenous interactions.

I choose to use the SDEM for several reasons.

Generally speaking, spatial spillovers are more likely to be local. Global ones remain rare (Vega and Elhorst, 2013; LeSage, 2014). Furthermore, according to regional science specialists, the SDM has low chances to provide proof of a causality between the dependent variable and the explanatory ones (Gibbons and Overman, 2012; Vega and Elhorst, 2013). These critics have been raised because there are both endogenous and exogenous interaction effects in SDM. Yet, in practice, these effects are hardly distinguishable from each other. Thus, without strong theoretical foundations that spatial spillovers are global, it is better to use SDEM and hence to identify exogenous interaction effects only (Gibbons and Overman, 2012; Vega and Elhorst, 2013; LeSage, 2014).

More specifically, descriptive statistics and theoretical foundations point out the SDEM as being the most suitable specification due to persisting inequalities between Chinese provinces. About the descriptive statistics, urbanization did not exceed 50% for any other provinces than eastern ones before 2010. The urban process started with eastern provinces in 1980, and slowly reached the central ones that passed the bar of the 30% between 1990 and 2000, and then the bar of the 50% in 2010 (Map 2.2). The process was slow, started with the eastern provinces to go softly westward. The pace of the process seems to corroborate the theory of localized interactions among provinces. Concerning the theoretical background, Henderson et al. (2009) studied rural-urban migration and also found the process to be very localized in China, compared to other countries. In the 1990s[11], local reorganization was responsible for half of China's urbanization increase. Long-distance migration is less common than in other large countries such as Brazil or the USA. Therefore, with all these elements, I expect the identification of local

[11]These years, many inland provinces passed the bar of the 30%, see Map2.2

spatial interactions in China.
Additionally, the global model (SDM) specifies the presence of feedback effect. In this case, it would mean that the increase of j's province urbanization rate will affect back the one of province i (the one responsible for the initial change, here, the east coast). Such concept is hardly defendable in this case.
Finally, in the SDEM design, it suggests that the channels of transmission of the spatial interactions between neighboring are the *determinants* of urbanization. It means that the growth of i's urbanization rate will not be explain by the growth of j's urbanization rate itself, but by all the factors that make province j attractive for would-be migrants. This design fits the theory. It is not because a city is big that it is attractive. It is attractive because it generates revenues through its wide economic activity and therefore, great job opportunities, but also, because the bigger the city, the better equipped it is in term of infrastructure. All these elements build a city attractiveness, and not the size of its population alone.
Thus, I estimate a SDEM as designed by Elhorst (2014), using the maximum likelihood (ML) estimator:

$$\begin{aligned} Y &= \beta_1 \cdot X + \beta_2 \cdot WX + u \\ \text{where} \quad u &= \lambda \cdot Wu + \varepsilon \quad \text{and} \quad \varepsilon \backsim N(0, \sigma_\varepsilon^2 I_N) \end{aligned} \tag{2.1}$$

where Y is a N x 1 vector reflecting the dependent variable *i.e.* the urbanization rate of each province of the sample (i=1,...,N). X is a N x K matrix of control variables. Its parameter β_1 is a K x 1 vector. The rate of urbanization is measured as the share of urban population in total population. X is a N x K matrix of control variables. Its parameter β_1 is a K x 1 vector. The list of controls is presented in Table A5. Their introduction in the model is being discussed in the subsection below. W is a spatially weighted matrix. It defines the measure of distance included in the model. The shape looks as follows[12]:

$$W = \begin{pmatrix} 0 & \frac{1}{d_{12}} & \frac{1}{d_{13}} & \cdots & \frac{1}{d_{1N}} \\ \frac{1}{d_{21}} & 0 & \frac{1}{d_{23}} & \cdots & \frac{1}{d_{2N}} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{1}{d_{N1}} & \frac{1}{d_{N2}} & \frac{1}{d_{N3}} & \cdots & 0 \end{pmatrix}$$

with d_{12} the distance in kilometers separating province 1 capital (here, Anhui) and province 2 capital (Beijing). The matrix is normalized by dividing each element (i, j) by the sum of the line. WX is the matrix of the spatially lagged endogenous

[12]The choice of a distance matrix is challenging, the matrix needs to fit the theory but also remain as simple as possible (LeSage, 2014). I use the distance between province capitals because they are the most attractive cities of each province, hence, the most relevant to consider when studying rural-urban migration.

variables which reflects neighboring provinces values. Thus β_2 is a spatial autocorrelation parameter. u is a vector of error terms; it includes a spatially correlated part ($\lambda \cdot Wu$) and an independently and identically distributed part (ε). Wu represents another part of the spatial interactions between provinces. Thus, λ is another parameter of spatial autocorrelation between provinces. This latter is defined as the presence of interdependence between neighboring areas (Le Gallo, 2004). Detecting spatial autocorrelation allow me to identify if neighboring provinces are urbanizing in a competitive ($\lambda < 0$) or complementary manner ($\lambda > 0$).
To control for natural endowments impacts on the urbanization process (proximity to a coast, better weather conditions, *etc.*), I include dummy variables that capture the province fixed effects (FE). Indeed, province FE remove the effect of those time-invariant characteristics so I can assess the net effect of the predictors on the outcome variable (Torres-Reyna, 2007). However, time FE are not included in the model. Indeed, time FE can prevent the regional economist from identifying spatial interaction because it is one way to control for it (Elhorst, 2014). By smoothing the shocks' impacts over time, I cannot observe whether neighboring provinces react the same way or not after a shock. It erases indications on the nature of their relationship (complementary or competitive). Besides, to build a 5-year periods sample, I average the annual explanatory variables. Thus, the observations will not be driven by short-term shocks.

2.3.2 The economic forces driving urbanization

Let's discuss what composes the matrix of control variable. To identify what could channel urbanization among provinces, a series of variables is used. Indeed, according to the laws of migration, the major causes of migration remain economic (Ravenstein, 1885). Now that the integration of distance and spatial interactions has been detailed, I focus on these remaining driving forces.
Population density is one feature of urbanization (Jedwab et al., 2017), along with market forces that play a big part in attracting future migrants (Krugman, 1996; Ravenstein, 1885). Indeed, the economic potential remains one of the major push toward cities (Seto, 2011). However, this effect has low chances to be monotonous. Black and Henderson (2003) study the determinants of urban development in the USA. They first find that market potential has a positive influence on urban growth. However as the market size grows, it provides more opportunities, but also more competition between cities. Differently said, as the market potential increases, the marginal benefits of market opportunities decrease. Thus, this paper highlights the likeliness of a threshold effect. Such ambiguity between urbanization and economic potential can also be true for China. Indeed, the cities showing the highest GDP (a suitable proxy for economic potential) are also the largest. Yet, the largest cities are called "hard conversion" areas (Song, 2014). It

means it is harder for rural migrants to legally move to these areas (due to the Hukou system). They have fewer chances to obtain a conversion of their Hukou status if they move to a large city. In this case, there could be a negative relationship between the province GDP and its urbanization rate. In addition, studies emerge on the urban push *i.e.* the massive air pollution in the biggest and richest cities, harmful for human health, generates new kind of migration flows from cities to rural areas (Jedwab et al., 2017). Hence, the impact of GDP on urbanization remain uncertain.

The GDP is an objective measure of economic potential. Often, one migrates to get “better” economic opportunities. According to Todaro (1969), rural-urban migration reacts to urban-rural differences in expected income. Migrants consider the labor market opportunities available to them in the rural and urban sectors and choose one that maximizes their expected gains from migration. Hence, the introduction of the urban-rural income gap is necessary in such model. Zhang and Shunfeng (2003) expose the relevance of this variable when studying rural-urban migration, in China.

Within the same logic, I include rural employment in the regression. Rural employment is highly correlated to rural poverty and can be considered as a rural push factor (Jedwab et al., 2017). It is also a main indicator of the labor market opportunities offered by the rural sector, a decisive factor according to Todaro (1969).

Furthermore, I integrate the weight of agricultural subsidies in the total amount of the local government expenditures. This proxy reflects government incentives which is important to account for (Seto, 2011). It can either generate a rural pull -by creating jobs in rural areas to prevent migration- or push -by enhancing productivity and releasing some workers for the urban sector (Jedwab et al., 2017).

Education plays also an important role in rural-to-urban migration. The more educated people are, the less distance matters in the migration choice (Schwartz, 1973). This result is true for China. Students represent a large share of inter-provincial migrants (Liang and White, 1997).

Finally, acknowledging the quality of the transportation system is crucial for a study on rural-urban migration. First, an efficient transportation system can significantly decrease the cost of migration. But it also countervails the disadvantages of distance (Ravenstein, 1885), which also reduces the psychic cost of long-distance migration. Also, without an efficient connection between cities, no synergy effect is possible. A proxy measuring the efficiency (rather than the length of the network, which means nothing if the quality of the roads or rails is low) of Chinese transportation system is a prerequisite for this study. The proxy used in the model is the amount of passengers that the transportation system[13] is able to carry every

[13]Both rail system and road networks are included.

year, weighted by the total population of the province.

2.3.3 Identification issues

Usual concerns about the empirical realization have been tackled.
First, the current study does not present any threat concerning multi-colinearity, even after the inclusion of the squared GDP that raises the VIF. A multi-colinearity bias occurs when explanatory variables look too much alike. If so, it modifies the estimator precision, and therefore, the coefficients' variance, leading to statistical bias. Here, even the inclusion of the squared GDP does not cause enough colinearity to affect the estimates (the VIF value remains low).
Also, the use of a maximum likelihood implies that the error term follows a normal law. The residues do verify this assumption.
Finally, investigating the determinants of urbanization leads to raising concerns about a potential bias due to the endogeneity of the control variables. It would mean that the explanatory variables are correlated with the error term. In this case, no true solution has been found. On the basis of current knowledge, it is impossible to instrument a variable when I use the ML estimator for macro-panel data. I then examine the potential causes of endogeneity, to evaluate the importance of the identification threat in this present case. Three causes can be responsible for endogeneity.
The first one is the measurement error in the data sample. Even though the quality of data from national yearbooks has been largely criticized. Holz (2014) and Chow (2006) find that evidence of data manipulation are not compelling. This being set aside, the only remaining risk would be an isolated measurement or typing error. Yet, by construction, the right-side variables are averaged on a 5-year interval. It decreases the chance that an isolated measurement error impacts the final results.
Second, if one omits a relevant explanatory variable, then it causes endogeneity. With spatial econometrics, this risk is reduced thanks to the introduction of spatial interaction between adjacent provinces, that were previously omitted. Here, with the SDEM, I manage to explain the whole spatial correlation occurring between Chinese provinces, it means that no relevant variables explaining spatial interaction between provinces, have been omitted[14]. Hence, even though variables might have been omitted, there are poor chances that they significantly impact the dependent variable. Also, all traditional non-spatial variables enhancing rural-urban migration, in both cross-section and time-series studies, have been included to limit this threat (Zhang and Shunfeng, 2003).
Thus, endogeneity is most likely due to the simultaneity of the causality between

[14] It is true because the term of spatial autocorrelation λ become none significant when including all the spatial explanatory variables.

the dependent variable and one or several explanatory ones. To reduce this risk, the only remaining option was to use a 5 years-lag for all the explanatory variables. In the dataset, the *GDP* has the highest chances to present a simultaneous causality with the urbanization rate. The relation between both variables has long been studied. The conclusion is different depending on the study area. In China, Zhang and Shunfeng (2003) find that "the causal link runs from economic growth to migration, not vice versa".

All together, after reviewing the potential causes of endogeneity, this study has low chances to present a substantial bias. But given that the threat exists, it is needed to remain cautious when interpreting the size of the coefficients.

2.4 Results

I report my main results in Table 2.2. As a first step, I run a simple FE regression, using only direct determinants of urbanization : $Y = \beta_1 \cdot X + u$. I run a F-test that endorses the relevance of province FE.

Yet, given the literature, I assume that spatial interactions exist between provinces regarding urbanization. To confirm or rule out this hypothesis, I run the same regression but this time, I allow the error term to be spatially correlated (Column 2, Table 2.2). It is called a Spatial Error Model (SEM) : $Y = \beta_1 \cdot X + u$ where $u = \lambda \cdot Wu + \varepsilon$. The spatial autocorrelation coefficient λ, ranging from -1 to 1, indicates the nature and intensity of spatial interdependence between individuals (Le Gallo, 2002). The spatial autocorrelation coefficient is highly significant (at 1% level) and really close to 1. Hence, the interdependence between Chinese provinces, regarding the urbanization process, is strong and positive. Adjacent provinces proceed to their urbanization in a complementary manner. Thus, the FE regression was biased, omitting explanatory variables (Le Gallo, 2002), in this case, the neighbors' determinants of urbanization.

Then, I introduce spatially lagged variables in the regression (Equation 2.1) to estimate which features are responsible for spillovers effects between provinces. Results are reported in Column 3, Table 2.2. First, the size and significance of the autocorrelation coefficient λ changes. It decreases from 0.941 to 0.238 and becomes none significant. It means that the spatially lagged variables included in the model are sufficient to explain all the spatial correlation found in the previous model. All together, two third of the synergy between the neighboring provinces has been explained.

By including spatially lagged variables (SDEM specification), I look into the transmission channels that explain the complementary relationship between Chinese provinces, regarding urbanization.

To begin with, one province economic dynamism (GDP per-capita as proxy) has a non-monotonic impact on one neighbor urbanization rate. At first, the neighbors economic growth has a positive and highly significant effect on one province urbanization. By assuming that i and j are neighboring provinces (based on the design of the spatial matrix), an increase of 2698 yuan of the GDP per-capita in j's province significantly boosts the urbanization rate in i province by one point of percentage. However, meeting a certain level of GDP per-capita, the more provinces economically grow, the less the neighboring province will urbanize. GDP is no longer a factor of complementarity, it triggers competition. Indeed, if the surrounding provinces reach a GDP per-capita of 29980 yuan[15], a rise of their GDP can significantly stifle one's urbanization. On Figure2.4, the first provinces reaching this threshold were Shanghai and Beijing in 2005. By showing tremendous GDP growth rates, these provinces seem to offer wide economic opportunities, which account for one of the main decision-making factor, when one individual is resolved to migrate. Such economic attractiveness can therefore be a factor of inter-provincial migration. The fact that largest cities are more attracting is widely acknowledged by authors as a source of inter-provincial migration. For instance, (Zhang and Shunfeng, 2003) only incorporate the distance between the origin province and the top-four receiving provinces (in which Beijing and Shanghai are included) to look into rural-urban migration. To attract urban dwellers and provide labor force to the secondary and tertiary sector[16], a province has to compete with the top receiving provinces. In 2015, even more provinces reach the GDP threshold. The relationship between provinces goes from complementary to competitive, consistently with the literature highlighting the sub-optimal size of most of Chinese cities (Au and Henderson, 2006). Indeed, as a consequence of restrictive migratory policy, small and medium-size cities have to fight to attract new urban dwellers. These cities are therefore far from reaching their optimal size.

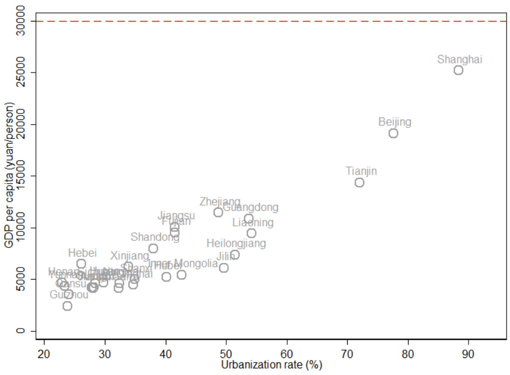
Nevertheless, the current relationship between neighboring provinces remains mostly complementary due to the impact of other significant variables (Column 3, Table 2.2). A highly populated province or one with a high capacity transportation system spurs its neighbors urbanization. Indeed, the rapid development of transportation system, especially between cities (for instance, the High-Speed Rail[17]) is a necessary condition for synergy among cities. It makes people more mobile and artificially reduce geographic distance between cities. An efficient transportation

[15]To calculate the threshold level, I compute the derivative of the regression 2.1 with respect to the variable GDP_j (with $j \neq i$ being a neighboring province).

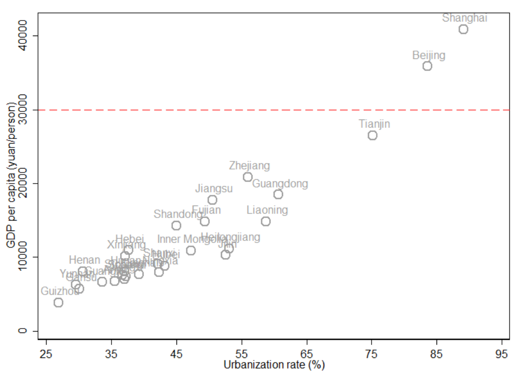
[16]As Henderson et al. (2009) argued, in China there are "Too many cities, Too few people", it is a common phenomenon when labor and capital become too mobile (Gordon and Richardson, 1997). It is also the consequence of Chinese restricted policy regarding migration (Hukou system).

[17]Source: Ollivier, Gerald and Amos, Paul (2016). High-speed Rail Has Grown at Dizzying Speed. Retrieved from:http://www.worldbank.org/en/news/opinion/2016/06/01/high-speed-rail-has-grown-at-dizzying-speed. Accessed 13.11.2017.

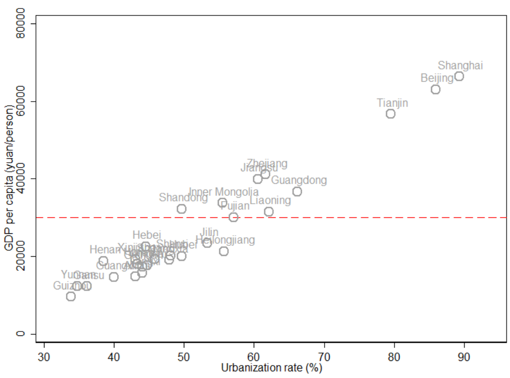
Figure 2.4: Provinces reaching the threshold value: the cities grow at the expense of their neighbors'



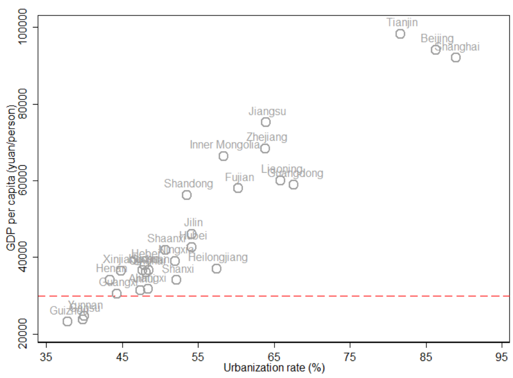
(a) 2000



(b) 2005



(c) 2010



(d) 2015

Legend: In *red*, the indirect threshold of neighbors' GDP on one province's urbanization (The urban process starts being competitive). Source: Threshold calculated by the author with the SDEM estimated coefficients.

system plays a major role in urban spreading.

Also, when rural employment is not dynamic across the province borders, it can impact positively and significantly its urbanization. Indeed, it gives an economic motivation for individuals in neighboring provinces -but still geographically close- to migrate toward cities, where the employment rate is higher in average. This result stresses again the importance of economic forces in the migrant decision.

Surprisingly, when a neighboring province allocates farm subsidies, it reduces one's urbanization. Even though this result is weakly significant, it can still be discussed. At first glance, one could think that farm subsidies would increase agricultural returns, and therefore rural revenues, which would lessen motivation to migrate to

cities, if the main motivation to migrate is economic.
But first, if these subsidies do increase agricultural performance, it would also give the rural dwellers the financial means to migrate to cities [18].
Second, these policies rather aim at preventing urban expansion than raising agricultural productivity (Liang et al., 2015). Indeed, the target is the landlord and not the farmer himself (Huang et al., 2011).
Third, the efficiency of these farm protection policies is not yet established (Lichtenberg and Ding, 2008). Part of the explanation is that the subsidy system is recent but also the amount allocated per landowner remains low compared to other countries (Huang et al., 2011).
Thus, increasing agricultural subsidies do not seem to be an efficient policy to mitigate rural-urban migration.

[18]Rural-urban migration generates tremendous costs (Sjaastad, 1962)

Table 2.2: Direct and Indirect driving forces in urbanization

	FE	SEM	SDEM
Indep. Var.	Dep. Variable: *Urbanization rate*		
Direct effects			
GDP	0.520	-0.080	-0.262*
	(0.363)	(0.139)	(0.153)
GDP^2	-0.012***	0.000	0.001
	(0.003)	(0.001)	(0.001)
Pop. Density	0.018***	0.000	-0.001
	(0.004)	(0.001)	(0.002)
Rural Employment	-0.066	-0.104***	-0.192***
	(0.152)	(0.037)	(0.047)
Income Difference	-1.078	-0.115	-0.122
	(0.739)	(0.236)	(0.285)
Education	0.021	0.053***	0.051***
	(0.051)	(0.016)	(0.018)
Transport Quality	0.011***	0.001	0.002**
	(0.002)	(0.001)	(0.001)
Agr. Subsidies	0.001	-0.003	-0.012
	(0.071)	(0.020)	(0.017)
Neighbors' effects			
GDP			2.698***
			(0.683)
GDP^2			-0.045***
			(0.005)
Pop. Density			0.029***
			(0.010)
Rural Employment			-0.393**
			(0.178)
Income Difference			-2.054*
			(1.134)
Education			0.007
			(0.055)
Transport Quality			0.007***
			(0.003)
Agr. Subsidies			0.168*
			(0.096)
Spatial Autocorrelation			
λ		**0.941*** **	**0.238**
		(0.021)	(0.259)
Threshold			29.98
R^2	0.46	0.40	0.56
F-statistics	17.19		
Observations	224	224	224
Number of provinces	28	28	28

Standard errors in parentheses & clustered at the province level.* p<0.10, ** p<0.05, *** p<0.01. All specifications include province fixed effects. I use a balanced province-level panel, with 5-year time periods going from 1980 to 2015. λ is the coefficient of spatial autocorrelation. Its significance means that there are strategic interactions between neighboring provinces. The threshold represents the non monotonic impact of GDP_j on i's urbanization rate. All independent variables are 5-year lagged.

