Tohoku University Research Center for Policy Design Discussion Paper

TUPD-2023-014

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November 2023

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Regional Policies' Impacts on Urban Migration: Evidence from Special Economic Zones in China*

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November 29, 2023

Abstract

Special economic zones (SEZs) have played an important role in developing China's economy. However, few researchers examine its importance in shaping China's urban population. This study empirically examines the impacts of SEZs on permanent urban migration in China, where the registered residential location determines a large portion of social welfare. Using the difference-in-differences approach and a specific set of urban region data, we obtain results undiscovered in previous research on regional economic policies' impacts on migration. In particular, establishing SEZs has positive but time-lagged impacts on permanent migration to urban regions.

JEL Classification: D1,O2,R5

Keywords— Special economic zones, urban migration, regional policy, China

*This work was supported by JST, the establishment of university fellowships towards the creation of science technology innovation, Grant Number JPMJFS2102.

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1 Introduction

Establishing special economic zones (SEZs) to attract investments and create jobs in less developed geographic areas has been a popular instrument of place-based policies in both developed and developing countries.[1] In China, SEZs were initially conceptualized as experimental grounds for market-oriented economic policies. They were embraced nationwide after their early success in attracting foreign investments and fostering economic growth.

While obtaining approval from a higher rank government is a prerequisite for establishing SEZs in China, the implementation process, encompassing decisions such as location choice, has notably decentralized. Zheng et al. (2017) document the two-step process of establishing SEZs by interviewing officials overseeing its implementation. First, the city government initiates the SEZ program with capital investment to improve the target area's infrastructure and set up a bundle of preferential treatments.[2] The mayor can use their political power to converge land uses of the designated area and decide the amount of capital investment. Second, the local government selects an administrative committee to undertake private negotiations with target firms to recruit them to invest in the zone (Zheng et al., 2017). The decentralized implementation feature of SEZs in China has given more flexibility to local governors in their operations (Xu, 2011). Besides general policy benefits for all firms, SEZ administrators could offer specific firms with certain policy benefits based on their judgments during negotiation.

Depending on the approving government's level, SEZs can be classified as state-, province-, and minor-level SEZs. The level determines the benefits to investors, with higher-ranked SEZs usually enjoying more flexibility in granting policy favors and attracting more investors. As of 2018, China had 552 state- and 1991 province-level SEZs, with almost every municipality having at least one SEZ.[3] Establishing SEZs has become a prominent policy used by China's local governments to develop the regional economy.

Several researchers have investigated the impacts of SEZs on regional economic development and generally agree that SEZs promote local economic activities. Studies based on firm-level data

[1]For example, the European Structure and Cohesion Funds primarily focus on less developed regions to improve their competitiveness (Camagni and Capello, 2015).

[2]These policy benefits usually include tax deductions, discounted land-use fee and utility prices, assistance for securing bank loans, and smoother administrative approval for exporting and importing.

[3]*China's SEZ Audit Announcement (2018 edition).* was published by the central government and included all officially recognized state- or province-level SEZs, available at http://www.gov.cn/zhengce/zhengceku/2018-12/31/content_5434045.htm

from developed countries show that the impacts of SEZs are generated either from attracting new firms to invest locally (Givord et al., 2013), or increasing incumbent firms' employment and productivity (Criscuolo et al., 2019). Studies on SEZs in China have reached similar findings. Wang (2013) is one of the earliest studies which quantitatively examines SEZs' roles in regional economic development, and reveals their significantly positive impacts on local investments, productivity, and economic growth. Lu et al. (2019) use firm-level data from the Annual Survey of Industrial Firms (ASIF) data set to test SEZs' impacts on new entrants and incumbent firms. The authors suggest that net entry plays a larger role in generating overall SEZ effects. With the same data set, Zheng et al. (2017) examine SEZs' spillover effects on host cities, and suggest that such effects are significantly and positively related to the overall level of human capital in the SEZ, the foreign direct investment (FDI) share, and industrial "synergy" between host cities and SEZs. Xi et al. (2021) find that the agglomeration effect is the source of the productivity advantages of the producer service firms in SEZs. Furthermore, Gao et al. (2021) raise an interesting question on the gestation period of SEZs. Using data from 46 SEZs located in Eastern China, they assess the causal relationship between the total factor productivity (TFP) of these SEZs and that of their host cities. The authors reveal that SEZs' impacts on regional economic development happen after a delay of at least a year.