2.5 Robustness checks

The results of this study, presented above, are robust to a series of alternative specifications, detailed in Tables 2.3 and 2.4.

2.5.1 Robustness to distance definition

I first verify that the main results are not driven by the definition of distance chosen in the model (Table 2.3). I run the SDEM with four additional weight matrix, each of them having a different definition of distance, one whom definition is compatible with the theory defended here, three that are not. I compare the results with those obtained using the weight matrix that fits the most the defended theory (Column 1) *i.e.* the distance being defined as the number of kilometers between the provinces capitals.
In Column 2, I present another matrix compatible with my initial assumptions. Each element of the matrix $w_{i,j}$ equals the inverse of the distance $1/d$. Note that the distance d is approximated by the kilometers separating the centroids of i's and j's provinces. With this alternative definition of distance, signs, significance, coefficients are nearly identical to the baseline matrix. Most importantly, even the threshold value remains stable, which makes the initial results even more convincing.
In Column 3 and 4, provinces are considered as neighbors if they share a common border. I present in Column 3 a basic contiguity matrix where each element $w_{i,j}$ = 1 if two provinces share a border and 0 otherwise. In Column 4, in the matrix displayed, each element $w_{i,j}$ equals to the inverse of the square distance $1/d^2$[19]. Hence, in accordance with the defended theory, it would mean that the influence of a city will stop at its administrative frontier. In a country like China, this approach is difficult to defend. On the one hand, it is due to the size of the provinces. The eastern part of the country is the starting point of the urbanization ripple effect (see Map 2.2). This part of the country has one characteristic, the provinces surface is rather small[20]. Second, Chinese cities are artificially closer thanks to tremendous public spending in transportation systems in the recent years. For instance, using a High-Speed Rail (HSR), Shanghai and Beijing are only 4h30 away[21]. Accordingly, it comes as no surprise when the results do not hold as I run the baseline model with these matrix. The definition of distance is too restrictive

[19]Note that the distance d is approximated by the kilometers separating the capitals of i's and j's provinces.
[20]The smallest provinces are either on the east coast or at the center of Mainland China (data from (China Data Center, 2017)).
[21]China currently has the world's largest HSR system, with more than 19,000 km of railways connecting 28 provinces. It accounts for 60% of the world's HSR network [22].

and does not enable me to analyze the phenomenon at the proper scale.
Last but not least, in Column 5, I run the SDEM specification with a random weighted matrix. In this matrix, the distance is randomly determined between i and j provinces. This type of matrix helps the regional scientist testing their theoretical model (Anselin et al., 2013). If their theoretical models explain in a relevant manner the spatial interaction between neighboring areas, then, when the distance matrix have random values for neighbors, the results should not hold. In this case, the results do not hold when I introduce a randomly weighted matrix, no coefficient remain significant among the spatially lagged variables.

Table 2.3: Robustness to changes in weight matrix

	Baseline	Centroïds	Contiguity	$1/distance^2$	Random
Indep. Var.	Dep. Variable: *Urbanization rate*				
Direct effects					
GDP	-0.262*	-0.303**	-0.433***	-0.327*	0.019
	(0.153)	(0.149)	(0.155)	(0.176)	(0.123)
GDP^2	0.001	0.002	0.002	0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pop. Density	-0.001	-0.000	0.001	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Rural Employment	-0.192***	-0.173***	-0.153***	-0.147***	-0.110***
	(0.047)	(0.050)	(0.049)	(0.051)	(0.037)
Income Difference	-0.122	0.113	0.677***	0.357*	-0.246
	(0.285)	(0.277)	(0.241)	(0.203)	(0.276)
Education	0.051***	0.041**	0.044***	0.032*	0.053***
	(0.018)	(0.019)	(0.017)	(0.018)	(0.017)
Transport Quality	0.002**	0.001*	-0.001	0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Agr. Subsidies	-0.012	0.007	-0.040	0.014	0.014
	(0.017)	(0.018)	(0.027)	(0.016)	(0.028)
Neighbors' effects					
GDP	2.698***	2.301***	0.111	0.424	-0.118
	(0.683)	(0.538)	(0.393)	(0.441)	(0.928)
GDP^2	-0.045***	-0.036***	-0.007**	-0.008*	0.011
	(0.005)	(0.006)	(0.004)	(0.004)	(0.009)
Pop. Density	0.029***	0.052***	0.023***	0.019**	-0.010
	(0.010)	(0.019)	(0.006)	(0.008)	(0.015)
Rural Employment	-0.393**	-0.247	-0.248**	0.063	0.056
	(0.178)	(0.190)	(0.107)	(0.153)	(0.380)
Income Difference	-2.054*	-2.595**	1.229**	0.756	-2.006
	(1.134)	(1.096)	(0.574)	(0.904)	(2.311)
Education	0.007	-0.106	-0.049	-0.132*	0.185
	(0.055)	(0.145)	(0.038)	(0.076)	(0.141)
Transport Quality	0.007***	0.014***	-0.004***	0.001	0.002
	(0.003)	(0.004)	(0.001)	(0.003)	(0.008)
Agr. Subsidies	0.168*	0.497***	-0.088	0.178*	0.308
	(0.096)	(0.160)	(0.074)	(0.092)	(0.188)
λ	0.238	0.530	0.911***	0.928***	0.959***
	(0.259)	(0.391)	(0.027)	(0.025)	(0.019)
Threshold	29.98	31.77			
R_2	0.555	0.465	0.242	0.397	0.030
Observations	224	224	224	224	224
Number of provinces	28	28	28	28	28

Standard errors in parentheses & clustered at the province level *** p<0.01, ** p<0.05, * p<0.1. All specifications are designed according the SDEM (Elhorst,2014), using the ML, and including province fixed-effects. Column 1 presents the baseline results *i.e.* the SDEM model with the weight matrix using the distance between the provinces capitals as a reference.

2.5.2 Robustness to model specification

As said before, two models dominate the regional science. The SDEM was the most suitable given the research question. But I also want to check if the results found with the baseline model completely depend on the empirical model. If not, then, the results will remain the same, even after a change in the model specification. It is the case here, the results are robust to the model specification (see Table 2.4). I first check the results robustness to the SDM, the specification designed to identify global spatial effects. Signs and significance remain intact for the main results (especially the turning effect of neighbors GDP on one province's urbanization)[23] I also test the robustness of the results with one last specification (Column 1), the Spatial Lag of X model (SLX). It also detects local spatial spillover. Its design looks alike the SDEM's, apart from the error term which is not allowed to be spatially correlated. It has a random distribution, there is not spatial autocorrelation coefficient (λ) to determine the nature and the intensity of spatial interactions. Hence, the SLX is designed as follows (LeSage, 2014) $Y = \beta_1 \cdot X + \beta_2 \cdot WX + \varepsilon$ with $\varepsilon \backsim N(0, \sigma_\varepsilon^2 I_N)$ The SDEM and the SLX results are exactly identical. It comes as no surprise since the spatially lagged variables explained all the spatial autocorrelation in the baseline model. Therefore, the coefficient associated with the spatial autocorrelation term was no longer significant, in the SDEM specification. Thus, the absence of the spatial autocorrelation term in the SLX model does not have a significant impact on the results.

[23] Note that no conclusion can be made on the coefficients' values since it is not possible to interpret them directly from this table (due to the design itself of the SDM).

Table 2.4: Robustness to model specification

	SLX	SDM	SDEM
Indep. Var.	Dependent Variable: *Urbanization rate*		
Direct effects			
GDP	-0.257	-0.201	-0.262*
	(0.155)	(0.146)	(0.153)
GDP^2	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Pop. Density	-0.001	-0.000	-0.001
	(0.002)	(0.001)	(0.002)
Rural Employment	-0.198***	-0.147***	-0.192***
	(0.050)	(0.038)	(0.047)
Income Difference	-0.111	-0.091	-0.122
	(0.316)	(0.225)	(0.285)
Education	0.051**	0.054***	0.051***
	(0.019)	(0.016)	(0.018)
Transport Quality	0.001*	0.001	0.002**
	(0.001)	(0.001)	(0.001)
Agr. Subsidies	-0.013	-0.006	-0.012
	(0.018)	(0.018)	(0.017)
Neighbors' effects			
GDP	2.680***	1.484**	2.698***
	(0.697)	(0.632)	(0.683)
GDP^2	-0.045***	-0.025***	-0.045***
	(0.005)	(0.006)	(0.005)
Pop. Density	0.029***	0.022***	0.029***
	(0.010)	(0.008)	(0.010)
Rural Employment	-0.380**	-0.257*	-0.393**
	(0.176)	(0.152)	(0.178)
Income Difference	-2.017*	-0.800	-2.054*
	(1.116)	(0.894)	(1.134)
Education	0.022	-0.005	0.007
	(0.048)	(0.043)	(0.055)
Transport Quality	0.007**	0.001	0.007***
	(0.003)	(0.003)	(0.003)
Agr. Subsidies	0.147*	0.057	0.168*
	(0.084)	(0.071)	(0.096)
λ			0.238
			(0.259)
Threshold	29.51		29.98
R^2	0.94	0.54	0.56
F-statistics	286.47		
Observations	224	224	224
Number of provinces	28	28	28

Standard errors in parentheses & clustered at the province level *** p<0.01, ** p<0.05, * p<0.1. All specifications include province fixed-effects and use the same baseline weight matrix (that uses the distance between province capitals as a benchmark). In Column 3 is represented the baseline model (SDEM). In colum 1, given the design of the SDM, the coefficients can not be interpreted directly. The objective, here, is to check the robustness of the GDP turning effect on urbanization. For this purpose, I only need to verify the sign and significance of both GDP and GDP_2, I do not need to go further in the interpretation of the SDM coefficients.

2.6 Conclusion

To wrap up, this study applies a spatial econometric model which examines the determinants of provincial urbanization without omitting a major factor: the proximity to growing cities. If anything, this chapter sheds light on local spillovers in China, regarding urbanization. Close provinces urbanize in synergy. Yet, a potential adverse impact on urbanization of proximity to a very attractive city such as the big eastern ones exists. Migrants preferences tend toward these cities rather than the neighboring ones. It echoes a great concern on Chinese urbanization.
First, evidence is found that cities at the top of urban hierarchy have negative impacts on their neighboring areas (Duvivier, 2010; Chen and Partridge, 2013). Indeed, the initial synergy is jeopardized when the neighboring province is too economically attractive. This result is consistent with one statement in migration. Migrants often prefer short-distance migration, but when migrants do travel long distances, they generally target one of “the great centres of commerce or industry” (Ravenstein, 1885) such as large cities. The attractiveness of large cities has been fed for decades by the Central government preferential policies (Démurger et al., 2002). Deregulation policies allowed coastal provinces to better integrate into international economy. They also permitted more migration to feed the expending economic activity in these concentrated areas. Central and western provinces did not benefit from the same kind of policies at first. Preferential policies had more to do with uneven regional urban process than geography. Yet, these results echo a great concern on Chinese urbanization. These mega-cities become hardly manageable or breathable in the long run (World Bank and DRC, 2014). As a solution, Henderson et al. (2009) advocates that restrictions on migration could be relaxed for intra-province movement but not for inter-province one. Indeed, as documented by Zhang and Shunfeng (2003), most of migrants living in eastern cities -cities with the highest GDP *i.e.* the most attractive economically- are from inland or western China. Regulating inter-province migration only would enhance the intra-province one and reduce urban development disparities in China. Another way to proceed would be to extend deregulation policies to medium and small-size cities, rather than freezing these policies for the larges ones.
If restrictions on migration are relaxed, this chapter also what factors drive urbanization at a province scale. The main one is rural employment. Indeed, at the province level (Direct effects in Table 2.2), the variable with the biggest and most significant influence on urbanization is rural employment. The higher the rate of employment is in rural areas, the less urbanization there is. It suggests that more economic activity in rural areas mitigates migration flows to urban areas. Thus, any external event impacting job opportunities in rural areas could, in turn, affect migration flows to urban areas. It is an intuition that I will look into in Chapter 3 and 4.

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Appendix to chapter 2

Definition of rural-urban migration

Rural-urban migration is "*a basic transformation of the nodal structure of a society in which people move from generally smaller, mainly agricultural communities to larger, mainly non-agricultural communities*" Retrieved from Akin L. Mabogunje (1970). "Systems approach to a theory of rural-urban migration". *Geographical analysis.*

Table A5: Definition of the variable used in the chapter

Variable	Definition
$Urbanization\ rate$	Proportion of the permanent urban resident on the total population (%)
GDP	Gross Domestic Product per capita (in thousands of RMB).
GDP^2	Square GDP per capita (in millions of RMB).
$Pop.\ Density$	Population density (1000 persons per square kilometers)
$Rural\ Employment$	Proportion of employed persons in rural areas in total labor force (%)
$Income\ Difference$	Income difference between urban and rural population (in thousands of RMB)
$Education_i$	Student enrollment in institutions of higher education (10000 persons)
$Transport\ Quality$	Flow of passengers on total population (%)
$Agr.\ Subsidies$	Share of agricultural subsidies on total local government revenue (%)

Source: NBSC.

Table A6: Distribution of provinces among Chinese main regions

Provinces	North-East	West	Center	East
Total	4	10	7	10
Anhui			•	
Henan			•	
Hubei			•	
Hunan			•	
Jiangxi			•	
Shanxi			•	
Guangxi			•	
Chongqing		•		
Gansu		•		
Guizhou		•		
Ningxia		•		
Qinghai		•		
Shaanxi		•		
Sichuan		•		
Tibet		•		
Xinjiang		•		
Yunnan		•		
Heilongjiang	•			
Inner Mongolia	•			
Jilin	•			
Liaoning	•			
Beijing				•
Fujian				•
Guangdong				•
Hainan				•
Hebei				•
Jiangsu				•
Shandong				•
Shanghai				•
Tianjin				•
Zhejiang				•

Chapter 3

Are cities shelters for rural dwellers experiencing weather variations? Evidence from China

3.1 Introduction

According to the IPCC (2018), at the current speed, global warming will reach 1.5°C between 2030 and 2052. It results in more extreme weather variations that significantly undermine crop production worldwide (Schlenker and Roberts, 2009; Challinor et al., 2014; Lesk et al., 2016). As a consequence, less people are able to earn a living from agricultural activities, giving incentives to out-migrate from rural areas to reach better life conditions (Martin et al., 2014; Falco et al., 2018). Rural-urban migration becomes an adaptation strategy to secure the household income during the year, when severe weather variations occur. In developing countries, the migratory response following weather anomalies is two-sided. On the one hand, in poor countries, people have fewer options to adapt to weather anomalies. They have low access to agricultural insurance and no possibility to self-insure. Migration becomes the last resort (Barrios et al., 2006; Beine and Parsons, 2015). On the other hand, farmers in poor countries have less access to credit and experience strong liquidity constraints. By further tightening their liquidity constraints, weather variations unable them to afford migration cost, prevent them from moving and trap them in the affected areas (Black et al., 2013; Mastrorillo et al., 2016; Cattaneo and Peri, 2016; Otto et al., 2017). In the end, no consensus holds on the impact, whether positive or negative, that weather variations have on migration, in the long run. More extreme temperature and rainfall flow could create an important pool of potential migrants searching for new ways to earn a living. It is important to assess what direction this pool of potential migrants takes.

The main problem when looking into climate change effects on migration, is the lack of external validity of most of the studies. What is true for a country can be false for another. Conclusions on this topic depend on many factors (Beine and Jeusette, 2018). Couple of them are the economic structure of the country *i.e.* the role of agriculture in the country remains dominant (Mendelsohn and

Dinar, 1999; Maurel and Tuccio, 2016; Falco et al., 2018); geographical factors *i.e.* whether the country is landlocked or not, the climate is arid or not (Barrios et al., 2006); population characteristics (Findley, 1994; Mastrorillo et al., 2016; Otto et al., 2017) and so on. Conclusions also depend on what the author defines as a climatic event. Indeed, it is needed to distinguish the papers studying natural disasters from those focusing on weather variations (Beine and Jeusette, 2018). These former are impredictable and are responsible for forced displacement because of the destruction of people's home. These latter are largely studied for their impact on agriculture and therefore rural income, which could, in turn, influence migration patterns. In this study, I will focus on the latter.

This chapter investigates the link from 1992 to 2012 between weather variations and city size around the affected area, using a very disaggregated panel of 0.5° grids as a unit. The implicit assumption is that climate change, through more frequent weather variations experienced in recent years, affects agricultural productivity. As a consequence the income of rural households will change, and with it, the incentives for farmers to stay in the countryside. To capture weather variations, I use the SPEI measure, a reliable indicator for the soil dryness (Vicente-Serrano et al., 2010). Proxying city growth requires some creativity. Indeed, in China, due to institutional constraints, migration is rather temporary[1] (Yang, 1997). I therefore need a higher frequency information on city size variation, than Census data provided by the National Bureau of Statistics of China (NSBC) and available every 10 years. Instead, I use nighttime light intensity as a proxy for urban expansion. In addition, this study focuses on short-distance migration. Indeed, I assess the effects of weather variations on urban areas surrounding the affected area. On Chinese scale, I consider as short-distanced a grid located within 400 kilometers. In average, it captures intra-province movement which is the most common form of migration for rural dwellers, in China (Wang et al., 2003; Zhao, 2005; Su et al., 2018). To the best of my knowledge, it is the first work to use geographical data to proxy urbanization, and quantify how it is affected by nearby weather variations, in China.

Doing so, I find strong evidence of a link between weather variations and city size in nearby areas. The effects are heterogeneous according to the type of weather variation. The most impacting weather anomaly is the rainfall shortage (negative SPEI). It affects migration as soon as the soil becomes dryer than usual, no matter how severe. In the short run, the year the rainfall shortage occurs, it triggers immediate and temporary mobility. Rainfall shortages hinder a good harvest in year t, therefore, the farmers out-migrate to cities to try their luck and earn a living.

[1]This point is further discussed in Section 3.2.2. In a word, institutional measures regulate long-run migration by removing basic rights to rural migrants when they move to cities. For instance, they do not benefit from access to the formal housing market, medical care, public schools for their kids and so on.

Furthermore, in this case, migrants do not necessarily migrate to the closest cities, but are willing to go a little further to look for better job opportunities. The next year following the rainfall shortage, city size decreases again, suggesting that migrants come back home. Results also show that rain surplus do not impact migration in general. When it actually impact migration behaviors, it occurs when the shock is severe (when SPEI > 1.5).
The rest of the chapter is organized as follows. Section 3.2 presents the literature on the link between weather variations and migration, to then expose China's particularities as a study case. Then, in section chap2:data, I present the source and construction of all the variables used in this work, as well as some descriptive statistics. In section 3.4, I present the empirical strategy to tackle the research question. Section 3.5 presents the main results to later on discuss them. In section 3.6, I conclude.

3.2 Theoretical background

This section highlights the link between weather variations and rural-to-urban migration and replaces this discussion into context given Chinese specificities.

3.2.1 Does the literature agree on some points?

There is no consensus on the existence of a link between migration to cities and weather variations in the literature. Results are often context-specific. Most likely, one of the most common coping strategy following weather variations remains to migrate out of the affected areas. In most countries, better work opportunities are found in the cities, thus adverse environmental conditions is likely to trigger rural-to-urban migration. This phenomenon is exposed by Beine and Parsons (2015), who analyze for the first time the macroeconomic impact of weather variations on global bilateral migration flows between 1960 and 2000. They do find strong evidence of rural-to-urban migration following weather variations. A lot of attention is also given to droughts, since their impact on agricultural productivity is wider (Challinor et al., 2014). Hence, Munshi (2003) find that rainfall shortages are responsible for emigration from rural Mexico to the US. In a word, "*the fact that these shocks lead to an increase in human mobility [...] is probably the effect that has received the most important attention from researchers in that literature*" sum up Beine and Jeusette (2018), in their 42-papers long meta-analysis on the relationship between climate change and migration.
Yet, if adverse environmental conditions can enhance mobility, migration remains quite selective. Important barriers to willingness remain economic. Harmful climatic conditions could erode potential migrants resources and eventually reduce

their mobility. Also, climatic variations are not impartial, they affect the rural poor in developing countries the hardest, that is to say the population the least able to self-insure or to adopt other coping behaviors. So weather variations could push the most vulnerable population further down into the poverty trap and have low impact on other layers of the population (Black et al., 2013; Mastrorillo et al., 2016; Otto et al., 2017). As an example, in Mali's case, Findley (1994) finds that episodes of drought lead to less migration toward other African countries due to the tightening of credit constraints and rising food prices following a decrease in crop production. More recently, (Cattaneo and Peri, 2016) also find that, in low-income countries, higher temperatures reduce the probability of migration to cities due to severe liquidity constraints. Yet, even though China does not belong to the low-income group, poverty traps do exist in rural China (even after the economic reforms of 1970s, see Jalan and Ravallion (2002)). It mainly affects rural households whose income rely on farm activities, meaning, those who are the most vulnerable to strong weather variations. Zheng and Byg (2014) underline this phenomena when interviewing households from three different villages that experienced episodes of droughts. Here, coping strategies depend on the household socio-economic features and their vulnerability pre-shock.

When the literature does not agree on the nature of migratory flows after weather anomalies, China's case is no exception. On the one hand, some studies do find that weather variations enhance migration. For instance, Barassi et al. (2018) investigate internal migration between Chinese provinces following climate anomalies (namely temperature, precipitation and sunshine variations) between 1987 and 2015. They find that increased temperature and precipitation significantly foster migration while greater sunshine hinders migration. Yang (2018) study also takes that direction. She uses a theoretical and an empirical model on individual-level panel data on more than 30,000 Chinese rural residents, to assess the influence of peaks of temperatures on their likelihood to migrate. Evidence shows that rural dwellers are keen to out-migrate to work outside their village, if the crop yields decrease in theirs. On the other hand, others stress the absence of migraton flows following weather variations. Zheng and Byg (2014) use a survey on 162 household from three different villages in Lijiang, Yunnan province, to estimate that, after a drought, farmers prefer to stay put.

If no consensus arise from the literature, there are still some favorable conditions for the existence of a link between weather variations and migration. First, climatic factors have the greatest impact on countries where rural dwellers are numerous (Barrios et al., 2006; Parnell and Walawege, 2011; Warner, 2010). More precisely, the importance of agricultural sector emerges as determinant to tackle this research question, from both micro and macro-level analyses (Mendelsohn and Dinar, 1999; Barrios et al., 2006; Maurel and Tuccio, 2016; Falco et al., 2018).

For this reason, many studies on climate change impact on urbanization focus on sub-Saharan Africa. For instance, Barrios et al. (2006) provide a significant proof of a causal link between rainfall variations over time and urbanization in sub-Saharan Africa, a link they find nowhere else in the developing world. Yet, this feature also applies for China. Indeed, while the developed countries average urbanization rate is up to 78%, China's one is still around 55% in 2015 according to the United Nations[2]. China remains mostly under urbanized (Chang and Brada, 2006). Bad harvests could be a final push to motivate farmers to migrate to more prosperous cities. That is what Yang (2018) and Minale (2018) prove in their respective studies on China. Yang (2018) demonstrates the negative effects of very high temperature on agricultural production, and later shows that people in the affected areas out-migrate in neighboring regions to look for other sources of income. Minale (2018) uses a longitudinal survey on individuals to prove that rural-to–urban migration remains the most frequent coping strategy when facing negative productivity shocks in agriculture. Namely, following a 1 standard deviation negative rainfall shock, farming is reduced by 4.5% and migration increases by nearly 5%. Thus, even in China's case, agriculture productivity is the channel of transmission through which weather variations affect rural-urban migration.

In line with this argument, presence of already dry land is a more favorable environment for the identification of such a link between weather anomalies and migration to cities. Indeed, these lands already suffer from aridity. This increases the risk of drought when there is a rainfall deficit, since drier soil absorbs more rainfall (Bloom et al., 1998). Crop production is even more vulnerable to varying rainfall. That is another reason why most studies focus on sub-Saharan Africa to highlight the existence of a link between weather variations and urbanization (Findley, 1994; Barrios et al., 2006). Yet, arid and semiarid regions occupy more than 50% of the Chinese territory (Chen et al., 2011). These regions are mainly located in the north and west of the country. As previously discussed, these regions are hit the hardest by climate change, and this conclusion is even more true in China. Northern China becomes particularly dry (Wang and Zhai, 2003; Ma and Fu, 2006) and drought-areas are mostly expanding in principal agricultural areas (Wang and Zhai, 2003). Thus, China appears as a suitable candidate to look for a link between weather anomalies and urbanization.

The literature agrees on one last point, there are possible heterogeneous results depending on the type of weather anomaly. For example, Barassi et al. (2018) find that, between 1987 and 2015, people more easily out-migrate to other Chinese provinces when precipitation or temperature are too important in their homeland. At the opposite, they are attracted to provinces with more sunshine. Again, the

[2] Annual percentage of population at mid-year residing in urban areas, collected by the United Nations (2018) from national statistical offices.

transmission channel from weather variation to migration is agriculture. Sunshine does not affect crop production the same that temperature or precipitation do. Another paper found different migratory response depending on the shock. Koubi et al. (2016) use survey data on five developing countries (Vietnam, Cambodia, Uganda, Nicaragua, and Peru) to assess the influence of environmental factors on internal migration. These environmental factors go from sudden to gradual environmental events, judging that drought is a gradual one, whereas flood is considered as a sudden one. Gradual/long-term environmental change, such as drought, lowers the likelihood to migrate whereas floods, as a sudden-onset event, increase it .

3.2.2 China, a singular case study

In China, migration remains largely uni-directional, people migrate out of rural areas to look for better job opportunities in cities. Indeed, China's urban growth went from 19.4% to 59.6% between 1980 and 2018[3] Rural-to-urban migration alone is at least responsible for 75% to 78% of this growth (Wang et al., 2003; Zhang and Shunfeng, 2003). This phenomenon is true for many different reasons. First, cities have better infrastructures which enable better life conditions (Liu et al., 2009). Compared to rural areas, cities allow a better access to high level education (Banerjee et al., 2012), to credit (Yuan and Xu, 2015), to health facilities (Gong et al., 2012), as long with a better provision in road and electricity infrastructure (Shenggen and Zhang, 2004). Second, the living standard is greater in urban areas. Job productivity and thus, wages are relatively higher in cities. In 2015, the average income perceived in rural areas only represents 37% of the average wage in urban areas (Ngai et al., 2016). Therefore, migrating could be economically efficient, since it would allow a better balance between rural and urban job productivity. Third, living conditions are deteriorating in the countryside, due to land scarcity and climate change. With increasing temperature which makes cultivable land dyer and increasing people density, land get scarce. Furthermore, local governments more and more use land as a financial resource by selling it to entrepreneurs for housing development (Lichtenberg and Ding, 2009). It results in a great degradation of soil quality of the remaining land used for farming Reuveny and Moore (2009).

Despite these great inequalities between urban and rural areas, migration remains remarkably low in China, due to strict institutional barriers but also to the land tenure system. *Hukou* system is the main barrier for rural-urban migration in China (Chan and Zhang, 1999). Introduced in 1958, this residence registration

[3] Author's calculation using National Bureau of Statistics in China (NBSC) data on total and urban population.

system for households restricts migration. To legally migrate inside Chinese territory, especially from a rural to an urban area, a migrant needs to convert its *Hukou* status from rural to urban. The bigger the city, the harder it gets. If migrants move without any *Hukou* conversion, they lose rights such as access to social protection, to public education, to housing market, to health coverage, and so on. It has been gradually relaxed since 1978 but essentially for migrants targeting small and medium-sized cities. Losing benefits if migrating keep increasing the opportunity cost of migration. Second, the singular land tenure system in rural China is also an obstacle for migration. Indeed, in rural China, farmers benefit from a land-use right, not a property one. Therefore, out-migrating potentially means losing some land, often without compensation Mullan et al. (2011). At best, migration induces a decrease of the household size which leads to a redistribution of some of the land toward more numerous families, in order to preserve "egalitarian land holdings" (Rozelle and Li, 1998). Also, the land rental market remains under-developed. Renting the land can not be a solution to compensate for the future loss of agricultural income. The lack of rental market further increases the migration opportunity cost (Hu et al., 2011).
As a consequence, in China more than anywhere else, migration is a temporary phenomenon (Yang, 1997). Migrants move for a short amount of time to diversify their source of income over a year, and later on, go back home to make sure they do not lose their land or they social benefits. Relatively high frequency data are needed to seize this movement of migrants.

3.3 Data and summary statistics

In this section, I provide detailed definitions of the variables used in this chapter, along with descriptive statistics about rising soil dryness in China.

3.3.1 Dependent variable

Light intensity at nighttime is used to estimate the city size. It captures outdoor light but also some of the indoor one. It has been extracted from the DMSP-OLS Nighttime Lights Time Series (Version 4) and provided by the National Oceanic and Atmospheric Administration (NOAA). This dataset is composed of 30x30 arc-second grids, covering -180 to 180 degrees in longitude and -65 to 75 degrees in latitude. Data is available annually since 1992 and up to 2013. The nighttime light intensity in each cell is represented by an integer varying from 0 (no light) to 63 (in dense areas). The idea is that, the more dwellers there are in a city, the more buildings, building floors, and windows are enlightened, the denser the light is at nighttime. In the dataset, the mean, the maximum and the minimum value

of the nighttime light intensity are documented for each grid. These variables are highly correlated to urbanization and can be used as a proxy.
The use of geographic data provided by satellites is far more convincing than statistical data that change over time, according to the statistical office in charge. Indeed, the urban population as documented by the NBSC has known substantial change in its definition throughout the study period. Before 2000-Population Census, the definition of urban population is strictly based on the city administrative borders, excluding, for example, some city dwellers if they do not own an urban-*Hukou*. Starting from 2000-Census, the definition of an urban area has been reshaped, using physical indicators such as proximity to urban constructions and population density. Furthermore, this present study needs high-frequency data to capture short-lasting migration. Such data are provided by the NBSC. Indeed, they give annual information on urban, rural and total population in China, based on the previous census. Problem is, to estimate annual variation, the NBSC use statistical inference (see Figure B4 in the Appendix). Such a calculation technique allow no reaction in the data, after a shock.
At the opposite, satellite data provide an annual variation of city enlightenment. It gives a more precise indication of city size variation and therefore on population movement toward these cities, in the short run. Zhang and Seto (2013) compare Google Earth images with NTL data and legitimate the use NTL to proxy city size. Namely, "where urbanization occurred, NTL have a high accuracy (93%) of characterizing these changes". Also, NTL are more accurate in predicting expansion for urban and peri-urban areas, because they are characterized by a great density of lights. Monitoring the growth of poorly lit areas such as countryside, with NTL variations, is not relevant. At the opposite, in China, migrants go from rural areas to urban and already densely lit areas. In this context, NTL are a good fit to proxy rural-urban migration. These latter are not suitable to study temporary migration.
Yet, remotely sensed data collected by satellites also need to be exploited with caution. First, satellite sensors age over time and are regularly replaced. Thus, the same digital number supposed to indicate intensity, does not necessarily represent the same level of light intensity across years and satellites. A comparison over years can therefore be problematic. This issue is treated here with year fixed effects as it is common in the literature[4]. Also, the proxy is not a completely accurate representation of the amount of light emitted by the city (called true radiance). First, the light sensor can saturate, it can not exceed 63. For this reason, it can be challenging when looking into very big cities, such as some Chinese ones. Second, one city size can be overestimated due to blooming. Indeed, the light tends to be magnified around certain type of terrain such as water or snow cover. Both

[4]Henderson et al. (2012)

problems will be treated by dropping the grids whom nighttime light intensity reaches the maximum value (63) as a robustness check.

3.3.2 Independent variables

As a climate variable, I use the SPEI index, obtained from the Global SPEIbase[5]. It comes from a gridded climate dataset available from 1901 to 2011, which gives monthly information on drought conditions worldwide (let alone the Antarctic). It is a precise indicator since the weather data are interpolated into 0.5° latitude/longitude grid cells. With such resolution, Chinese territory is divided into 4041 grids. It has been calculated based on monthly precipitation, temperature and potential evapotranspiration[6], time-series observations by meteorological stations, provided by the Climatic Research Unit of the University of East Anglia (also known as the CRU ts3.24 dataset). Temperature (TMP) is expressed in degrees Celsius. Precipitation refers to the total amount of precipitation (PRE) in millimeters reported by the meteorological stations. The potential evapotranspiration (PET), measured in millimeters of water lost per day, refers to "*the combination of two separate processes whereby water is lost on the one hand from the soil surface by evaporation and on the other hand from the crop by transpiration is referred to as evapotranspiration*"(Allen et al., 1998)[7].
In simplified terms, the SPEI consists of standardized values of the difference between precipitation and evapotranspiration. This difference gives an indication of the water surplus or deficit over a month. As evidenced by Vicente-Serrano et al. (2010), SPEI is among the most precise indicators to capture droughts under global warming scenarios. Indeed, the SPEI integrates the PET variations from its average, which is likely to happen in countries facing global warming and therefore high level of heat flux or solar radiation. It also allows the comparison of very different climate areas because it is normalized. This latter matches this study context, given China's wide territory, that goes from subtropical climate to arid but also cold temperate zones. An exhaustive definition of the SPEI is provided by Vicente-Serrano et al. (2010).

[5]http://spei.csic.es/database.html

[6]Both climatological variables are thoroughly described by Harris et al. (2014).

[7]Namely, evaporation from a cropped soil is mostly determined by the fraction of solar radiation reaching the soil surface. A larger share of solar radiation reaches the soil when the crop is small, because its foliage is not big enough to create any shade. But once the crop is well developed and completely covers the soil, transpiration is the main cause of water loss. The PET is mainly based on temperature, wind speed, soil heat flux and solar radiation.

Table 3.1: Interpretation of the SPEI

Value	Interpretation
2.00 and greater	Extremely Wet
1.50 to 1.99	Very Wet
1.00 to 1.49	Moderately Wet
0.99 to -0.99	Near Normal
-1.00 to -1.49	Moderately Dry
-1.50 to -1.99	Very Dry
-2.00 and less	Extremely Dry

Source: Interpretation provided by the National Oceanic and Atmospheric Administration (NOAA) and their National Weather Service[a].

[a]https://www.ncdc.noaa.gov/monitoring-content/sotc/drought/2017/08/noaa-nws-hnl-spi-table-micronesia-samoa-aug17.pdf

Following SPEI little brother, the Standardized Precipitation Index[8], one could interpret the SPEI values as described in the Table 3.1. There are several degrees of intensity when studying weather variations. Normal values of SPEI are somewhere between 0.99 and -0.99. Beyond these, the SPEI index show abnormal deviation from its historical average. These values will be used to build the $Flood_{i,t}$ and $Drought_{i,t}$ dummies. But to isolate the impact of extreme weather events and assess whether the severity of the shock matters, I also build $Extreme\ Flood_{i,t}$ and $Extreme\ Drought_{i,t}$ dummies when SPEI values go beyond -1.5 and 1.5.

$$Flood_{i,t} = \begin{cases} 1 & if\ SPEI_{i,t}\ \geq\ 1 \\ 0 & if\ SPEI_{i,t}\ <\ 1 \end{cases}$$

$$Extreme\ Flood_{i,t} = \begin{cases} 1 & if\ SPEI_{i,t}\ \geq\ 1.5 \\ 0 & if\ SPEI_{i,t}\ <\ 1.5 \end{cases}$$

$$Drought_{i,t} = \begin{cases} 1 & if\ SPEI_{i,t}\ \leq\ -1 \\ 0 & if\ SPEI_{i,t}\ >\ -1 \end{cases}$$

[8]It obeys to the same logic than the SPEI except that it does not take the PET into account, and therefore is less complete and relevant under global warming context (Vicente-Serrano et al., 2010).

$$Extreme\ Drought_{i,t} = \begin{cases} 1 & if\ SPEI_{i,t}\ \leq\ -1.5 \\ 0 & if\ SPEI_{i,t}\ >\ -1.5 \end{cases}$$

3.3.3 Summary statistics

Table 3.2 presents basic statistics of the variables used in the chapter. It highlights the diversity of weather areas in China. Indeed, the annual averaged temperature goes from -34.2°C for some grids to 33.5°C for others, during the study period. Similarly, some grids know absolutely zero millimeters of rain when others are flooded under 909.7 millimeters of water a year.

Table 3.2: Summary statistics

Variables	Mean	Std. Dev.	Min.	Max.	N
NTL	1.404	4.99	0	63	
SPEI	0.055	1.12	-3.667	3.886	
TMP	6.86	12.926	-34.2	33.5	
PRE	48.866	68.128	0	909.700	
PET	76.904	44.482	0	240	15,492,246
Flood	0.222	0.416	0	1	
Extreme Flood	0.109	0.311	0	1	
Drought	0.188	0.39	0	1	
Extreme Drought	0.087	0.282	0	1	

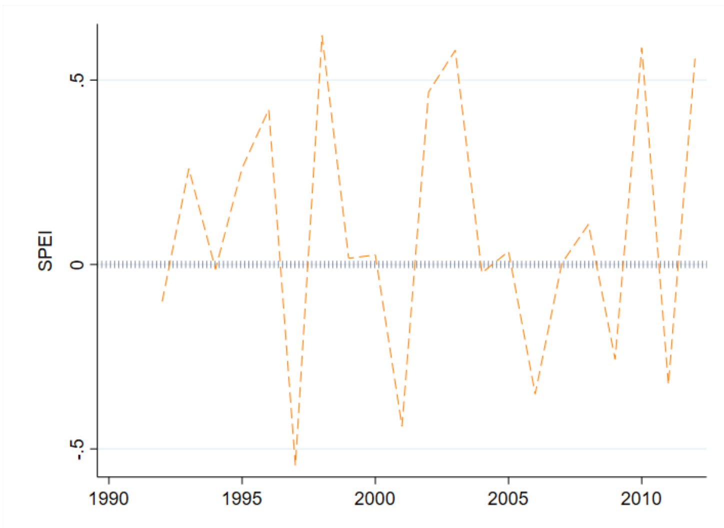
Notes: NTL is a measure of light intensity at nighttime, it is an integer ranging from 0 (empty area) to 63 (very dense are). The SPEI indicates whether there is a drought or not in the area. It is a standardized value, the lower the dryer the area is. Temperature (TMP), Precipitation (PRE) and Evapotranspiration (PET) are not variables directly used in this study, but they are used to SPEI and give valuable information on the evolution of climate indicates in China. Flood, Drought, Extreme Flood, Extreme Drought are the dummies built from SPEI value. See further detailed definition of the variables in Table B7 in Appendix..

Between 1992 and 2012, weather variables show clear patterns of global warming[9]. No clear conclusion can be made on the occurrence of extreme weather events looking at the SPEI variations, over time, in China (see Figure 3.1). What one can observe is the variations of the three climate indicators used to compute the SPEI. First, there is an increase of global temperature in China (Figure 3.2a). Second, the total amount of precipitation tends to decrease over time (see Figure 3.2b). Thirdly, the water in the soil, in turn, evaporates most rapidly over time *i.e.* the PET is rising (see Figure 3.2c). It means that China becomes dryer and dryer.

[9] See Facts from the NASA website on Climate (*url:* https://climate.nasa.gov/evidence/). Global Warming equals to rising temperature and higher frequency of extreme weather events.

These increasing temperature and evapotranspiration are especially worrying for agricultural productivity. Indeed, global warming has long been evidenced as a factor of decreasing crop yields (Lobell et al., 2011). It could be responsible for one third of crop yield variation in recent years (Ray et al., 2015). On the one hand, temperature keeps increasing, slowly exceeding the thresholds that allow optimal crop yields. To get an order of magnitude, Schlenker and Roberts (2009) assess these thresholds as being around 29°C for corn, 30°C for soybean, 32°C for cotton and so on. Above these values, a rise of temperature is very harmful for the agricultural production. On the other hand, Kang et al. (2009) edit a review of the literature on the impact of climate change on crop yield. Doing so, they show that lack of precipitation is even more harmful for agriculture than an increase in temperature. By impacting harder crop production, the lack of precipitation has also more impact on farmers income, which is the main determinant in the decision process for migration.

Figure 3.1: SPEI variations over time



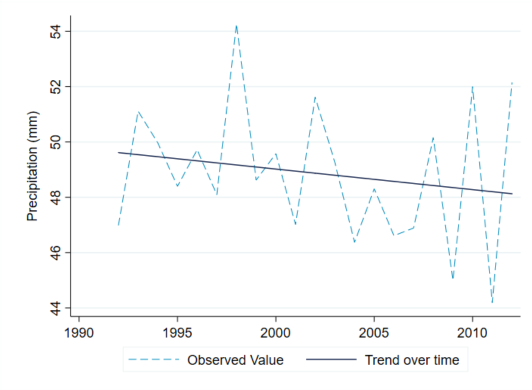
Source: Author's elaboration from Global SPEI dataset.