Meanwhile, very few researchers have systematically examined the roles of regional economic policies in shaping migration. Exceptions include Xie et al. (2018), who revealed the correlation between SEZ location and population density. However, the authors do not provide enough evidence to confirm the role of SEZs in urban population changes. Cerqua et al. (2022) also link regional economic policies and population changes, and demonstrated the causal relationship between receiving the European Structural and Cohesion Funds, and migration flows in EU-15 regions. Against this background, we quantitatively analyze the impacts of regional economic policies on permanent migration to urban in China. Specifically, using the Difference-in-Differences (DID) approach, we compare changes in urban migration rates before and after the establishment of SEZs, examine if SEZ establishment positively affects migration to urban areas, and also measure the gestation period for this effect.

Our research contributes to the literature on urban population change. First, we provide new evidence to support the link between regional economic policies, such as SEZs, and urban migration, which has been an under-researched topic. We focus on SEZs as a fundamental component of China's regional economy. With more than two-thirds of the cities having at least one state-level SEZ,[4] investigating SEZs allows us to gain a more in-depth understanding of regional economic policies.[5] Second, we use the event study model to distinguish the heterogeneous treatment effects of SEZs over exposure time. Third, our unique data set on urban population allows us to more accurately assess the population change in urban districts, making our conclusions useful for urban development. Finally, this research complements existing studies (Wang, 2013; Lu et al., 2019) on SEZs by extending the research focus beyond economic development to urban population change. Our results not only provide policy suggestions to local governments in China but also offer insights for other countries concerned about the long-term impacts of economic policy on migration.

The remainder of this work is organized as follows: Section 2 summarizes the literature on migration, and Section 3 explains our hypothesis and the household registration system essential to our research. The DID methodology and data are described in Sections 4 and 5, respectively. Section 6 provides the empirical results and discussions about the results. Section 7 summarizes our conclusion.

2 Literature Review

Migration studies span a range of fields and methods. In general, two broad approaches are employed to model factors behind migration: migration decisions and spatial equilibrium models (Mazumdar, 1987; Greenwood, 1997; Jia et al., 2023). Migration decision models investigate factors behind individuals' or households' migration decisions. They assume that migration decisions are rational choices that balance expected moving costs and potential relocation benefits to maximize individual utility. These studies model the probability of migration using various household survey data. Meanwhile, spatial equilibrium models focus on the spatial general equilibrium

[4] *China's SEZ Audit Announcement (2018 edition).*

[5] In different research or policy contexts, SEZs in China are often referred to by different names. For instance, Gao et al. (2021) use the term Development Zones to highlight their regional development aspect, while Zheng et al. (2017) use Industrial Parks to focus on SEZs targeting the manufacturing industry. Third, general public references occasionally confuse the Open Economic Status with SEZs. Here, we follow the definition of SEZs provided by Givord et al. (2013), considering it as an which broadly includes any districts with favorable fiscal or institutional treatment. This definition allows us to include all Chinese SEZs in our research.

reached through migration and examine population flows across regions. They employ aggregated data to investigate how regional characteristics, such as GDP and unemployment rates, account for such flows.

While methodological differences exist, both models emphasize regional heterogeneity as the determinant of migration. Under this push-pull framework, different characteristics of origin and destination regions provide potential incentives for migration (King, 2012; Niu, 2022) and valuable research insights as we look into the impacts of SEZs. SEZs are closely related to improving migrants' economic welfare because local governments may provide extra social benefits to attract labor to meet SEZs' demands and non-economic concerns–all these function as pull factors to bring migrants to urban regions. The early literature on migration in China favors the push-pull framework because China has yet to establish a database to track internal migration. Zhao (2004) offers a comprehensive summary of these studies and observes that the rural-urban income disparity is the most influential factor affecting household migratory decisions. Other factors, such as gender, marriage, family members, and age, also significantly shape migrants' decisions.