As previously discussed, since the transmission channel of the impact of global warming on migration goes through crop productivity, weather variations would not impact city size if the agricultural sector was not major (Barrios et al., 2006; Falco et al., 2018). As showed on Figure 3.3, land used to grow crops represents more than 50% of Chinese territory in 2015 according to the Food and Agricultural Organization. These are lands particularly vulnerable to temperature and precipitation anomalies. It also represents more surface compared to Sub-Saharan Africa

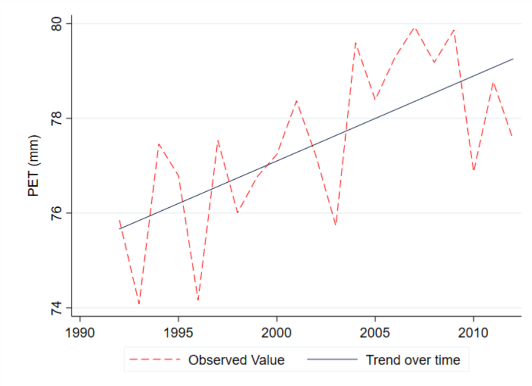
Figure 3.2: Evolution of climate variables between 1992 and 2012

(a) Temperature

(b) Precipitation



(c) Potential Evapotranspiration

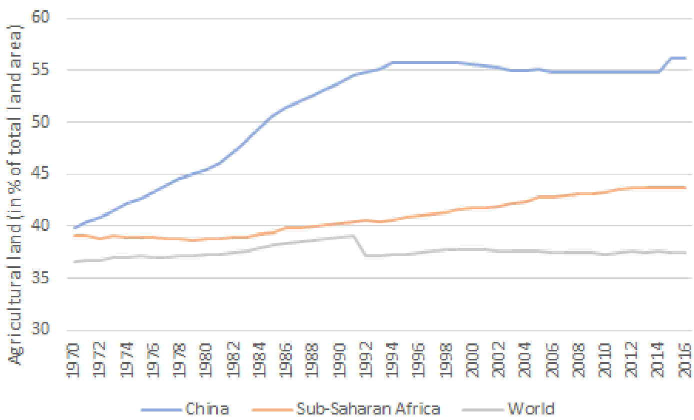


Source: Author's elaboration from CRU ts 4.0 data (Time-series data from the Climate Research Unit, update 4.0).

or the world average. Furthermore, in economic terms, Chinese agricultural sector still represents more than 20% of the national production of wealth in 1992[10]. It keeps decreasing during the study period, but still represents around 10% of the national GDP in 2012 (see Figure B5 in the Appendix). Even though the importance of agricultural sector decreases, it still is a major activity for Chinese rural areas.

[10]Data from the NBSC data on national accounts.

Figure 3.3: Share of the agricultural land in China compared to other regions



Notes: Agricultural land refers to the share of land area that is arable, under permanent crops and under permanent pastures (expressed in percentage). A thorough definition of this indicator is provided in the paragraphe 3.6 in the Appendix. Source: Author's elaboration from the FAO.

3.4 Empirical framework

In this section, I assess the impact of surrounding weather events on one grid's city size. To do so, I run several specifications, all using Fixed Effects (FE) estimator to control for time invariant grids characteristics, such as proximity to the coast, the presence of a large city with restrictive *Hukou* conversion system, and so on. I also take into consideration the various degrees of intensity of weather anomalies. Then, I check to what extent distance matters when migrating following weather variations.

First, using SPEI, I build four different dummy variables to capture more or less extreme weather variations. It goes from abnormal amount of rainfall (deficit to surplus) with the *Flood* and *Drought* variables; to severe floods and droughts with the *Extreme Flood* and *Extreme Drought* dummy variables. Given that the *Flood* and *Drought* variables are inversely correlated, putting only one of them in a regression would lead to an omitted variable bias. The main specification includes the climate dummy variables all together (see Equation (3.1c)). I also present the results when isolating each climate variable alone (see Equations (3.3.2) and (3.3.2)). Indeed, since the climate variables are highly and significantly correlated, putting them all together could cause multicollinearity among the predictors. In such case, small changes in the model or the data could cause substantial variations in the coefficient width, sign or associated p-value [11].

$$NTL_{i,t} = \alpha + \beta_1 \cdot Flood_{i\leftrightarrow 400km,t} + \beta_2 \cdot Flood_{i\leftrightarrow 400km,t-1} + \gamma_i + \gamma_t + \varepsilon_{i,t} \quad (3.1a)$$

$$NTL_{i,t} = \alpha + \beta_1 \cdot Drought_{i\leftrightarrow 400km,t} + \beta_2 \cdot Drought_{i\leftrightarrow 400km,t-1} + \gamma_i + \gamma_t + \varepsilon_{i,t} \quad (3.1b)$$

$$\begin{aligned} NTL_{i,t} = \alpha &+ \beta_1 \cdot Flood_{i\leftrightarrow 400km,t} + \beta_2 \cdot Flood_{i\leftrightarrow 400km,t-1} \\ &+ \beta_3 \cdot Drought_{i\leftrightarrow 400km,t} + \beta_4 \cdot Drought_{i\leftrightarrow 400km,t-1} \\ &+ \gamma_i + \gamma_t + \varepsilon_{i,t} \end{aligned} \quad (3.1c)$$

where $NTL_{i,t}$ denotes the nighttime light intensity of the grid i at year t. $Flood_{i\leftrightarrow 400km,t}$ represents a surplus of rainfall in any grid within 400 kilometers of distance of grid i, at year t. $Drought_{i\leftrightarrow 400km,t}$ denotes a deficit of rainfall in any grid within 400 kilometers of distance of grid i, at year t[12]. γ_i stands for grids fixed effects. They first control for grid-specific time invariant characteristics such as geographic location, soil type, slope and quality. These characteristics can make an area more or less attractive to migrants and need to be controlled. They also sweep out any differences in the use of night lights versus daytime activities among the grids, public versus private lighting, conditions for generating electricity in the area, and so on. γ_t denotes for year fixed effects. They first and foremost control for the shocks common to all grids in a given year. It could be a national agricultural policy (such as the one in 2010 in China), cost shocks such as energy and fertilizer prices, or even technological shocks. They also sweep out any differences in lights sensitivity across satellites (Henderson et al., 2012). $\varepsilon_{i,t}$ denotes the error term. In this model, the reported standard errors are robust and clustered at the country-pair level. β_1, β_2, β_3 and β_4 are key parameters of interest. They capture the impact of the weather variations on nighttime lights in surrounding areas. No extra control is added in the model. Indeed, I make the implicit assumption that weather variables vary in an unpredictable manner. I acknowledge that the general trend goes toward increasing temperature, due to pollutant economic activities. Yet, on daily basis, variation of temperature, precipitation and potential evapotranspiration is not dependent on any economic forces have low chance to be correlated to societal or economics conditions. Yet, to suffer from an omission variable bias, two conditions have to be satisfied: (1) the omitted variable X_i needs to be a determinant of $NTL_{i,j}$ ($\neq 0$) and (2) X_i has to be correlated with the included regressors in the regression $Flood_{i,t}$ or $Drought_{i,t}$ ($\neq 0$). Given that the predictors are geographic variables, the likelihood to satisfy both conditions is quite low. This study does not need additional control variables.

[11] As discussed by Paul Ranjit Kumar in his paper "Multicollinearity: Causes, effects and remedies" (2006)

[12] Note that a grid is 50 square kilometers big, so a 400 kilometers perimeter does not represent a lot of neighbors for a wide territory as China.

Second, considering as neighbor a grid that is within a 400 kilometers distance is a choice mostly based on technical reasons[13]. Indeed, China has a wide territory and defining at what point a weather shock is too far to impact one area is rather difficult. In average, a Chinese province surface is around 282,537 square kilometers. Hence, in average, a province is 531 kilometers wide[14]. So 400 kilometers represent a quite restricted perimeter for a wide country as China. When moving 400 kilometers away in China, a farmer migrates within the province borders, in average. I therefore chose to use the 400 kilometers criteria to determine what is a neighbor, in the main specification. This perimeter allows me to study short-distance and intra-province migration at China's scale. Further regressions are run, by modulating this distance criteria to check that the main results hold.

3.5 Results and Discussion

This section presents and discusses the effects of neighbors' weather variations on one grid's city size. Results differ depending on the intensity of the weather shock and how far is the area where the shock occurred.

Table 3.3 shows how urbanization of one grid reacts to weather anomalies happening within a 400 kilometers distance. Columns (1) and (2) respectively isolate the effects of rainfall surplus and deficits occurring either the current or the past year, on grid i city size. Column (3) presents the effects of the climate variables all together. When alone in the regression, both types of climate variables ($Flood$ and $Drought$) are significantly impacting i's NTL. However, they do not impact the neighbors urbanization the same way. $Flood$ have the opposite effect on i's urbanization than $Drought$. When putting both variables together, $Flood$ is no longer significant. At the contrary, $Drought$ impact remains highly significant and the coefficients are exactly the same. Droughts have substantial impact on neighboring city growth when floods do not.

Three features can explain this heterogeneity in migratory responses depending on the nature of the weather variations. First, droughts are estimated to have a greater impact on agriculture than floods. Indeed, the literature stresses the impact of global warming and the increasing dryness that comes along, on crop yields (as documented in Challinor et al. (2014) meta-analysis). This observation is especially true for China. Drougts are the kind of weather anomalies that affect the most agricultural production. Namely, decreasing consecutive wet days combined with increasing consecutive dry days are the main factors responsible for crop destruction in China (Zhang et al., 2015). In addition, China is already

[13] The more neighbors I define, the more observations I have, the more difficult it becomes to run a model on Stata software

[14] Author's calculation based on Wikipedia data on Chinese provinces.

Table 3.3: Weather variations and internal migration in the main specification

	(1)	(2)	(3)
Indep. Var.	Dependent Var.: $NTL_{i,t}$		
$Flood_{i\leftrightarrow 400km,t}$	-0.008***		-0.000
	(0.002)		(0.002)
$Flood_{i\leftrightarrow 400km,t-1}$	0.014***		0.002
	(0.002)		(0.002)
$Drought_{i\leftrightarrow 400km,t}$		0.045***	**0.045*** **
		(0.003)	(0.003)
$Drought_{i\leftrightarrow 400km,t-1}$		-0.061***	**-0.060*** **
		(0.003)	(0.003)
Obs	15,492,246	15,492,246	15,492,246
Adj-R^2	0.151	0.151	0.151
Year FE	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes

Notes: Standard errors are clustered by pair of neighbors and are denoted in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In this specification, grids within 400 kilometers to each other are defined as neighbors. By using this definition, there are 709,916 pairs of neighbors in the sample.

a very dry country (Piao et al., 2010), hence, droughts affect a larger share of the total crops. 22% of the sown area is highly vulnerable to droughts against 17% for floods (Piao et al., 2010). Hitting the hardest crop production and thus, rural population revenue, it comes as no surprise that it impacts rural-urban migration the hardest. Second, if both droughts and floods impact agricultural returns and therefore, farmers' revenues, only floods substantially impact cities infrastructure. Indeed, Benson and Clay (2000) consider different types of hazards and their varying effect on infrastructure and economic sectors. On the one hand, droughts have low consequences on infrastructure and productive capacity[15], but have an heavy impact on crop and livestock resources. On the other hand, floods cause extensive damage to both infrastructure and productive capacity. As Otero and Marti (1995) describe, floods can prevent clean water supply, damage buried pipes, energy and communication networks, all of which impact cities with a large concentration of

[15] When drougts have effects on infrastructures, it is throught the dysfunction of hydroelectric powerplants that could affect electric supply in cities. It also materialises through the damage of railways and highways through foundation distortions (Otero and Marti, 1995).

inhabitants the hardest. Thus, floods are particularly harmful for cities. Note that, they are also damaging for agriculture since they can wipe out agricultural yields. But then, for farmers living in affecting areas, neighboring cities are not considered as a preserved source of opportunities. Cities are not perceived as shelters. Hence, such events do not trigger migratory movements toward closest cities.

Migratory response also seem to vary along time. As a first step, when a rainfall deficit occurs in the surrounding areas, it immediately and positively impacts i's city size at period t (see Column (3)). As previously discussed, since drought hits the crop production the hardest, it has bigger chance to destroy the farmer's whole production in t. Thus, it suggests that farmers are unable to maintain the household income by staying put, in year t. Farmers have great incentives to migrate to the closest neighboring city to secure an income for the current year. As a second step, the year after (when the rain shortage happened in $t-1$), a decrease in grid i's city size occurrs. It could be interpreted as a return home for migrants. Indeed, the migrant objective is to maintain the household income after a shock on agricultural production. Migration is rather temporary (Massey et al., 1993; Potts, 2010). It is especially true in China when going back home equals to benefiting from public services again. The strict institutional regulations concerning internal migration encourage to go back home instead of settling in cities. Over all, the coefficients have a low magnitude. There are only few rural-to-urban movements after rain shortage.

Table 3.4 reports the impact on urbanization of more extreme and therefore potentially more destructive weather variations (see the construction of the variables in equations 3.3.2 and 3.3.2). The objective is to investigate whether the severity of the weather anomaly matter to trigger a migratory response. For the main specification in column (3), the conclusion remains exactly the same regarding droughts impact on urbanization, with identical signs, significance and coefficients. Differently, when focusing on extreme rainfall surplus, I find a negative and significant impact on grid i's city size (even though the impact is quite low since the coefficient is close to zero). Even though floods have less impact on migration than droughts, when the shock is severe enough, it does affect population displacement the following years. Precisely, in the short and medium terms, people migrate less toward cities. City size decreases. Two factors can be responsible for this result. First, when the shock is extremely severe, farmers face liquidity problems, and have no means to finance migration. Rural population is particularly vulnerable to natural disasters due to their socio-economic characteristics - they have lower income that urban dwellers (Ngai et al., 2016) - but also they live in areas provided with much less infrastructures (Shenggen and Zhang, 2004). Hence, this poor population, predominantly represented in rural areas, can not afford to hold an income in a liquid form in case of risk (Jalan and Ravallion, 2001). Rural pop-

Table 3.4: Extreme weather variations and internal migration

	(1)	(2)	(3)
Indep. Var.	Dependent Var.: $NTL_{i,t}$		
$Extreme\ Flood_{i\leftrightarrow 400km,t}$	-0.018***		-0.016***
	(0.003)		(0.003)
$Extreme\ Flood_{i\leftrightarrow 400km,t-1}$	-0.003		-0.006**
	(0.003)		(0.003)
$Extreme\ Drought_{i\leftrightarrow 400km,t}$		0.041***	0.040***
		(0.004)	(0.004)
$Extreme\ Drought_{i\leftrightarrow 400km,t-1}$		-0.039***	-0.040***
		(0.003)	(0.003)
Obs	15,492,246	15,492,246	15,492,246
Adj-R^2	0.151	0.151	0.151
Year FE	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes

Notes: Standard errors are clustered by pair of neighbors and are denoted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

ulation is therefore more vulnerable when a severe weather shock occurs. They are more likely to remain trapped in their homeland rather than being able to migrate. Second, as discussed above, neighboring cities can not be considered as safe shelters full of job opportunities since they are also impacted by floods. Under these circumstances, urban population itself could flee from the affected zone *i.e.* the city, impacting negatively the NTL level in the present regression.

Table 3.5 exposes the heterogeneous impact on city size depending on the distance at which the weather variations occurred. No matter how close, rainfall surplus keep having no impact on neighbors city size (except for migration in t when a flood occurs in $t-1$, 200 kilometers away). It is consistant with the argument that, given that the cities are also as strongly impacted by the flood than rural areas, cities are not attractive for potential migrants. At the opposite, rainfall shortages keep encouraging immediate migration to neighbors cities in t. But migrants still return home the next year, when a new agricultural cycle starts, since the coefficient associated with NTL is negative when the drought occurred in $t-1$. Note that, the coefficients associated with droughts' effects on neighboring city size in t are bigger when the city is 400 than 100 kilometers away (respectively 0.45 and 0.29). When people immediately migrate to a neighboring city the year

Table 3.5: Weather variations and internal migration with several definitions of neighbors

	(1)	(2)	(3)	(4)
	100km	200km	300km	400km
Indep. Var.	Dependent Var.: $NTL_{i,t}$			
$Flood_{i\leftrightarrow 400km,t}$	-0.001	-0.009*	-0.000	-0.000
	(0.010)	(0.005)	(0.003)	(0.003)
$Flood_{i\leftrightarrow 400km,t-1}$	-0.018*	-0.017***	-0.006*	0.002
	(0.009)	(0.005)	(0.003)	(0.002)
$Drought_{i\leftrightarrow 400km,t}$	0.029***	0.034***	0.046***	0.045***
	(0.011)	(0.005)	(0.004)	(0.003)
$Drought_{i\leftrightarrow 400km,t-1}$	-0.116***	-0.091***	-0.073***	-0.060***
	(0.010)	(0.005)	(0.003)	(0.003)
Obs	916,014	4,119,654	9,067,190	15,492,246
Adj-R^2	0.282	0.210	0.174	0.151
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered by pair of neighbors and are denoted in parentheses. *** p<0.01, ** p<0.05, * p<0.1. First column, are considered as neighbors, grids that are 100 kilometers around. In column (2), are considered as neighbors, grids that are 200 kilometers around.

the drought occurs (in t), they do not necessarily go to the closest cities and can aim at further ones. One possibile explanation is that, even though droughts have smaller effects on cities than floods, they may still cause some dysfunctions in the closest cities. As evidenced by Desbureaux and Rodella (2019), droughts can also impact urban areas, even though they do not rely on agricultural sector. Then, the further rural migrants would go, the best chance they have to migrate in a city not impacted by the same variations. This result could also reflect that some migrants are willing to travel more distance to find better job opportunities. The other results do not support this belief. Indeed, for all other kind of weather shocks, the coefficients' magnitude decreases along with the distance. It means that the further the weather variation occurs, the less impact it has on neighbors city sizes. Thus, in average, distant cities are less if not at all impacted by rural migration following weather shocks. In Table 3.6, I check that the results found in Table 3.4

also hold no matter how close the weather variation takes place. In presence of severe droughts or floods, rural population do not migrate to neighboring cities, no matter the distance. The only migration occurring takes place in year t, right after severe droughts. This migration targets rather 400 kilometers away cities than close ones.

Table 3.6: Extreme weather variations and internal migration with several definitions of neighbors

	(1)	(2)	(3)	(4)
	100km	200km	300km	400km
Indep. Var.	Dependent Var.: NTL			
$Extreme\ Flood_t$	-0.031***	-0.040***	-0.021***	-0.016***
	(0.012)	(0.005)	(0.004)	(0.003)
$Extreme\ Flood_{t-1}$	-0.036***	-0.030***	-0.015***	-0.006**
	(0.011)	(0.005)	(0.004)	(0.003)
$Extreme\ Drought_t$	0.036**	0.038***	0.045***	0.040***
	(0.015)	(0.007)	(0.005)	(0.004)
$Extreme\ Drought_{t-1}$	-0.096***	-0.069***	-0.056***	-0.040***
	(0.014)	(0.007)	(0.004)	(0.003)
Obs	916,014	4,119,654	9,067,190	15,492,246
Adj-R^2	0.282	0.210	0.174	0.151
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered by pair of neighbors and are denoted in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In the first column, are defined as neighbors, counties that are 100 kilometers around. Second column, are considered as neighbors, counties that are 200 kilometers around.

3.6 Conclusion

This chapter uses satellite data to proxy urban growth, and estimate the impact on city sizes of surrounding weather variations. I find strong evidence of a link between weather variations and city size in nearby areas. Yet, the effects are heterogeneous according to the type of weather variation.

First, the most impacting weather anomaly is the rainfall shortage (negative SPEI). It affects migration as soon as the soil becomes dryer than normal, no matter how severe. In the short run, the year the rainfall shortage occurs, it triggers immediate movement out of rural areas. Rainfall shortages hinder a good harvest in year t, therefore, the farmers out-migrate to cities to try their luck and earn a living in a more diversified and less agriculture-related economy. Furthermore, in this case, migrants do not necessary migrate to the closest cities, but are willing to go a little further to look for better job opportunities. The next year following the rainfall shortage, migrants come back home. It allows me to extract the main motive for migration in China. Farmers aim at softening their budgetary constraint in the short-run. Migration is thus a coping strategy the year a weather shock occurs. Migrants return home afterwards, when there is no longer disturbance for the next harvest.

Second, I find that rainfall surpluses have almost no impact on migration behaviors. They only do when the shock is particularly severe (SPEI > 1.5). In that case, people are actually even less likely to migrate out of rural areas. It supports the literature showing that weather shocks only exacerbate existing vulnerabilities and inequalities (Otto et al., 2017). One consequence is that it can tighten households' budgetary constraint so hard that it prevents them to migrate after weather shocks. Under these circumstances, migration is not a suitable adaptation strategy for Chinese countryside.

Rural population needs actual coping strategies to avoid the worsening of their financial conditions after every weather shock. Indeed, the stakes are high even at a macro-level since adopting long run adaptation strategies could reduce climate-induced damages on crop profits by 30 to 50% by the end of the century (Huang et al., 2018). On the one hand, *ex ante* risk management measures could reduce the risk. For instance, land-use regulations are one of them. A correct balance between urban and vegetation/ecological areas mitigates the occurrence of floods (Shi et al., 2005). Currently, land remains an easy source of revenue for local governments (Lichtenberg and Ding, 2009). They sell parcels of land to project developers as a source of funding, and participate into speeding urban sprawl, regardless of the balance between urban and ecological areas. On the other hand, rural population also lacks of both *ex ante* and *ex post* assistance. In developed countries, private companies and government funds play a huge part in compensating the cost of climatic events. Yet, the penetration rate of private insurance is particularly low in China (Wu et al., 2012). It is a key component in the fact that weather anomalies worsen existing vulnerabilities. *Ex ante* and *ex post* strategies are crucial for disasters to stop hardening poverty conditions in rural areas and to prevent uncontrolled migration toward cities.