With limited available household survey data, early quantitative studies on migration in developed countries focus on aggregated data. Zipf (1946) is one of the starting points of these migration studies. Mazumdar (1987) utilizes the idea of gravity models as follows:

$$\hat{Migration}_{ij} = \log K + a_1 \log Population_i + a_2 \log Population_j - a_3 \log Distance_{ij} \tag{1}$$

where a_1, a_2, and $a_3 > 0$; K is the constant; and $Migration$, $Population$, and $Distance$ are the migration flow from region i to region j, both regions' populations, and the distance between them, respectively. The model describes the hypothesis that the gross migration flow is proportional (inversely proportional) to the population of (distance between) the two regions. Latter studies add several variables to form the modified gravity model to capture characteristics of origin and destination regions, such as unemployment rates, urbanization degree, various natural amenity variables, and public expenditures (Greenwood, 1997).

The modified gravity models are developed from the general equilibrium perspective. Assuming that income differences are the main driver behind rural-to-urban migration, Harris and Todaro (1970) model an equilibrium with two industry sectors to show that migration to urban areas is positively related to the expected urban-rural earning differential. Roback (1982) further introduces the housing sector and local amenities into general equilibrium models, and argues that migrants' utility depends on normal wages, housing costs, and local amenities. The author's empirical results suggest that the value of local amenities is reflected in wage differences and housing costs. Using data from the United States, Banerjee and Kanbur (1981) show that such equilibrium models can apply to developing countries too.

Recent studies have attempted to introduce the dynamic concept. Following the idea developed by Auerbach and Kotlikoff (1987) on fiscal policy effects, the dynamic general equilibrium models add the time-varying idiosyncratic shocks to the economy. Davis et al. (2021) model the migration rates' change in response to productivity shocks. Their findings suggest that TFP accounts for 77% of the variance of population growth rates among American cities. Bairoliya and Miller (2021) consider life-cycle stages in China and examine how social insurance affects rural-to-urban migration decisions. The authors' results indicate that enrolling migrants into urban health insurance strongly incentivizes rural-to-urban migration at all ages.

While most economic factors are well represented in equilibrium models, more recent studies using household survey data focus on individual-level non-economic factors in China. Fan and Xiang (2020) utilize questionnaire survey data from Henan province to investigate rural labor's migratory destination preferences. The authors reveal that besides economic concerns, family social ties determine migration destinations. The authors further suggest that migration is a family decision where migrants seek to balance higher income, and providing support for children and aging parents often left behind in rural villages. Other studies also indicate that besides higher income, non-economic benefits provided by host cities, such as suitable climate, better healthcare, and education, are significantly important when attracting migrants (Mullan et al., 2011; Zhou, 2014; Wang et al., 2022a).

Researchers in China have long noticed SEZs' impacts on migration to urban areas and its role in the urbanization process. Chen (1987) argues that establishing SEZs has brought much more socio-economic advantages for Shenzhen than those for other cities. By comparing the benefits Shenzhen offers with those of other major cities in China, the author concludes that Shenzhen has developed various strong, appealing images directly by virtue of being designated as an SEZ.

However, to the best of our knowledge, very few quantitative studies examine the impacts of SEZs on urban migration. One such study has been conducted by Xie et al. (2018), who build a data set from the 1982, 1990, 2000, and 2010 National Censuses to highlight the geographic population distribution, and measure the correlation between SEZs and urban population growth rates. Using Google Earth map, the authors identify urban districts by pinpointing continuously built-up areas and measure the population of each urban district by combining the identified urban districts with district-level National Population Census data. Allowing the measurement of the relationship between the location of SEZs and local population, the authors find that the geographic distribution of SEZs significantly correlates with urban population growth rates; older SEZs have higher urban populations.

3 Hypotheses

Research demonstrates that SEZs have a significantly positive impact on local economic development. Combining migration theory, one can clearly argue that SEZs can attract temporary migrants by providing better employment opportunities and increased income. Empirically, the extra job vacancies generated by SEZ establishments are usually filled by labor migrants. However, some unexplored research questions are whether the welfare provided by SEZs is large enough to encourage migrants to settle down in the urban regions permanently or if the establishment of SEZs can reduce the entry barriers for Hukou migrants. Here, our main objective is to examine SEZs' impacts on Hukou migrants.

The Household Registration System, or *Hukou* system, fundamentally distinguishes migration behaviors in China from those in developed countries. The Hukou system was first introduced in 1951 in urban regions and then extended to rural villages in 1955. It was originally designed to serve as a monitoring mechanism for population migration but soon became a tool for the government to control population mobility (Cheng and Selden, 1994). Before the Hukou system reform in the 1980s, the average migration rate in China was kept at a very low level of approximately 0.2% (Zhao, 2004; Chen and Fan, 2016).[6]

In response to the growing demand for rural labor to settle in urban regions, local governments began exploring methods to reform the Hukou system. Several "Hukou selling" policies were implemented in the 1980s, where local governments would charge an "Urban Capacity Fee" in exchange for transferring Hukou to their regions. These moves were typically driven by local

[6]The migration rates here are defined as the rural-to-urban population over total urban population.

governments in smaller cities as a method to fund their rapid urbanization process, while major cities, such as Beijing or Shanghai, were less eager to undertake reforms (Wing Chan and Buckingham, 2008). The nationwide reform of the Hukou system happened in 1997 with the publication of the Pilot Program for Small Town Hukou System Management Reform.[7] However, the Hukou transfer policy designs were, to a large extent, still decentralized to local governments. While most researchers would expect Hukou reform to encourage rural residents to migrate, evidence shows that they have become less eager to transfer their Hukou into cities over recent years (Chen and Fan, 2016).

Indeed, even after the Hukou system reform, studies still identify the Hukou system as the major obstacle to rural-to-urban migration, preventing residents from acquiring numerous urban benefits, such as education and healthcare (Whalley and Zhang, 2007; Mullan et al., 2011). In addition, migrants without local Hukou suffer several unfair treatments in workplaces, such as pending wage arrears (Zhou, 2014). Studies from an urban development perspective, such as that of Fan et al. (2015), further imply that the Hukou system's negative impacts on labor mobility could reduce migrants' housing demand and hinder urban developmental sustainability. Mu et al. (2021) evaluate the migration pattern using data from the 2015 population census and conclude that Hukou substantially impacts migration directions. Individuals whose Hukou are registered in larger and more developed cities are less likely to move to smaller cities or rural areas than those registered in smaller cities.

Recent studies attempt to explain the low willingness to transfer Hukou. Some studies reveal that rural residents still have inferior access to urban benefits even after Hukou transfer, reducing their willingness to migrate (Wu and Zheng, 2018; Qian and Florence, 2021). Other studies argue that transferring Hukou to urban areas implies a loss of protection and security from giving up access to rural lands (Chen and Fan, 2016). More recent studies have noticed a significant time lag in acquiring Hukou after moving into the city. For example, Liu and Shi (2020) found that it took approximately five years to acquire a Beijing Hukou.