Last, these findings seem to be inconsistent with what actually happens in other developing countries. Indeed, as demonstrate Koubi et al. (2016) work on five different developing countries based on survey data, droughts, since they are a gradual environmental event, are less likely to trigger migratory movement than floods, a sudden-onset disaster. Indeed, rapid-onset events force displacement by definition, since they are responsible for the destruction of people home. Lacking of place to live, the population uses this disaster to start fresh in a non-affected area. This incentive is less strong if the natural disaster is gradual. This difference between gradual and rapid-onset events should be closely examined in Chinese case to better understand what is done differently. One of the most important feature influencing migratory response is public intervention (Mbaye, 2017). Yet, rapid-onset disasters, by causing tremendous physical damage in a short amount of time, are handled quickly to be able to rescue the affected population. At the opposite, slow-onset events are more predictible and can be prevented with *ex ante* measures. Still, very often, governments wait until physical damage is as severe as for sudden-onset disasters to intervene (OCHA, 2011). Thus, in comparison, slow-onset disasters are being tackled very late by governments. That is what I intend to do in Chapter 4.

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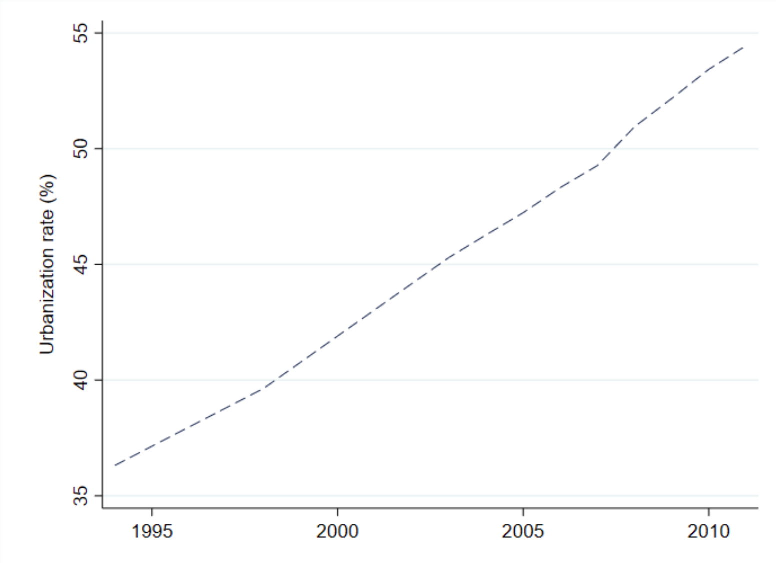
Appendix to chapter 3

Figure B4: Urbanization trend using Census data



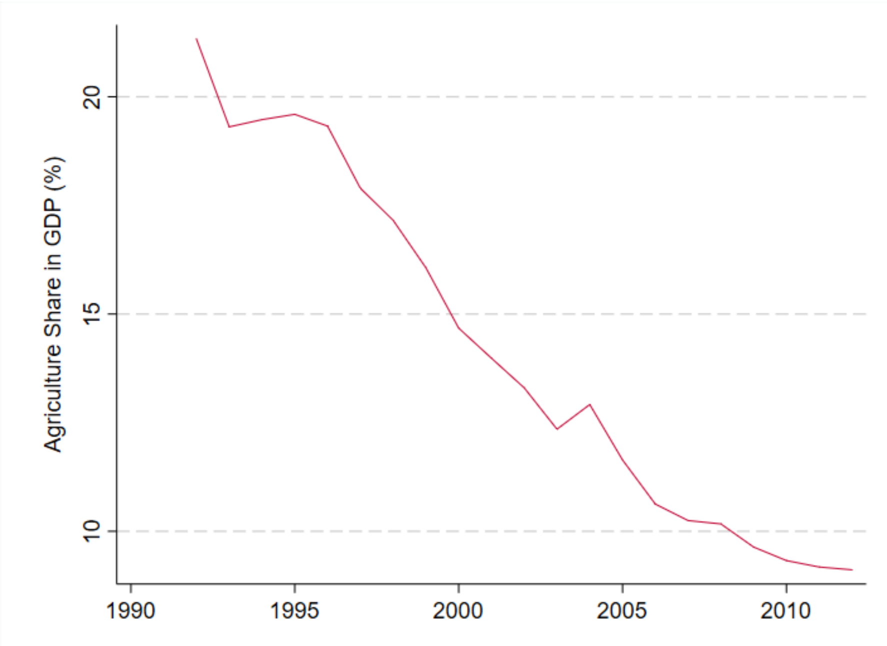
Note: The urbanization rate is the share of urban population (according to 2000-Census definition) in the total permanent population at year-end. Source: Author's calculation from NBSC data.

Table B7: Variables definition

Variable	Definition	Source
Nighttime Light (NTL)	Yearly measure of light intensity at night. It ranges from 0 (desert area) to 63 (dense area). Cloud-free measure made from satellite data.	NOAA National Geophysical Data Center
SPEI	Indicator of drought conditions in a country. It consists of standardized values of the difference between precipitation and evapotranspiration.	Global SPEIbase
Temperature(TMP)	Mean temperature in a month, expressed in degrees Celsius	CRU ts3.24 dataset
Precipitation (PRE)	Total amount of precipitation in millimeters	CRU ts3.24 dataset
Evapotranspiration (PET)	Measure in millimeters of the water lost per day by the soil.	CRU ts3.24 dataset

Note: All weather variables are It is interpolated into 0.5° latitude/longitude grid cells. Source: Author's elaboration from NOAA, the Global SPEIbase and the CRU ts3.24 dataset.

Figure B5: Importance of the agricultural sector in national wealth



Source: Author's elaboration from NSBC national accounts data.

Definition of agricultural land

Below is the long definition provided by the FAO of the UN of what represents agricultural land:
"*Agricultural land refers to the share of land area that is arable, under permanent crops, and under permanent pastures. Arable land includes land defined by the FAO as land under temporary crops (double-cropped areas are counted once), temporary meadows for mowing or for pasture, land under market or kitchen gardens, and land temporarily fallow. Land abandoned as a result of shifting cultivation is excluded. Land under permanent crops is land cultivated with crops that occupy the land for long periods and need not be replanted after each harvest, such as cocoa, coffee, and rubber. This category includes land under flowering shrubs, fruit trees, nut trees, and vines, but excludes land under trees grown for wood or timber. Permanent pasture is land used for five or more years for forage, including natural and cultivated crops.*"

Chapter 4

When does it go back to normal? A Natural Experiment on Wenchuan earthquake impact on migration to cities

4.1 Introduction

From 2000 to 2016, China has experienced in average three natural disasters a month[1]. In the economic literature, migratory response is different whether the natural disaster has a slow or rapid-onset[2]. Indeed, for instance, Koubi et al. (2016) examine five different developing countries migratory response following gradual and sudden-onset events. They find that droughts, a gradual environmental event, are less likely to trigger migratory movement whereas floods, a sudden-onset disaster enhance migration. In constrast, in this thesis previous chapter, findings show the exact opposite for China. Namely, floods trigger less movement than droughts. These contrasting results could be imputed to Chinese particular context, in particular rapid intervention led by a strong Central government, following natural hazards. Because China presents a particular setting, this chapter proposes to investigate the use of migration as an *ex post* risk management strategy when a severe sudden-onset disaster occurs. This chapter also discusses the importance of government intervention post-disaster, and how reconstruction is linked to disturbances in migratory behaviors.
The present chapter aims at further examining migratory response after a sudden-onset disaster, that is to say, an earthquake, and check if the efficiency of public intervention in China is responsible for the low migratory impact. Indeed, most of the time, migration is a coping strategy for the affected population, particularly

[1]Calculated based on the data from 2000 to 2016, using Emergency Events Database (EM-DAT) thoroughly discussed in Section 4 and 5.

[2]By rapid-onset disasters, scientists refer to natural disasters that arrive rapidly and with short if not zero warning. Are part of that list floods, volcanic eruptions, earthquakes, tornadoes, wildfires, tsunamis (Bates, 2002). Slow-onset disasters are gradual. Droughts, desertification are considered as such.

in developing countries. Namely, when such natural hazards occur, people have three possible adaptation strategies: either they stay put, waiting for the disaster to end, accepting related costs; they stay put but have risk mitigation strategies that lower their economic losses; or they flee from the devastated areas, that is to say, home. One migrates if no other adaptation strategy is provided by either public or private sectors. In particular, in the literature, public intervention or political changes can make unnecessary the use of migration as a coping strategy after natural disasters (Cavallo et al., 2013; Mbaye, 2017). Often, distinction is made between developed countries and developing countries. These first ones have better risk management strategies due to technological abilities that enable to limitate the risks *ex ante*, but also enough wealth to finance *ex post* intervention and reconstruction. Developing countries often lack of all of the above (Mirza, 2003; Reuveny, 2007; Noy, 2009). China is a mix, with enough wealth to interviene efficiently after the disaster, but not enough risk management measures *ex ante* to mitigate the damages[3]. To better understand to which extent Chinese government actions impact the use of migration as a coping strategy following a disaster, I use a strong earthquake occuring in China in 2008, as a natural experiment, to monitor variations in internal migration and how it coincides with Central Government schedule.

On May 12, 2008, a 8.0 magnitude earthquake took place at the center of Sichuan province, 80 kilometers away from the provincial capital Chengdu. It is the deadliest earthquake that hit China, since the 1976-one in Hebei, that killed over 240,000 persons, and the strongest since the 1950-one that stroke Tibet with a 8.5 magnitude[4]. Fifteen million persons lived in the affected area, and approximately one third were left homeless after the earthquake due to the destruction of their houses[5]. This earthquake triggered forced movement (Bates, 2002; Black et al., 2011). Yet, forced movement does not mean migration. Indeed, in this present chapter, I identify to what extent this sudden-onset disaster impact migration, to later verify if public authorities intervention allowed a fast "back to the trend" migratory patterns in the affected areas.

To do so, I first assess the impact of Wenchuan earthquake on Sichuan cities' size. Indeed, in China, migration largely remains a one-way movement *i.e.* from countryside to cities[6]. Rural-urban migration is still the main source of size variation

[3]This statement was true at least before Wenchuan earthquake. Since then, reconstruction uses improved material so that buildins resist to disasters Xu et al. (2014a).

[4]From EM-DAT (2018) listing.

[5]Sudden natural disasters turn a livable place into an unfit one for human habitation, for a finite length of time.

[6]This feature is thoroughly discussed in Section 4.2.3.

for Chinese cities[7] (Zhang and Shunfeng, 2003). Hence, if there are disturbances in migratory flows following a natural hazard, it necessarily translates into variations in rural-urban movement and therefore in city size. I also examine if migratory behaviors eventually go back to their original trend. If they do, I verify that this "back to trend" phenomenon coincides with the government intervention following the natural hazard. To tackle this topic, two issues were raised. First, high-frequency data are necessary to assess immediate movement to cities following natural disasters. Census data have large time intervals that do not suit the search for temporary movement. Going through the literature, I decide to use annual density of nighttime lightening to proxy city size. Indeed, the more inhabitants there are in a city, the more houses are illuminated at night, the lighter the city gets, the denser luminosity is. Second, it is difficult to isolate the impact of a natural disaster alone on migration patterns. To do so, I match Sichuan province with a counterfactual built using the Synthetic Control Method (SCM). This technique developed by Abadie and Gardeazabal (2003), enables me to create a virtual counterfactual that has similar migration patterns pre-shock. Therefore, the differences post-shock can be interpreted as due to the earthquake. Also, in this chapter, to check whether migration patterns diverge from the trend, I focus on intra-province migration based on the literature. After sudden natural shocks, migration is rather short-distanced, people move within their state if not county (Smith and McCarty, 1996; Smith et al., 2006; Black et al., 2011). In China particularly, intra-provincial migration ranges from 75 to 78% of total migration (Wang et al., 2003; Zhao, 2005). It is the most common form of migration.

Doing so, this work provides evidence of negative effects of Wenchuan earthquake on Sichuan city size. In accordance with the results in this thesis previous chapter, natural hazards prevent migration from happening. Cities, probably also affected by the event, no longer attract migrants. Plus, results also show that, three years after the shock, in 2011, the effects on migration are null. Sichuan experiences a "back to trend" migratory behaviors, suggesting that rapid-onset naturals disasters have no permanent impact on migration patterns. The timing of this return-to-trend exactly coincides with the end of the three-year reconstruction plan led by Chinese government. As a conclusion, Chinese intervention was first successful in offering solutions to the affected population that did not need to use migration as a coping strategy to lessen the costs of the natural hazard; but also in reestablishing the attractivity of cities as migration destination three years later, when reconstruction was completed. This work indicates the effectiveness of Chinese reconstruction within 3 years.

The rest of the chapter is organized as follows. Section 4.2 reviews the specific

[7]Due to a rigid birth policy, the natural growth rate of the population in cities is the second source of city size growth in China, but not the main one.

characteristics of this case study, namely the economic impact of the earthquake, the planification of the reconstruction but also Chinese history regarding internal migration. Section 4.3 provides an overview of the literature that studied migration as an adaptation strategy to natural disasters. Section 4.4 describes the variables used in this chapter, discusses their use and presents some stylized facts. Section 4.5 details the empirical strategy necessary to isolate the effect of the shock on migration patterns. Section 4.6 enables a discussion on the main results. In Section 4.7, I run placebo tests to check these results' robustness , to later conclude in Section 4.8.

4.2 National Context

4.2.1 Economic impact of Wenchuan earthquake

As stated above, the northwestern part of Sichuan province experienced a 8.0 Ms magnitude earthquake, in Wenchuan county. It ruptured the floor at the epicenter, Yingxiu Town (depicted with a red marker on Figure 4.1), 75km westward from Chengdu City, leaving a 15km depth fracture. This area is mountainous and mostly rural. The closest urban areas are located on the basin, *i.e.* the flat region colored with the lightest green on Figure 4.1. In total, Chinese officials estimated the reconstruction cost to be 1 trillion yuan (147 billion US dollars)[8]. It represents Sichuan entiere economic output in 2007.
Indeed, earthquakes in general but Wenchuan one especially, trigger different types of damage [9]. First, the earthquake caused breaches in that soil nearby Beichuan-Yingxiu Fault. It induced land displacement and therefore building damage. Second, the earthquake is responsible for severe geolocigal disasters, the so-called aftershocks. There were generally rockfalls, rock avalanches, debris flows, but above all landslides. 1,701 landslides occurred and generated substantial damages (Cui et al., 2011). In this case, this phenomena is further exacerbated by the fact that the epicenter is located in a mountainous area. Most of the aftershocks moved northeast from the epicenter, along the Beichuan-Yingxiu Fault, in Longmenshan Zone (represented by a red line on Figure 4.1), reaching Gansu and Shaanxi provinces (Cui et al., 2011). As a consequence, complete villages were buried, roads were blocked, buildings destroyed. Note that damages even touched Sichuan economic corridor, namely, the cities of Mianyang, Deyang, Guangyuan and Dujiangyan, known for their factories and active participation in the province

[8]Source: The newspaper the Guardian that quotes the National Development and Reform Commission plan for reconstruction. Url: https://www.theguardian.com/world/2008/aug/15/chinaearthquake.china

[9]Further details can be find in Yuan (2008) paper.

business. But as recalls Yuan (2008), the intensity of the aftershocks attenuated really quickly between the epicenter located in the mountains and the cities situated on Sichuan basin. Thus, cities are located in a less intensely-hit area.
Still, in numbers, it is hard to distinguish which area has been the most affected by the earthquake. Some economists tried to estimate direct and indirect costs related to the disaster, by economic sectors or type of structures. For instance, Yuan (2008) calculates the direct economic losses due to Wenchuan earthquake in several areas, by building a loss ratio by subregion, taking many factors into account such as the building type and size, the replacement price, and so on. He finds that buildings in the countryside are the most hardly hit. Indeed, in Sichuan, economic losses due to countryside houses destruction were up to 1.624 billion yuan against 74 million yuan for urban ones. Yet, when distinguishing economic sectors, he finds that enterprises are more expensive to rebuild than the agricultural sector (respectively 1.223 billion for this first against 608 million yuan for the latter). Different technique but same conlusion for Wu et al. (2012). They include costs related to changes in production capacity and spillover effects in the local economy related to the disaster to estimate the cost of Wenchuan earthquake by sector[10]. They find that the manufacturing sector alone lost 85.35 billion yuan in 2008, when the agricultural sector only lost 8.36 billion yuan due to the earthquake. As an explanation, they argue that the manufactoring sector suffers from larger economic losses due to its high quantity of productive capital compared to another sector such as the agricultural one, equipped with less sophisticated infrastructures.

[10]To do so, they use an Adaptive Regional Input–Output model based on Sichuan Provincial Bureau of Statistics data.

Figure 4.1: Wenchuan earthquake epicenter

Notes: Yingxiu is the epicenter of Wenchuan earthquake. The red line represents Beichuan-Yingxiu fault of Longmenshan zone. It concentrates most of the aftershocks and therefore, most of the damage. Chengdu, on the southeast part of the map, is the capital of Sichuan Province. Source: 2019 satellite data extracted from Google map by the author.

4.2.2 Organization of the reconstruction

Apart from few exceptions, reconstruction is largely government-led. Most of the reconstruction is based on a three-year planned released couple of months following the disaster, on August 12, 2008. Six goals aimed to be achieved within 3 years, namely: "*rebuilding a house or apartment for every family; ensuring the job stability for at least one member of each family, with annual disposable personal income exceeding the pre-disaster level; providing basic social welfare for disaster survivors, i.e., 9-year free public education, public health and basic medical care, social welfare and other basic public services; restoring and upgrading public facilities and infrastructures; further developing the economy of earthquake stricken area; improving the ecological environment with enhancements in ecology, environment, disaster mitigation and preparedness capacities*" (quotation from Xu et al. (2014a)).

To do so, the government enforced an original measure such as the Paired Assistance Program *i.e.* a non-affected province or municipality was financially support and materially assist a severely affected county[11] (Huang et al., 2011). Hence, fundings were made available quickly. Local governements funded around 70 billion yuan of the reconstruction via this partnership program (Huang et al., 2011) and the Central government released a 1.7 trillion yuan to finance the three years' recovery plan [12]. Before the earthquake, Sichuan province was underdeveloped (Xu et al., 2014a). As a consequence, the government managed to complete their objectives within 3 years, resulting in positive effects on both social and economic features (Dunford and Li, 2011).

Yet, one usual actor was missing in the funding of disaster-related economic losses. Indeed, one important feature of the reconstruction following Wenchuan earthquake in China is that most people and small businesses were not covered by insurance. Furthermore in China, even though private homeowners had insurance, earthquakes were not covered before Wenchuan one. Hence, insurance companies contribution to the reconstruction following the disaster did not exceed 0.3% of the total economic losses (Wu et al., 2012). This phenomena is a common feature for developing countries and contrasts with the majority of the economic litterature based on disasters occurring in developed countries. For instance, for Huricane Katrina in 2005, a large share of the economic losses was paid off by either in-

[11] 19 provinces or municipalities were paired with the 19 most affected counties whom list is provided in Table C6 in the Appendix. The paired assistance consists in giving away at minimum 1% of its financial income in the previous fiscal year, but also in providing services such as renconstruction planning, supervision, repairing residential and public services facilities and so on.

[12] Source: The State Council, in a press conference on Wenchuan earthquake recovery and reconstruction fully completed, that took place in 2012, which was partly retranscribed in Xu et al. (2014a) book.

surance companies or the U.S. federal government. Here, the central government has a owner-driven strategy to rebuild residential houses. The main advantage of this strategy is that the owner runs the reconstruction from start to bottom. The owner is the best suited to match the means with the needs. The organization is therefore efficient, since the Central government, far from the affected areas, would have been less performant in estimating the needs. The disadvantage is that most of the money for the reconstruction was raised by contracting loans. As a consequence, households debt skyrocketed in 2008, even though they benefited from small grants from the government and preferential loans with zero interet rate (Huang et al., 2011). Hence, as explain Wu et al. (2012), it further reduced household resources (already weakened by the potential destruction of their workplace) and their consumption, in order to pay off their increasing debts. This strategy ended up holding back economic development and increased vulnerability in some communities, especially in rural areas as Dunford and Li (2011) argues[13]. This reconstruction funding largely based on households can be a motive for migration to cities, so that at least one member of the family can provided a decent wage, necessary to refund the loan.