Under the push-pull framework, SEZs impact migrants in the following ways. First, SEZs provide extra job opportunities in the host urban region to attract migrants. Studies show that SEZs could bring in new investments (Wang, 2013), and their effects are mainly from net entry firms (Lu et al., 2019). As firms and capital are attracted to the SEZs, they bring in extra

[7] *Xiao Chengzhen Huji Guanli Zhidu Gaige Shidian Fang'an.*

labor demand for the urban region. Furthermore, the improved productivity by SEZs leads to higher income, which helps migrant workers offset the costs of settling down. Furthermore, by contributing to the economic performance of the host city, SEZs indirectly improve welfare. This is further enhanced by infrastructure improvements, which are usually involved while creating SEZs. Based on this discussion, we propose the following hypotheses:

1. SEZs positively attract migrants to settle down in host municipalities.

2. SEZs' impacts on urban migration lag over time; that is, the impacts will not occur instantaneously but years after their implementation.

4 Methodology

4.1 Static Two-way Fixed DID Model

Numerous studies have employed the DID approach to analyze policy impacts. Its simplicity and potential to circumvent endogenous problems have helped its adoption (Bertrand et al., 2004). The DID estimation usually comprises identifying a specific intervention or treatment, which is the establishment of SEZs in our case. Then, the difference in outcomes before and after the intervention for groups affected by the intervention is compared to that for unaffected groups. Under the parallel trends assumption, where the outcomes of both the control and treatment groups would have followed the same trend if the treatment was absent, such DID outcomes become the estimates of the average treatment effect for the treated sub-population. The DID model suits our research because the intervention is well-defined over time.

A canonical DID approach regression model with only two periods (before and after the treatment) can be expressed as:

$$Y_{it} = \alpha D_i + \beta T + \gamma DID + u_{it} \tag{2}$$

where i represents individual units. D_i denotes whether a unit is in the treatment or control group; specifically, $D_i = 1$ and $D_i = 0$ if i is in the treatment or control (untreated) groups, respectively. T represents the periods, where $T = 1$ and $T = 0$ for the post- and pre-treatment periods, respectively. Y is the outcome variable and u_{it} is the error term. The term DID constitutes the

DID variable as demonstrated in Table 1.

(Table 1)

Estimating Equation (2) gives us the estimate of the treatment effect γ. Suppose that treated units are in group g and never treated units are in group c. By the definition of the DID approach, we use TE to denote the true treatment effects:

$$TE = Y_{g,T=1} - Y_{g,T=0} - (Y_{c,T=1} - Y_{c,T=0}) \tag{3}$$

We know that for the treatment group, $D_i = 1$, and for control group, $D_i = 0$, from the values in Table 1. Then, we have:

$$Y_{g,T=1} - Y_{g,T=0} = \alpha + \beta + \gamma + u_{g,T=1} - \alpha - u_{g,T=0} \tag{4}$$

$$Y_{c,T=1} - Y_{c,T=0} = \beta + u_{c,T=1} - u_{c,T=0} \tag{5}$$

Combining Equations (4) and (5) with Equation (3), and taking expectations on both sides, we get:

$$E[TE] = E[\gamma] \tag{6}$$

This shows that parameter γ in the model (2) is the DID estimator of the average treatment effect.

As mentioned at the beginning of this section, the important assumption required by the DID approach is the presence of parallel trends between the control and treatment groups. This can be inferred from our calculation: when taking expectations to remove our error terms, we assume $u_{g,T=1} - u_{g,T=0} - u_{c,T=1} + u_{c,T=0} = 0$. Hence, we are subject to standard OLS assumptions, including $E(u_{it}) = 0$ and $E(u \mid D, T) = 0$. To keep our model consistent with the above assumptions, we implicitly assume a common trend in outcome variables between the control and treatment groups in the absence of treatment.

The canonical DID model (2) describes the approach to estimating the effect of a single policy implemented simultaneously for all units. While it helps us demonstrate the DID approach's basic ideas, the assumption of only two periods and groups each does not fit our research context. The establishment of SEZs is staggered across urban regions over around 20 years. Conflating the urban regions with various treatment times into a unified treatment group is unlikely to provide a valid estimate of the policy effect because urban regions in China have faced tremendous changes over the past 20 years. Moreover, with most urban regions being treated by 2019, the number of urban regions suitable for the control group is relatively small, reducing the DID comparisons' validity.