4.2.3 Chinese mobility habits

To better understand Chinese habits in terms of internal migration, let me first recall that, as in many other developing countries, migration in China goes mostly from rural to urban areas. According to the National Bureau of Statistics in China (NBSC), China's urbanization has grown from 19.4% to 52.6% between 1980 and 2012. Rural-to-urban migration alone is responsible for 75% of the urban growth from 1978 until 1999 (Zhang and Shunfeng, 2003). Part of the explanation comes from the large income difference between rural and urban ones. Indeed, as Ngai et al. (2016) demonstrate, migration in China is a movement out of agriculture due to a wide productivity gap between urban and rural employment, which results in huge difference in wages. Namely, in average, in 1980, rural income represents 45% of the urban income to fall to 37% in 2015, according to NBSC data. In turn, rural dwellers have high incentives to flee the countryside to earn a living. They end up inflating the labor supply for low-qualified urban jobs such as street cleaning, retail services, housekeeping services and construction (Chan and Zhang, 1999). Another line of explanation for the migration to be largely from rural-to-urban in China, is the uneven provision of infrastructure. Due to preferential policies from both local and central governments (Zhang and Zou, 2012), rural areas benefit from a poor network of infrastructure (Liu et al., 2009). It goes from the access to

[13]It also echoes with the fact that most of the houses that needed to be rebuild were in rural area, as discussed in the previous section.

secondary or higher education institutions in rural areas (Banerjee et al., 2012), to the access to credit (Yuan and Xu, 2015), to road network and access to electricity (Shenggen and Zhang, 2004) and to access to health facilities (Gong et al., 2012). Many papers document the widening gap in health status between urban and rural dwellers in China (Shen et al., 1996; Yan-Ping et al., 2009; Liu et al., 1999; Luo et al., 2009). According to the 2011 Edition of the Chinese Health Statistical Digest, as a consequence of uneven healthcare availability, neonatal mortality, infant mortality and the mortality of children older than than 5 years old are greater in rural areas compared to urban ones (respectively 10% vs 4%; 16% vs 6%; 20% vs 7%). Therefore, incentives to migrate to cities are high when willing to pursue higher education, access to health facilities or reach a greater standard of living. Last but not least, the land tenure system remains highly informal in China, increasing the cost of migration for anyone willing to migrate to rural areas. Land allocation in rural areas being discretionary (Rozelle and Li, 1998), obtaining land-use rights for a migrant remains quite uncertain. Also, overtime, lands are used as a source of municipal revenue. For this reason, they are sold to entrepreneurs by local governments (Lichtenberg and Ding, 2009). Added with the increasing degradation of soil quality (Reuveny and Moore, 2009), it results in a shortage of farmland. As discussed by Zhao (1999), it is the major reason for labor migration out of rural areas and further reasons why migration to rural areas is unlikely in China.

Hence, to prevent massive migration toward cities in China, the Central Government enforced institutional measures to inhibit migration. The biggest of all is the *Hukou* system. It is a Household Registration System where the residence status depends on the place of birth. For instance, when migrating in a different administrative region, Chinese citizens lose access to many services such as the official housing market, educational structure, medical care, some public subsidies and so on[14] (Wang, 2004). This residence permit (the *Hukou*) is delivered by the police and can change over time. Yet, converting a *Hukou* from a rural to an urban one is difficult, and it is even truer when targeting a large city. With this system, the central government prevents mass migration, but also hinders a rural dweller to seek for a better-paid job by legally moving to neighboring urban areas. This system keeps being reformed and softened since 1970, but remains a major obstacle for permanent migration in China. Another major institutional barrier for migration would be the Chinese tenure system. Indeed, in China, private prop-

[14]Indeed, the intuition is that the Central Government would be unable to provide the same quality of public services in cities if the urban population doubled too rapidly. Hence, they accept to welcome rural migrants if and only if they do not benefit from the same public service than the residential urban population. The process to become an official urban resident is much longer and allow the government to have time to adjust its offer in public services in the meanwhile. This measure is supposed to prevent unplanned city growth.

erty is not widespread. Farmers families have a right to use the land, but do not own it. Therefore, it raises two types of concerns when willing to migrate. First, people out-migrating from rural areas can have their land-use rights seized in their absence, without any compensation Mullan et al. (2011). If not loosing the land, migration could result in a redistribution of part of the household land, because the size of their household got smaller, so redistribution of some hectares could be enforced to preserve “egalitarian land holdings” (Rozelle and Li, 1998). Second, with such insecure land tenure system, the land rental market is still very limited. Though, renting the left-behind farm usually represents a great way to offset the loss of the agricultural income. The inability to rent the land here, further increases the opportunity cost of leaving the farm (Hu et al., 2011). In a word, the uncertainties around the land tenure system in China skyrocket the cost of migration out of rural areas. Therefore, it comes as no surprise that economists prove that land rights insecurity not only constrain migration but also shortens out-migration duration for rural dwellers, in China (Yang, 1997; Zhao, 1999; Oi, 1999; De La Rupelle et al., 2009; Mullan et al., 2011).

4.3 Ambiguous link between earthquakes and migration

The literature emphasizes two sorts of consequences following natural disasters. First, people from affected areas can benefit from the reconstruction, which can either give job opportunities and prevent migration; or increase the level and quality of local infrastructures following the reconstruction. Thus, earthquakes could be responsible for the so-called “creative destruction”. Halliday (2006), for instance, uses panel data of rural households including years 1997, 1999 and 2001, to investigate the role of migration to the United States (US) as an *ex post* risk management strategy in El Salvador. He knows how many migrants there are per households, thus he can measure the migrant flow per household by computing the difference in migrant stocks between two time periods. He finds that disasters that impact agricultural conditions do increase migration to the US. It also impacts remittances *i.e.* migration objective is to provide a stable income for the household stayed at home. Halliday (2006) is also able to focus on the impact of earthquakes since some of them occured at the beginning of 2001. He shows evidence that 2001 earthquakes reduced net migration to the US. The more damage the earthquake causes, the less likely it is to send a household member to the US. He provides evidence that this impact on migration has everything to do with the reconstruction back home, and less to do with the impossibility to finance migration. Hence, migration is a coping strategy if and only if the physical damages are not too severe. Otherwise, all the help possible is needed for the reconstruction. This result particularly echoes Wenchuan earthquake given that residential houses reconstruction was owner-based. Hence, on the one hand, reconstruction in countryside demands some workforce. On the other hand, reconstruction is still largely owner-funded, hence a stable income is needed in every household to allow the loan repayment.

Gignoux and Menéndez (2016) look into long-term effects of a series of earthquakes on economic outcomes of a set of earthquakes taking place in rural Indonesia since 1985. They use data from a longitudinal household survey along with data on local ground tremors provided in the US Geological Survey. They find that people do not migrate out of affected areas. At the opposite, migration even diminishes following an earthquake. These results are correlated with the fact that individuals from affected areas do not economically suffer from the earthquakes. Indeed, Gignoux and Menéndez (2016) find that affected individuals suffer from economic losses in the short-run but they recover in the medium-run (between two to five years after the shock). More importantly, they can exhibit income and welfare gains in the long-run thanks to the reconstruction of local infrastructures within six to twelve years. In terms of context, one noticeable difference with Wenchuan earthquake is that earthquakes studied here are undoubtedly numerous, but they are also less extreme. Yet, the additional cost due to a more severe earthquake may not be a problem to generate economic wealth in the long-run. Indeed, studying Vietnam, Noy and Vu (2010) finds that the more costly a natural disaster is (because of the amount of destruction of productive capital), the better impact it has on the economy.

At the opposite, others works highlight the increasing migration following a sudden-onset disaster[15]. When natural hazards enhance migration, it is because they affect the population income source. For instance, comparing 2004-hurricanes and Katrina, Smith and McCarty (1996); Smith et al. (2006) find that Katrina created more permanent migration than the 2004-hurricanes that occurred in Florida, USA. The rationale for this finding is that Katrina was far more damaging economically than the 2004-hurricanes. It implied more job losses and therefore, more motivation to migrate[16]. Differently, looking at a tropical cyclone in Dominican

[15] This case study focuses on earthquake impact on migration. These case studies being not so frequent in the literature, I might refer to other analysis focusing on other types of natural shocks. Natural disasters with a sudden onset (such as tropical cyclones, earthquakes, etc.) are comparable since they have similar patterns in terms of destruction and can trigger similar responses from the population. I will therefore quote papers on tornadoes and hurricanes along with the earthquakes ones.

[16] For both events, when they moved, it mostly remained temporary and within a short-distance (within the same state if not county). It is an additional motivation to look into variations in intra-provincial migration in China, following a sudden-onset event.

Republic in 1979, Belcher and Bates (1983) question households on their intention to migrate in a survey. People do not necessary migrate if the tremendous damages strike their community, but do migrate if the annual harvest has been destroyed. The ones who intended to stay put, despite the disaster, also grow crops that can be harvest several times a year.

Most studies assessing the effects of natural disasters on migration, use survey data. When these are not available, economists use all sorts of data and still manage to draw a conclusion. It is the case for Boustan et al. (2012), they only use 1920s and 1930s US census data to look at the population response to hurricanes, earthquakes, floods and tornadoes. Even though they find that tornadoes trigger out-migration from young men, no conclusion can be made concerning earthquakes given their rarity in between the census periods. In his book, to reach a conclusion, Burton (1993) focuses on two major earthquakes in Central America (in Managua, Nicaragua, 1972) and uses a population census two years after the shock to seize how many displaced people went back home. There were 420,000 inhabitants in Managua before the earthquake, in 1972. Half of that amount were displaced because of destroyed infrastructures. In 1974, Managua population had grown to 650,000. Therefore, Burton (1993) considers that most of the initially displaced population came back home. Other authors, with no access to quality datasets, use satellite data. For instance,Klomp (2016) uses nighttime light intensity to assess the impact of natural disasters on multiple countries. This cross-country analysis emphasizes negative impact of natural disasters on light density in the short-run, to later on have no effect at all on the outcome.

Last but not least, to assess the impact of natural disasters on economic outcomes, most economists undertake impact analysis methods. Cavallo et al. (2013) are the first to gauge the average impact of natural catastrophies on economic outcomes using the Synthetic Control Method. They run a macro-panel study on several countries affected by different kind of natural disasters. For each country affected by a large disaster, they compute a synthetic counterfactual to compare it with. They show that only large natural disasters have a negative effect on economic growth, in both the short and long terms. Yet, when controlling for major political changes following the disaster (such as radical political revolutions), natural disasters had no significant impact on economic growth anymore, no matter their severity. In Chinese's case, no major nor minor political change occurred either before or after Wenchuan. But if so, since Sichuan counterfactual is created using other Chinese provinces governed by a strong Central administration, any policital change affecting one province would affect all of them. To that extent, any Chinese province is a suitable counterfactual for Sichuan.

4.4 Data and stylized Facts

4.4.1 Data description

In this chapter, I assess the impact of Wenchuan earthquake on Sichuan city size, using data going from 2003 to 2012[17]. First step is to divide the sample in three categories. Sichuan is one of them, it is the province affected the hardest by Wenchuan earthquake. I make the assumption that the attractivity of its cities was impacted. The other provinces damaged by the earthquake are another category. I do not focus on them in this chapter. The last category covers the control provinces *i.e.* regions that experienced no significant damage following the earthquake. They are used to build a counterfactual for Sichuan. The classification of Chinese provinces is made based on the EM-DAT database. It lists worldwide natural disasters and their human and economic impacts. It is provided by the Centre for Research on the Epidemiology of Disasters (CRED) and the Catholic University of Louvain. The provinces considered as affected by the earthquake experienced either economic damage (relatively to properties, crops, livestock) or human casualties following the event[18]. Even though the whole territory felt the shock tremors[19], I do not exclude any other provinces from the donor pool than those listed in the EM-DAT since it takes significant economic damages in an area to impact local migration. Simple tremors do not cause that much impact. Therefore, are included in the donor pool the following 21 provinces: Anhui, Beijing, Fujian, Guangdong, Guangxi, Hainan, Hebei, Heilongjiang, Inner Mongolia, Jiangsu, Jiangxi, Jilin, Liaoning, Ningxia, Qinghai, Shandong, Shanghai, Tianjin, Tibet, Xinjiang and Yunnan (colored in blue in Fig. 4.2). They are the control provinces.

Second step is to match Sichuan characteristics with its counterfactual ones so that the counterfactual and Sichuan have the exact same urban trend before the earthquake. Standard statistics are used to do so. The first one is NTL value in 2005, that is to say, couple of years before the shock. So that cities luminosity is comparable between each province. Second is the birth rate, because set rural-urban migration aside, the second source of urban growth is natural growth rate. Hence, the birth rate provides information on importance of urban areas in a province (Zhang and Shunfeng, 2003). Third and not least, the GDP per capita

[17]The objective is to have equivalent time horizons before and after the shock that happened in 2008. Dependent variable data were not available after 2012.

[18]In Figure 4.2, are depicted as “Other provinces” all the areas – other than Sichuan – affected by Wenchuan earthquake.

[19]Some buildings in Shanghai financial district were evacuated because of strong tremors felt after the 8.0 magnitude earthquake in Sichuan, state local reporters. Source: An online article on Reuters website. China’s tallest building evacuated after earthquake. URL: https://uk.reuters.com/article/idINIndia-33530720080512. Accessed: 05.06.2019.

Table 4.1: Summary statistics

Variable	**Mean**			**Std. Dev.**			**N**		
	Sichuan	Controls	Other	Sichuan	Controls	Other	Sichuan	Controls	Other
NTL	1.27	7.75	6.53	0.31	9.60	8.6	8	184	248
Birth rate	9.31	11.24	11.39	0.32	3.08	2.8	8	184	248
GDP per capita	15076.66	27870.62	24760.4	6297.15	17523.26	16410.35	8	184	248
Educational Achievement	102.5	99.03	99.15	1.41	2.06	2.6	2	120	170
Transport	224.83	223.83	242.46	40.51	171.85	190.62	8	182	246

Notes: These statistics are run between 2003 and 2012, that is to say before and after the shock.

Figure 4.2: Sichuan and the donor pool

Notes: The other provinces painted in red on the Figure are all the provinces that are also affected by the Wenchuan earthquake, and can therefore not be used to build Sichuan counterfactual. As a consequence, they do not belong to the donor pool. Source: Author's elaboration.

is one of the predictor of city size in this chapter. Indeed, economic incentives remain the main reason for a rural dweller to migrate. Then proxies for education and road structures were used to match control provinces with Sichuan, since the search for better education and an efficient transportation infrastructure also enhance rural-urban migration as Hofmann and Wan (2013) and Banerjee et al. (2012) respectively demonstrate. Basic statictics are depicted in the following section on Table 4.2. Further detailed definitions of the variables used to match Sichuan with its control provinces are presented in Table C7 in Appendix.

Table 4.2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
NTL	6.53	8.60	0.02	45.98
Birth rate	11.39	2.80	5.71	17.94
GDP per capita	24760.40	16410.35	4317	85213
Educational Achievement	99.15	2.60	88.90	108.70
Transport	242.46	190.62	0.20	784.59

Notes: *NTL* refers to Nighttime lights within a province. The nighttime light intensity in each province is represented by an integer varying from 0 (no light) to 63 (dense and therefore bright areas). The *Death Rate* is the ratio of the number of deaths to the average population in a year. The *GDP per capita* is expressed in yuan per person. The proxy for *Educational Achievement* refers to the percentage of graduates of primary schools that actually enter to secondary schools. The *Transport* proxy equals to the volume of passengers transported by the railway system every year. It is expressed per 100 million passengers.

4.4.2 Defining city size

To assess the impact of a shock on city size, I use a measure of light intensity at nighttime. The Nighttime Lights (NTL) are provided by the National Oceanic and Atmospheric Administration (NOAA). This indicator is constructed based on information from the Operational Linescan System (OLS) collected by the Defense Meteorological Satellite Program (DMSP) satellites. This dataset, composed of 30x30 arc-second grids, covers -180 to 180 degrees in longitude and -65 to 75 degrees in latitude worldwide. It captures daily information on outdoor but also indoor light. Even though information on enlightment is updated daily, data are aggregated annually and are only available from 1992 to 2012. That light is mainly the result of eletricity-powered brightness (Mellander et al., 2015). Furthermore, cloud-free imagery is used, so that smog in big cities have no impact on the intensity of the light captured. In this chapter, I use an aggregated version of this data at the province level. Therefore, within a given province, the nighttime light intensity is an integer varying from 0 (no light) to 63 (in dense areas). Yet, if NTL do provide precise information on light density, it is pointed out by the litterature as a controversial indicator for city size.

First, NTL are not a perfectly accurate representation of the amount of light emitted by a city (called true radiance). Indeed, light sensors saturate when reaching 63. Thus, the growth of a large city is no longer observable when it keeps expanding wherease its light density already reached 63. For this reason, it is challenging to monitor very big cities, such as some Chinese ones. Also, the city size can be overestimated due to blooming. To be precise, the light can be magnified around certain type of terrain such as water or snow cover. The light would reflect on water, and bright lighter than the same amount of light nearby another type of terrain. Yet, with aggregated data at provincial level, the light sensor never approaches saturation (see the summary statistics in Table 4.2 for information on the maximum value of NTL in the sample). To avoid saturation issues, I exclude provinces owing big saturated cities from the sample *i.e.* Shanghai, Beijing, Chongqing, Guangdong. When running the SCM, the results remain unchanged. The chances that over-glowing affect my results are low.

Second, according to the economic litterature, NTL can be used to approach many different economic aggregates. The main one remains economic activity. Indeed, economists made a great deal of effort to approach economic activity using NTL (Ebener et al., 2005; Doll et al., 2006; Ghosh et al., 2010; Henderson et al., 2012). But as Mellander et al. (2015) demonstrate, NTL only reflect economic variations through the information they provide on population concentration. They show that NTL are not correlated to actual economic aggregates such as wages. Lights at night are strongly correlated to economic activity through "population and establishment density". Thus, NTL can be directly used to proxy population density.

The litterature does offer a myriad of studies using NTL as proxy for urban growth. Over time, it provides strong evidence that lights at night accurately reflects city size. Among the first, Elvidge et al. (1997) estimate that NTL are "excellent" to identify urban areas. Comparing NTL with Google Earth images, Zhang and Seto (2013) come to the same conclusion. They estimate the measurement error of NTL as a proxy for urbanization. Namely, they search for cases in which NTL exhibit variations in light density even though the size and density of urban areas were not actually modified in reality. They find that "where urbanization occurred, NTL have a high accuracy (93%) of characterizing these changes" at a global scale.

Lastly, in a context-specific study, the litterature points out that the relevance of NTL as a proxy for urbanization depends on various factors. Namely, if Chen and Nordhaus (2011) admit that NTL provide an insight of national economic activity, this results holds only for countries characterized by low-quality statistical systems. Otherwise, NTL bring no added value to economic aggregates. They use the Penn World Table (PWT) provided by Summers and Heston (1991) to grade national statistical systems. According to this ranking, Chinese statistical offices provide low-quality national data. Using NTL to seize urban expansion would therefore bring added value compared to the use of national statistics. In addition, regional scientists come together to conclude that NTL fail at monitoring variations in luminosity in poorly lit areas (Zhang and Seto, 2013). The indicator is only

consistent when focusing on urban or peri-urban areas. Yet, as further detailed in Section 2.2, migration in China is massively from rural to urban areas. Hence, migrants target already densely lit areas. In this context, monitoring variations in migrants influx amount to observing variations in city size. Thus, the use of NTL is suitable for the point of interest of this chapter.
The litterature offers a similar judgement. The use of lights at night takes a prominent place in the study of Chinese urbanization (Yi et al., 2014; Tan, 2015; Gao et al., 2016; Li and Zhou, 2017; Ju et al., 2017). Liu et al. (2012) even estimate the risk of effort in using NTL to proxy urban growth. They find that, between 1992 and 2008, NTL data allow to extract Chinese urban expansion with an overall accuracy rate up to 82.74%. These results are also confirmed by Ma et al. (2012). They provide proof that brightness at night is a consistent explanatory indicator for urban variation over time, in China, by looking at NTL variations between 1994 and 2009 in 200 prefectural cities.
Looking at the data, NTL also appear as a proxy for city size. First, NTL better approach city size than economic activity. Indeed, when comparing satellite data to the ones provided by the NBSC, I find that NTL are more correlated to the urban share that it is to GDP (see Table 4.3). The correlation rate between NTL and the $Urban\ rate$ is positive and up to 0.81 when it falls to 0.38 with the GDP[20]. NTL variations evolve closely to the share of urban population within China. It therefore appears as a good proxy. Second, the objective of this chapter is to assess the population movement following a sudden shock. Yet, data on urban population are census-based and are only collective every 5 or 10 years. The NBSC does provide annual information on urban share but it is only the result of statistical inference. Indeed, when displaying the national trend of the urban share in China, it has a linear evolution over the years (see Table 4.3). This calculation technique leaves no possibility to catch any variation in migration following a shock. Therefore, the alternative of NTL, that is to say, the urban share as calculated by the NBSC, is not suitable for the focus of this study. Thus, as conclude Xu et al. (2014b), even though NTL are an imperfect measure of urbanization, it remains a convincing indicator to observe urban areas over time.

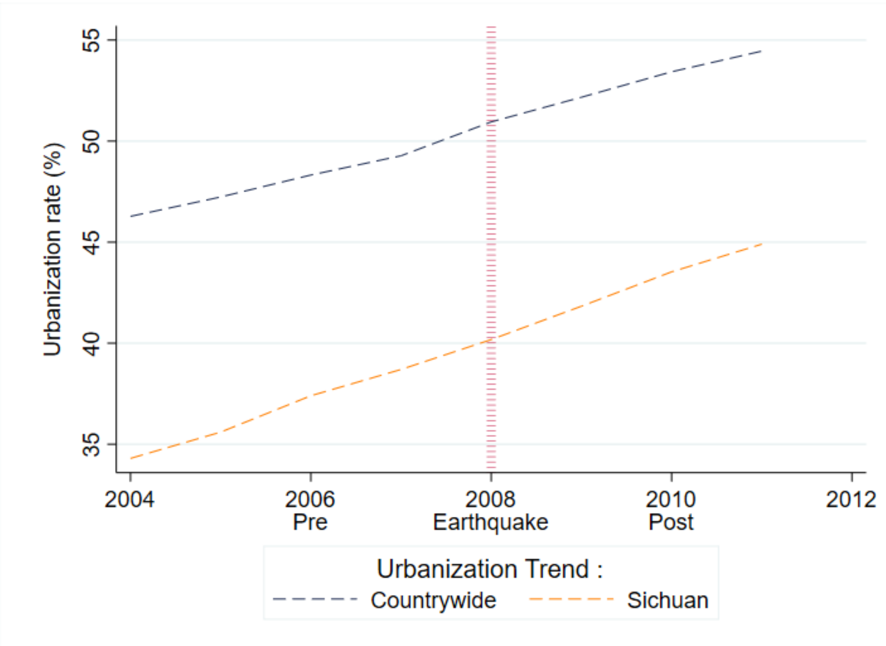
[20]Other aggregates are included in Table 4.3, such as urban and rural population but also GDPs for the primary and secondary sector. With no surprise, NTL are positively correlated to the amount of urban population and the volume of the industrial GDP but are negatively correlated to the number of rural inhabitants and to the agricultural GDP.

Table 4.3: Comparaison of correlation rates between urban and economic proxies

Variables	*NTL*	*Urb. rate*	*Urb. pop.*	*Rural pop.*	*GDP*	*GDP Prim.*	*GDP Sec.*
NTL	1.00						
Urban rate	**0.81***	1.00					
Urban pop.	0.23*	0.23*	1.00				
Rural pop.	-0.18*	-0.34*	0.73*	1.00			
GDP	**0.38***	0.37*	0.92*	0.52*	1.00		
GDP Prim.	-0.07*	-0.11*	0.80*	0.84*	0.75*	1.00	
GDP Second.	0.33*	0.30*	0.91*	0.55*	0.99*	0.78*	1.00

Notes: *NTL* is the Nighttime Lights variable, used as a proxy to assess city size in China. The *Urban rate* is the ratio of urban dwellers in the total population. GDP is the gross domestic product. *GDP Prim.* and *Second.* are respectively the GDP of the primary and secondary sectors, that is to say the agricultural and industrial ones. The GDPs are expressed in 100 million of yuan. See further detailed definition of the variables in Table C8 in Appendix. These statistics are run between 2003 and 2012, that is to say before and after the shock.

Figure 4.3: The Urbanization rate over time as defined by the NBSC in Sichuan and China



Notes: The *Urban rate* is the ratio of urban dwellers in the total population. This data is collected by the National Bureau of Statistics of China from census data.

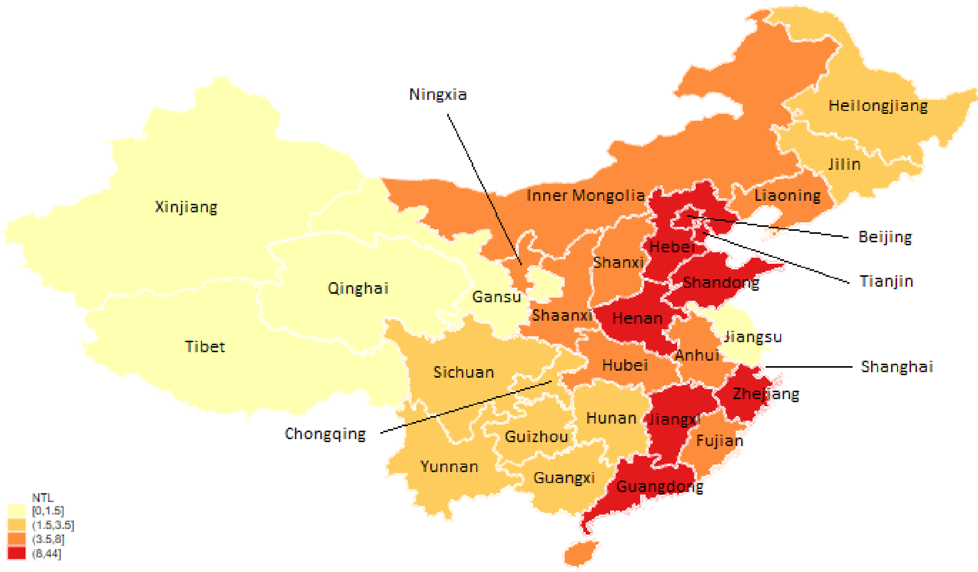
4.4.3 Stylized facts

Studying thoroughly the data, NTL did decrease in Sichuan, following the 8.0 magnitude earthquake. As depicted in Figure 4.4, NTL decline between 2008 and 2009. This decline in NTL is not a countrywide tendency [21]. It is not even a tendency among the provinces significantly affected by the earthquake, let alone Sichuan. On Figure 4.2, are painted in red all the provinces affected by the earthquake[22]. They could experience significant variations of their NTL in 2009. Though, they do not suffer from drastic declines in NTL trends and seem less affected than Sichuan. As the epicenter of the earthquake, Sichuan stands out as an exception. This study aims at thoroughly investigating the impact of Wenchuan earthquake on internal migration in Sichuan.

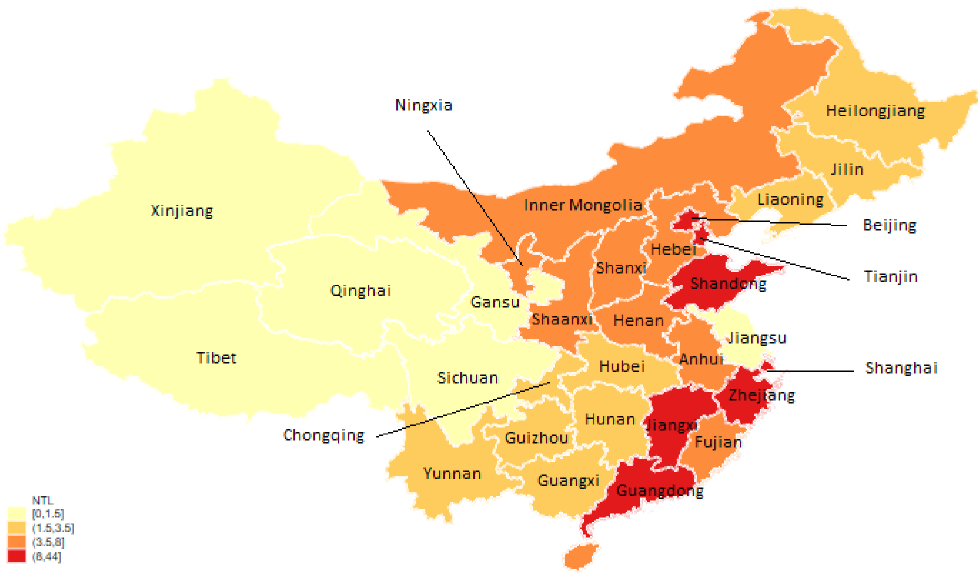
[21]Only two other provinces had decreasing NTL between 2008 and 2009, one of them -Henan-being considered as severely impacted by the earthquake according to EM-DAT database, and therefore, is not used to build Sichuan counterfactual. The other province, Hebei, has not been considered as significantly affected by Wenchuan earthquake according to the EM-DAT. So it is part of the provinces usable to construct Sichuan counterfactual. Nevertheless, the SCM did not select this province to build Sichuan counterfactual, given that they do not have enough similarities (the province has no weight in the donor pool).

[22]Are considered as significantly affected by the earthquake, all the provinces that suffered economic damage or human fatalities following the disaster. Such a list is available in the EM-DAT database.

Figure 4.4: Trends in Nighttime Ligths countrywide



(a) 2008



(b) 2009

Note: The legend has been computed by Stata using NTL quantiles in 2009. Source: Author's elaboration on NOAA data.

4.5 Empirical strategy

In this section, I present the method used to measure the impact of an earthquake on city size within the same province, and to some extent, population movement from rural-to-urban areas. To do so, I use the SCM to select provinces that have the same NTL trend, and therefore, would have the same behavior in the absence of any natural disaster. I will refer to this group of provinces as the donor pool or control group. From this group of provinces, I can build a robust counterfactual, and, down the road, assess the impact on Sichuan rural-to-urban migration, actually due to Wenchuan earthquake. Therefore, I refer to Sichuan as the treated province, the treatment being the earthquake that occurred in the province. To apply the SCM, I process in three steps. First, I select the Chinese provinces suitable for the donor pool. Indeed, to be part of the donor pool, the provinces must not be impacted by the same treatment than Sichuan that is to say, by the earthquake. This procedure has been done and motivated in the data description. Second, I compute the synthetic control group i.e. the weighted average of provinces that will represent Sichuan counterfactual. With a data-driven method, I build a virtual province that closely matches Sichuan NTL trends in the pretreatment period that is to say, right before Wenchuan earthquake in 2008. Lastly, I compare Sichuan NTL trends with those of Sichuan counterfactual, in the post-treatment period *i.e.* fom 2009 to 2012. Comparing the counterfactual with the observed NTL integer in Sichuan, after 2008, offers an estimation of the treatment effect. Below, I describe in details how I carry out theses steps.

First, as explained above, I classify Chinese provinces depending on whether they are significantly affected by the earthquake. Using the EM-DAT, I include 21 provinces in the donor pool: Anhui, Beijing, Fujian, Guangdong, Guangxi, Hainan, Hebei, Heilongjiang, Inner Mongolia, Jiangsu, Jiangxi, Jilin, Liaoning, Ningxia, Qinghai, Shandong, Shanghai, Tianjin, Tibet, Xinjiang and Yunnan. They are the control provinces.

Second step is to compute the synthetic control unit. Following Abadie et al. (2015), suppose that J is the number of control provinces (the 21 provinces that were never significantly affected by the earthquake) that is to say, the donor pool. Let X_1 be a $(K \times 1)$ vector containing characteristics of the treated unit. More precisely, it is composed of predictors of NTL variations in Sichuan between 2004 and 2008. Province level predictors for the NTL integer are: the pretreatment value of NTL (the value of NTL in 2005), the birth rate ratio, the GDP per

capita, a proxy for schooling, and a proxy for the transportation system[23]. Let X_0 be a $(K \times J)$ be the matrix containing the values of the same variables for the provinces in the control group. W is a $(J \times 1)$ vector of nonnegative weights $(w_1, ..., w_J)$ such as $w_1 + ... + w_J = 1$. W determines the relative importance of the control provinces in the donor pool and it is defined so that the characteristics of the treated province resembled as closely as possible to those of the synthetic control. Hence, the intuition is to minimize the difference between $X_1 - X_0W$ *i.E.* the difference between Sichuan characteristics and those of the synthetic Sichuan, in the pretreatment period[24].
Therefore, I follow Abadie et al. (2015) and choose the $\boldsymbol{W}^*$ that minimizes the following expression[25]

$$\sum_{m=1}^{k} v_m(X_{1m} - X_{0m}W)^2 \quad with \quad \sum_{j=1}^{J} w_j = 1,\ w_j \geq 0 \tag{4.1}$$

For $m = 1, ..., k$, X_{1m} represents the value of the m-th predictor for the treated province and X_{0m} is the $(1 \times J)$ vector containing the values of the m-th variable for the control provinces. v_m corresponds to the weight that captures the relative importance of each m-th predictor in the synthetic counterfactual. The more predictive power a variable has on the outcome (*i.e.* Sichuan NTL) in the pretreatment period, the highest weight it gets assigned. Suppose that Y_0 and Y_1 are the outcome matrices respectively for the control provinces and Sichuan, then, the counterfactual outcome equals to $\boldsymbol{Y_1^*} = Y_0W$. It represents the NTL progression in Sichuan after 2008, in the absence of a 8.0 magnitude earthquake. Knowing this, one can estimate the treatment effect *i.e.* the effect of the natural disaster on NTL trend in Sichuan. It can be calculated by taking the difference between $\boldsymbol{Y_1^*}$ and Y_0.

[23]Here, I use standard predictors to match the control provinces with Sichuan: the past value of NTL being one of the most important factor that predicts future level of NTL, then the birth rate being a proxy for natural growth rate of the population, the GDP being an economic proxy, a schooling proxy, and an infrastructure proxy. These are the educational, infrastructure, economic proxies that minimize the matching errors between Sichuan and its counterfactual (see Section 5).

[24]According to Abadie and Gardeazabal (2003), estimating a synthetic counterfactual that is a combination of control units is a better approximation of the treated region than using another region alone. Nevertheless, one needs to be careful because the identification strategy mainly relies on matching the behavior of the outcome variable of interest during the pretreatment period. See Table 4.4 to monitor this point.

[25]It is equivalent to saying that I select the weights that minimize the Root Mean Square Prediction Error (RMSPE), see Abadie et al. (2015). The RMSPE measures the lack of calibration between the trend of the outcome variable for the treated unit and its synthetic counterfactual, in the pretreatment period.

4.6 Results

In this section, I discuss the effects that a severe earthquake has on rural-to-urban migration in Sichuan. Most of SCM identification validity relies on the ability to compute a counterfactual that best matches Sichuan trends in NTL in the pretreatment period (that is to say, between 2004 and 2008). So I first check that synthetic counterfactual is close enough from Sichuan in the pretreatment period, to get to solid conclusions later on. Then, I present the main results of this chapter. In the last subsection, I check that these results are not due to hazard.

4.6.1 Building a robust counterfactual

As detailed in the methodological section, I chose the $\boldsymbol{W}^*$ that minimizes the RMSPE. By approaching zero (0.047 to be precise), the weight matrix does validate this condition. In other words, the gap between the trend of the outcome variable of Sichuan and the one of synthetic Sichuan are close to be null in the pretreatment period, with the selected weight matrix. Another manner to check that the gap is small between NTL tendencies of Sichuan and synthetic Sichuan is to graph both of them. Figure 4.5 supports that there is a reasonably good match between Sichuan and its counterfactual, since both trends are principally overlapping between 2004 and 2008.

Table 4.4 compares the pretreatment characteristics of Sichuan to those of synthetic Sichuan and the rest of China. In columns (1) and (3) are reported characteristics for Sichuan and China, respectively. Between 2004 and 2008 -the pretreatment period-, there is no common trend between Sichuan and the rest of China, regarding the predictors. Sichuan has a lower birth rate, per capita GDP and a less efficient railway system. At the opposite, it has a higher rate of achievement between the primary and secondary school. With such pretreatment differences, no conclusion can be made regarding the impact of the treatment on Sichuan's NTL by simply analyzing the variations of these same predictors, post-treatment. On the other side, Table 4.4 suggests that synthetic Sichuan provides a better comparison pre-treatment than China. Synthetic Sichuan offers a closer if not identical pre-treatment NTL level, GDP per capita and education achievement rate. Overall, synthetic Sichuan represents a close match, close enough to interpret the differences between Sichuan and its counterfactual post-treatment, as the treatment effect.

Table 4.5 reports the weight of each province in the synthetic version of Sichuan, before 2008. The closest match for Sichuan corresponds to a weighted average of

Table 4.4: Predictor Balance

	Sichuan		China
	Real (1)	Synthetic (2)	(3)
NTL in 2005	1.12	1.12	5.85
Birth rate	9.28	14.23	11.48
GDP per capita	10116.06	13086.29	17738.12
Schooling	102.50	99.75	98.80
Transport	195.77	211.96	209.94

Notes: The birth rate is the ratio of the number of births to the average population in a year. The GDP per capita is expressed in yuan per person. The proxy for schooling refers to the percentage of graduates of primary schools that actually enter to secondary schools. The transportation system efficiency proxy is the volume of passengers transported by the railway system every year. It is expressed per 100 million passengers per kilometers. These statistics are run between 2003 and 2007, that is to say before the shock.

Xinjiang, Jiangxi and Jilin[26]. All the other provinces in the donor pool obtain zero weights. These weights are obtained by minimizing the RMSPE, that is to say, the potential errors made when matching Sichuan and its virtual counterfactual, before the treatment.

[26]Note that all three provinces are located in very different areas of China. It is important to note in Chinese context since the country is known to suffer from great regional disparities, especially between the coastal area and inland China.

Table 4.5: Weight associated for each donor pool province

Donor pool	Weight
Anhui	0
Beijing	0
Fujian	0
Guangdong	0
Guangxi	0
Hainan	0
Hebei	0
Heilongjiang	0
Inner Mongolia	0
Jiangsu	0
Jiangxi	0.304
Jilin	0.146
Liaoning	0
Ningxia	0
Qinghai	0
Shandong	0
Shanghai	0
Tianjin	0
Tibet	0
Xinjiang	0.55
Yunnan	0

Source: Author's elaboration on NOAA data.

4.6.2 Major findings

Looking at Figure 4.5, Sichuan and its counterfactual matches closely, until 2008, year of the 8.0 magnitude earthquake. Post-disaster, a gap appears between Sichuan and its counterfactual. This gap embodies the impact of the earthquake on Sichuan NTL, namely the treatment effect. In 2009, the NTL in Sichuan has decreased by 14% compared to its counterfactual where no natural disaster occurred[27]. As argued in Section 3.1, since most of city size growth is due to rural-urban migration, a decreasing trend in city growth in Sichuan can be interpreted as a decreasing trend in rural-urban migration. In accordance with the results of Gignoux and Menéndez (2016) and Halliday (2006), Wenchuan earthquake decreases migration toward more attractive areas, in this case, cities. Two features can explain this result. First, as Halliday (2006) finds, reconstruction needs to be done in rural areas. All household members are therefore needind since reconstruc-

[27]The treatment effect is obtained by subtracting $\boldsymbol{Y_1^*}$ and Y_0 *i.e.* the NTL of the synthetic counterfactual minus the observed NTL of Sichuan.

tion is owner-based regarding residential housing. Second, in the very short-run, cities may not be regarded as full of job opportunities. Indeed, in Gignoux and Menéndez (2016) paper, it takes between at least two years to reconstruct and therefore allow the economy to recover from the disaster. Within this amount of time, Sichuan cities still lack of infrastructures and public services. As a result, they do not attract rural migrants any more.

Second remarkable fact looking at Figure 4.5, the negative impact on Sichuan NTL is short-lasting. Even a large and destructive disaster as a 8.0 magnitude earthquake does not seem to have a lasting impact on migration. The treatment effect is back to zero when reaching 2011. Thus, in Chinese case, natural disasters, regardless on how destructive they are, do not have a permanent impact on migration patterns. In this case, it takes three years after the event to reach a full recovery and go back to business as usual. Again, it echoes Gignoux and Menéndez (2016) findings, in which Indonesian rural households fully recover from earthquakes in the mid-run, that is to say from two to five years following the shocks. Yet, unlike Gignoux and Menéndez (2016), cities did not become more attractive than before the earthquake, it is only a "back to trend" phenomenon.

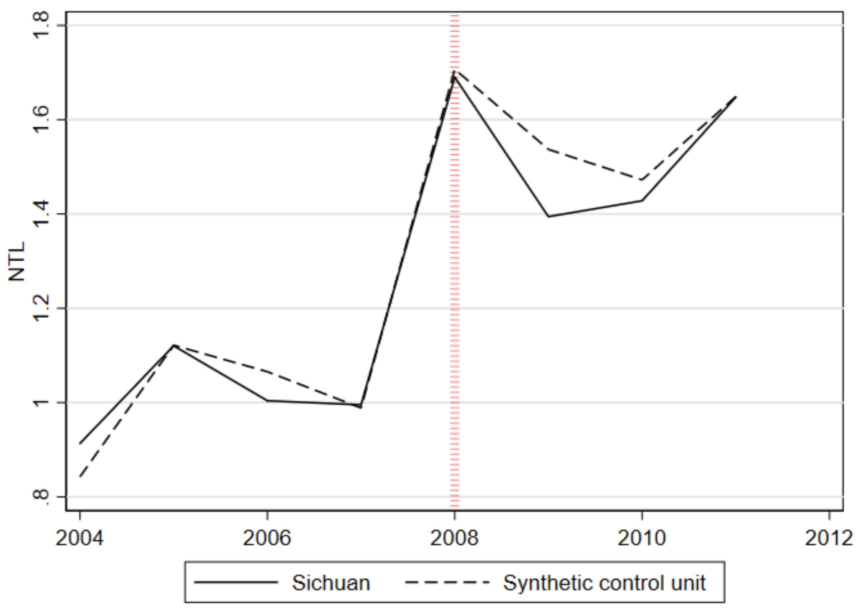
Third, it took exactly three years for Sichuan city size trend to go back to its post-shock trend level. Three years is also precisely the amount of time the Central government to took to complete its reconstruction goals. They rebuilt all the residential houses destructed; guaranteed job stability for at least one household member; provided basic public services such as social welfare for the victims, free education for the youth, medical care, and so on; restored and upgraded infrastructures; developed the economy of the most affected areas; extended disaster mitigation capacities. Cities did not become less or more attractive. Rural areas were not overlooked by the reconstruction plan either. Chinese government reconstruction plan following Wenchuan earthquake was efficient.

Last but not least, the impact of such a devastating event remains quite low in proportion. Since the economic reforms in 1970s, Wenchuan earthquake remains the most destructive natural event, in terms of economic loss. According to a statement from the central government[28], the earthquake left 5 million people homeless. Intuitively, one could expect larger consequences on migration patterns. But looking at the results, the inhabitants still did not leave their township of birth. The institutional constraints regarding internal migration certainly played a major role in mitigating the impact of any natural disaster on migration. It also echoes the work of Belcher and Bates (1983) which shows that migration does not depend on how great the economic damages are for the community but rather depends on whether the potential migrant lost or not the annual harvest along

[28]Reported by the New York Times, in an online article written by Jake Hooker on May 26, 2008: https://www.nytimes.com/2008/05/26/world/asia/26quake.html

with the natural disaster.
Both results confirm the literature considering that sudden-onset disasters prevent migration in the short-run, to later on have no impact at all in the long-run (after three years). Given the timeline, it has more to do with public intervention than monetary liquidity constraints. Indeed, the reconstruction plan was completed within years. Yet, some of the houses reconstruction in affected areas was owner-founded by bank loans. Population liquidity constraints were still tight three years after the shock because they still needed to repay the loan. I further discuss the results in Section 7.

Figure 4.5: NTL trends for Sichuan and its counterfactual



Source: Author's elaboration on NOAA data.

4.7 Placebo Tests

A question remains concerning whether the gap depicted in Figure 4.5 reacts to the earthquake or is simply due to the incapacity of this study to reproduce the NTL trend for Sichuan, in absence of an earthquake. Following Abadie and Gardeazabal (2003), I perform a placebo study. In other words, I run the same SCM on a province that did not get treated and check if there is also a gap post-2008. The idea is to compare the NTL variation of a province similar to Sichuan, in which no natural disaster occurred, to the NTL variation of its synthetic counterfactual in which no natural disaster occurred either. Doing so, I evaluate whether the gap observed for Sichuan was initiated by factors other than the earthquake. I chose to run this placebo study using Xinjiang province, the province with the greater weight in the donor pool. Indeed, Xinjiang accounts for 50% of the combination of control provinces in the synthetic Sichuan (see Table 4.5). Therefore, as explained above, I compute a synthetic Xinjiang *i.e.* a weighted combination of other Chinese provinces, by minimizing the RMSPE [29]. I present the weight combination and the predictors balance in the Appendix on Tables C10 and C9.

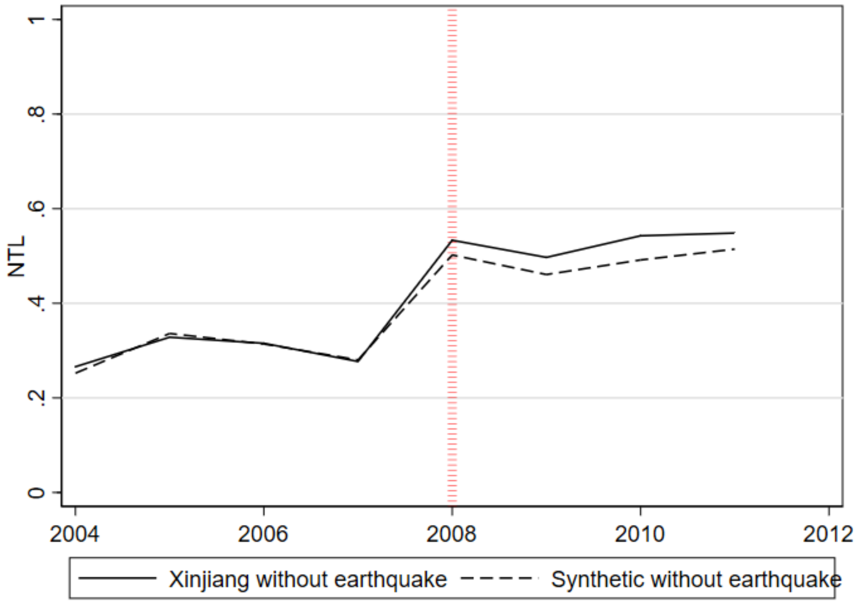
Figure 4.6 shows the actual NTL trend for Xinjiang and the one computed for its synthetic counterfactual. First, the match between Xinjiang and synthetic Xinjiang is convincing, given that the NTL are overlapping before 2007. Starting from 2007, a small gap develops between Xinjiang and its counterfactual. Starting in 2007, this gap has low chances to be caused by the 2008-eartquake. Also, the NTL trends are exactly parallel, no drop occurs following the 2008-earthquake. Thus, as expected, the earthquake did significantly not affect Xinjiang NTL (listed as unaffected in the EM-DAT database). Results obtained with Sichuan are therefore not due to hazard.

Lastly, I run another placebo test, but this time, I decide to test whether the NTL react to a change in the shock year. Hence, I run the same SCM twice, still by minimizing the gap in NTL tendencies before the shock. But now, I first pretend that the shock occurs in 2007 and then pretend that it happens in 2010 [30]. If a drop occurs before and after these false shocks, then the results presented earlier are only due to hazard. Looking at Figure 4.7, there is no real gap growing between the synthetic Sichuan and Sichuan after the fake shock. The drop in tendency persists to be in 2008. The synthetic Sichuan and Sichuan trends start coming back together around 2010.

[29] Note that Sichuan is excluded from Xinjiang donor pool.

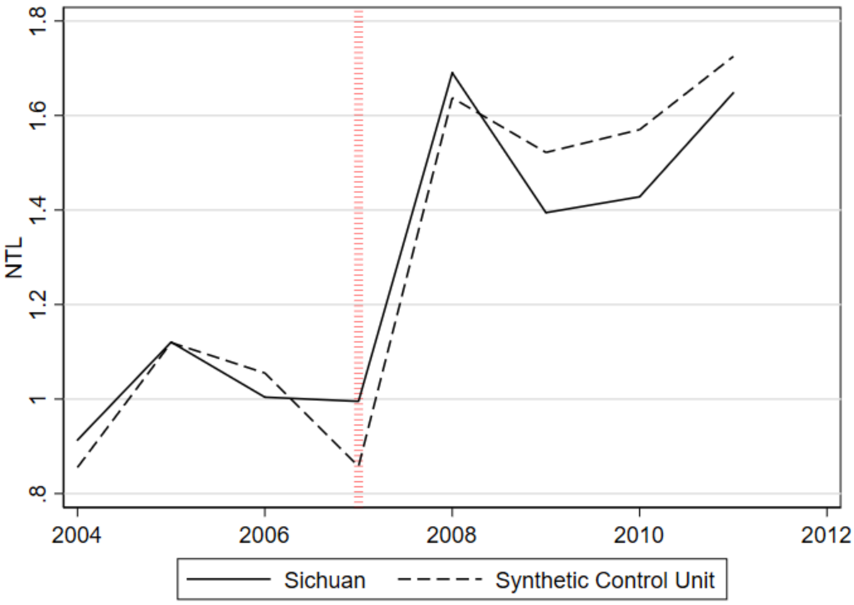
[30] Weight combination and predictors balance are available in the Appendix for both years: see Tables C11 and C12 for 2007 and Tables C13 and C14 for 2010.

Figure 4.6: Placebo test on Xinjiang Province

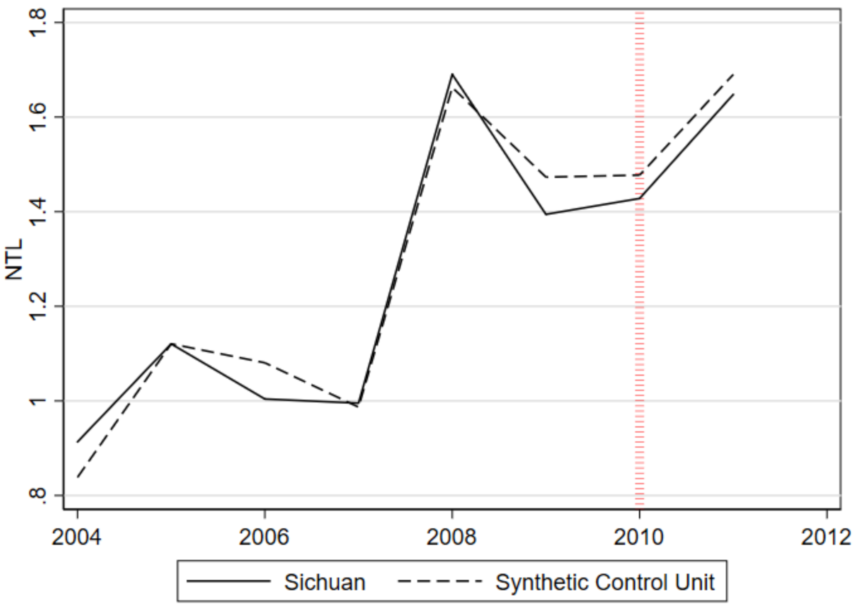


Source: Author's elaboration on NOAA data.

Figure 4.7: Placebo test on different dates



(a) 2007



(b) 2010

Source: Author's elaboration on NOAA data.

4.8 Conclusion

Using the synthetic control method to construct Sichuan counterfactual, I find that Wenchuan earthquake in 2008 has a negative impact on city size in Sichuan, in the short-run. I interpret this as the result of decreasing rural-urban movements in the short-run. This effect becomes null in the long-run, so sudden-onset disasters do not seem to impact permanently migration patterns. It suggests that when facing natural disasters, people in China rather stay put to reconstruct than because of liquidity constraints. Indeed, it also took exactly three years for the reconstruction plan to be completed. Within this amount of time, every household had at least a house or apartment, and a stable job allowing them to earn at least as much as in their pre-shock situation. The Chinese government also provided upgraded public services and infrastructures. As a result, city size and to a certain extent, city attractiveness to migrants went back to its pre-shock level. Cities did not become more attractive than rural areas, these latter were not neglected by the reconstruction plan. Unlike Halliday (2006), Noy and Vu (2010) or Gignoux and Menéndez (2016), this work shows no evidence of creative destruction following the earthquake. Indeed, it only exhibits a return-to-trend phenomenon.

If the results suggest the effiency of the Chinese government following Wenchuan earthquake, the private sector was complety missing from the rescue forces. Indeed, insurance companies contribution to the reconstruction following the disaster did not exceed 0.3% of the total economic losses (Wu et al., 2012). Currently, farmers still do not have a widespread access to crop insurance in China (Boyd et al., 2011). Even though crop insurance exist in theory, it is still hardly affordable for small farmers, that is to say, the most vulnerable population regarding natural hazards (Wang et al., 2012). Thus, the government has a role to play in cultivating the disaster insurance market, make its access easier and more affordable, but also by creating strong incentives for the farmers to subscribe. Hence, efficient coping strategy in rural areas will reduce the willingness to move, and above all, hinder the creation of poverty traps after a natural disaster.

These results also echo the previous chapter of this thesis. Indeed, I found that severe flooding have negative consequences on migration toward neighboring cities while droughts have positive ones. It is consistent with the fact that floods are more likely to impact cities' attractivity because they are as harmful for urban infrastructures and industrial sector that they are for agriculture (Otero and Marti, 1995; Benson and Clay, 2000). In this case, cities are not shelters any more. Their size does not grow, it even decreases, exposing a less common migratory trend for China *i.e.* a movement of people outward the cities.

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Appendix to chapter 4

Table C6: List of the affiliated pairs from the Paired Assistance Program

Supported areas	Supporting areas
Sichuan	
Wenchuan	← Guangdong
Beichuan	← Shandong
Qingchuan	← Zhejiang
Mianzhu	← Jiangsu
Dujiangyan	← Shanghai
Shifang	← Beijing
Jiangyou	← Henan
Pingwu	← Hebei
Anxian	← Liaoning
Pengzhou	← Fujian
Maoxian	← Shaanxi
Lixian	← Hunan
Heishui	← Jilin
Songpan	← Anhui
Xiaojin	← Jiangxi
Hanyuan	← Hubei
Chongzhou	← Chongqing
Jiange	← Heilongjiang
Gansu	
Seriously affected district in Gansu province	← Shenzhen
Shaanxi	
Seriously affected district in Shaanxi province	← Tianjin

Notes: Supported areas are counties while supporting areas are municipalities or provinces. Counties are small administrative areas whereas province or municipalities are bigger ones with substantial financial means. Source: Author's elaboration from the United Nations Centre for Regional Development data, compiled in their Report on the 2008 great Sichuan earthquake.

Table C7: Variables used in the Synthetic Control Method

Variable	Definition	Source
Nighttime Light (NTL)	Yearly measure of light intensity at night. It ranges from 0 (desert area) to 63 (dense area). Cloud-free measure made from satellite data.	NOAA National Geophysical Data Center
Birth Rate	(Number of birth/Average Number of Population)$\times$ 100	NBSC
GDP per capita	Indicates the gross domestic product in yuan per person.	NBSC
Schooling	(Number of students Entering in Junior Schools / Number of graduates from primary school) $\times$ 100. When it exceeds 100, it means that some students were transfered from other provinces and/or cities.	NBSC
Transport	Volume of passenger traveling by train. Expressed in terms of 100 million persons. Built as an indicator of the transport development scale.	NBSC

Source: Author's elaboration from NOAA and NBSC data.

Table C8: Variables from the Correlation Table

Variable	Definition	Source
Urban ratio	(Number of people living in a city/Total population)$\times$ 100	NBSC
Urban Population	Urban population ($\times$ 10000 persons) as a mix of administrative and statistical definition. Considers as an urban dweller, a person living in an area under the jurisdiction of a city but also living close to urban construction, densely populated area (more than 1500 people per km2), etc.	NBSC
Rural Population	Total population except urban population.	NBSC
GDP Prim.	GDP of the primary industry referring to agriculture (including farming, forestry, animal husbandry and fishery). Expressed in 100 million yuan.	NBSC
GDP Second.	GDP of the secondary industry referring to the industrial (including mining and quarrying, manufacturing, production and supply of electricity, water and gas) and construction sector. Expressed in 100 million yuan.	NBSC

Source: Author's elaboration from NBSC data.

Table C9: Weight by province for Xinjiang donor pool

Donor pool	Weight
Anhui	0
Beijing	0
Fujian	0
Guangdong	0
Guangxi	0
Hainan	0
Hebei	0
Heilongjiang	0
Inner Mongolia	0.241
Jiangsu	0
Jiangxi	0.103
Jilin	0
Liaoning	0
Ningxia	0
Qinghai	0
Shandong	0
Shanghai	0
Tianjin	0
Tibet	0.656
Xinjiang	0
Yunnan	0

Source: Author's elaboration on NOAA data.

Table C10: Predictor Balance

	Xinjiang	
	Real (1)	Synthetic (2)
NTL in 2005	0.33	0.34
Birth rate	16.25	15.15
GDP per capita	14078.75	12138.61
Schooling	99.15	95.16
Transport	114.26	74.52

Notes: Statistics under "Real" are observed statistics for Xinjiang province between 2003 and 2008. Statistics under "Synthetic" are statistics for the Synthetic Control Unit used as a counterfactual for Xinjiang, between 2003 and 2008. Among these statistics, the birth rate is the ratio of the number of births to the average population in a year. The GDP per capita is expressed in yuan per person. The proxy for schooling refers to the percentage of graduates of primary schools that actually enter to secondary schools. The transportation system efficiency proxy is the volume of passengers transported by the railway system every year. It is expressed per 100 million passengers per kilometers.

Table C11: Province weights for Sichuan donor pool when matching predictors values between 2003 and 2007

Donor pool	Weight
Anhui	0
Beijing	0
Fujian	0
Guangdong	0
Guangxi	0
Hainan	0.041
Hebei	0
Heilongjiang	0
Inner Mongolia	0
Jiangsu	0
Jiangxi	0.393
Jilin	0
Liaoning	0
Ningxia	0
Qinghai	0
Shandong	0
Shanghai	0
Tianjin	0
Tibet	0
Xinjiang	0.566
Yunnan	0

Source: Author's elaboration on NOAA data.

Table C12: Predictor Balance between 2003 and 2007

	Sichuan	
	Real (1)	Synthetic (2)
NTL in 2005	1.12	1.12
Birth rate	9.30	15.09
GDP per capita	9167.08	11569.47
Schooling	103.50	99.18
Transport	186.40	215.77

Notes: Statistics under "Real" are observed statistics for Sichuan province between 2003 and 2007. Statistics under "Synthetic" are statistics for the Synthetic Control Unit used as a counterfactual for Sichuan, between 2003 and 2007.

Table C13: Weight for Sichuan donor pool when matching predictors values between 2003 and 2010

Donor pool	Weight
Anhui	0
Beijing	0
Fujian	0
Guangdong	0
Guangxi	0
Hainan	0.041
Hebei	0
Heilongjiang	0.157
Inner Mongolia	0
Jiangsu	0
Jiangxi	0.410
Jilin	0
Liaoning	0
Ningxia	0
Qinghai	0.433
Shandong	0
Shanghai	0
Tianjin	0
Tibet	0
Xinjiang	0
Yunnan	0

Source: Author's elaboration on NOAA data.

Table C14: Predictor Balance between 2003 and 2010

	Sichuan	
	Real (1)	Synthetic (2)
NTL in 2005	1.12	1.12
Birth rate	9.30	13.45
GDP per capita	12216.37	13861.64
Schooling	102.50	99.24
Transport	207.00	228.72

Notes: Statistics under "Real" are observed statistics for Sichuan province between 2003 and 2010. Statistics under "Synthetic" are statistics for the Synthetic Control Unit used as a counterfactual for Sichuan, between 2003 and 2010.

Conclusions

In the present thesis, I highlight the impact of environmental shocks on population movement or rather, lack of movement, in a country where costs of migration are particularly high. Acknowledging that economic reasons remain the main motive to migrate, I show that environmental variations can trigger population migration to cities, but it is true only in the short-run, when rural dwellers face droughts. Otherwise, strict institutional barriers and efficient intervention post-disaster prevent abnormal migration flows toward urban centers. China, as a field of study, represents the case of a developing country with tremendous incentives to out migrate from rural areas, with greater job opportunities and income, but also health and educational infrastructure; but also great migration costs, through the loss of social benefits but also the lack of land-use rights. The present dissertation aims at contributing to this literature with the three empirical chapters detailed below.

Chapter 2 investigates the potential causes of urbanization in China, and more particularly the wide differences among eastern and western regions. The literature explaining spatial inequality in a national urban process through geographical factors is quite recent. Existing studies rather focus on absolute geographical factors as push or pull forces toward cities, letting aside any complementary or competitive evolution of urbanization between neighboring areas. Therefore, this work contributes to the literature by analyzing urbanization through a new perspective. I take into account the effect of proximity to dynamic cities either as a driving force or a obstacle for a city growth. In addition, the model used here enables me to identify which factor allow any link between two urbanizing areas. The results provide evidence of a synergy effect between neighboring provinces, when urbanizing, in China. The factors driving urbanization in one province, also impact positively its neighbors', creating a virtuous circle of urbanization among provinces. Yet, results also show that the relationship is not monotonous. A threshold effect does exist. Up to a certain point, the neighboring province is so economically attractive - meaning great GDP per-capita, dense population, efficient transportation system- that it becomes a favorite destination. Then, the relationship between neighboring provinces becomes competitive.

Chapter 3 emphasizes the link between weather variations and rural-urban migration in China. I imply that weather anomalies affect crop yields as well as farmers' income. It later affects their incentives and financial means to move to cities, modifying cities size. To test this assumption, I use a grid-level panel dataset, going from 1992 to 2012. The present work first contributes to the literature by the original use of nighttime lights as a proxy for city size. This indicator based on satellite data is suitable to capture temporary migration toward already dense areas. Alternative data, such as the use of low-frequency census data is not suitable for a study on short-term population movement. Second, this chapter contributes to settle the on-going debate on the impact of weather variations on Chinese internal migration. It first shows evidence of an immediate migratory response toward cities following slow-onset events such as rainfall shortage. Second, results also suggest that migrants return home one year following the shock. It would further motivate the idea that Chinese farmers migrate to maintain a certain level of income for the household, in the short-run. Last, this chapter contributes to highlight the heterogeneous response in migration whether the climatic event has a slow or rapid-onset. Indeed, people move if there is a drought, but do not if a flood of equivalent intensity occurs.

Finally, chapter 4 uses Wenchuan earthquake in 2008 as a natural experiment to investigate migratory response after a sudden-onset disaster and check if the efficiency of public intervention in China is responsible for the low migratory impact. To do so, I use high-frequency satellite data, that capture annual light density at night, to proxy the evolving size of cities. In China, since natural population growth rate is quite low due to the still on-going One Child Policy, rural-urban migration is responsable for most of the city size growth. As for the empirical technique, I match Sichuan province with a counterfactual built using the Synthetic Control Method (SCM). Results show negative effects of Wenchuan earthquake on Sichuan city size. In accordance with the results in this thesis previous chapter, natural hazards prevent migration from happening. Cities, probably also affected by the event, no longer attract migrants. Plus, results also show that, three years after the shock, in 2011, the effects on migration are null. Sichuan experiences a "back to trend" migratory behaviors, suggesting that rapid-onset naturals disasters have no permanent impact on migration patterns. The timing of this return-to-trend exactly coincides with the end of the three-year reconstruction plan led by Chinese government. Yet, the missing actor of this reconstruction was the private sector. Indeed, insurance companies only contributed to 0.3% of the total economic losses.

To conclude, these three chapters intend to seize the forces behind city size variation, and to a certain extent rural-urban migration, especially after environmental shocks and/or variations, in a developing country characterized by great migration costs. Indeed, in developing countries, migration to cities remains one of the most widespread adaptation strategy when external shocks occur in a localized area. Developing countries are often not wealthy or not technically qualified enough to adopt alternative adaptation strategies on a large scale. It is still the case for China up to a certain extent. Indeed, even though migration is costly, it can still be a risk management strategy following environmental variations, such as droughts (Chapter 3). But with proper risk management measures *ex post*, migration patterns can go back to normal quickly (Chapter 4). Since Asia is the most affected and damaged part of the world due to both climatic variations and natural hazards, this thesis could be the additional proof that adequate risk management strategies can prevent the use of migration as a coping strategy to face these events. The adoptation of risk management strategies are context-specific, and Chinese case, presented here, sheds the light on some efficient measures to undertake post-disaster.