Therefore, we start with a more commonly employed DID specification (Beck et al., 2010) and focus on the group-time average treatment effect, where the groups are defined by the period when units are first treated. We begin our empirical research by estimating the following static two-way fixed effect DID model:

$$pop_{it} = \alpha + \tau D_{it} + \delta Z_{it} + v_i \mathbf{A} + \mu_t \mathbf{T} + \epsilon_{it} \tag{7}$$

where pop_{it} is the outcome variable measuring the migration rates of urban region i in year t. Z_{it} is a set of control variables for controlling the common trends in migration rates among the sampled urban regions. $\mathbf{A}$ and $\mathbf{T}$ are vectors of dummy variables that account for the province and year-fixed effects, respectively; hence, v_i and μ_t are estimates of time-invariant province characteristics and shocks in year t that is experienced by all sample regions, respectively. ϵ_{it} is the error term. D_{it} is the DID variable of our interest; we follow the staggered treatment adoption assumption in the literature for urban region i that received an SEZ in year M, $D_{it} = 1$ for all $t \geq M$, and 0 otherwise. This assumption indicates that once treated, the policy effects last throughout the end of our sample period, which is consistent with the case for SEZs. τ indicates the impacts of SEZs on urban migration rates. A significant and positive τ would suggest that SEZs promote inward migration flows to their host urban regions, and vice versa. Equation (7) is estimated with the OLS method.

4.2 Event Study DID Model

The static DID model estimates the overall effects of policies in a unified manner. While it is useful for evaluating whether SEZs impact migration flows in urban regions, it does not provide insights into how SEZs' effects vary with the length of exposure to the treatment. The permanent migration we focus on does not usually respond instantly to policies. After a migrant moves to an urban region to take up a job opportunity, transferring their Hukou to the host urban region may take years (Liu and Shi, 2020). They also need time to overcome barriers related to settling down. Therefore, we attempt to capture the heterogeneity in treatment effects over time and study how long it takes for the SEZ establishment to impact the population. To capture such heterogeneous treatment effects over time, we use the following event study DID model along the lines of Jacobson et al. (1993) and Wang (2013):

$$pop_{it} = \alpha + \sum_{k=-L}^{-2} \tau^k D_{it}^k + \sum_{k=0}^{K} \tau^k D_{it}^k + \delta Z_{it} + v_i \mathbf{A} + \mu_t \mathbf{T} + \epsilon_{it} \tag{8}$$

Equation (8) is similar to the static DID (Equation (7)) except for the DID variables. In Equation (8), D_{it}^k is our event study DID variable, which represents k period ahead/behind initial treatment date for urban region i that receives an SEZ in year M. To check the effect of having an SEZ for N years, we have $D_{it}^k = 1$ if $k = N$ and $t = M + N$, and 0 otherwise. k ranges from $-L$ to K and $k \neq -1$, indicating that we are estimating the treatment effects each year from L before the treatment and to K after the treatment using the year before the treatment as base year for comparison. τ^k is the coefficient of interest. For positive k, τ^k represents the average effects of being treated for k periods; for negative k, τ^k represents the average deviation in outcomes k periods before the treatment. We expect non-significant τ^k for negative k, indicating the parallel trends before the treatment, and positive and significant τ^k for k above certain criteria, showing SEZs' time-lagged effects on migration.

5 Data Definition

By China's administrative structure design, a province is divided into several prefectures (*Xian*) and cities (*Shi*), each having a prefecture- (*Xianjishi*) or city-level municipality (*Dijishi*) in the center which administrates nearby counties and villages. In practice, a nearby city typically administrates a prefecture-level municipality, and therefore, its statistics are aggregated into the city's population in reports and surveys. However, the China City Statistic Yearbooks provide a unique set of City District statistics. The City District (*Shixiaqu*) is described as the areas directly governed by the city-level municipalities, generally referring to the urban regions of the cities. This allows us to focus our study on urban regions.

The sample period is from 1998 to 2019. We use 1998 as the starting year because China initiated its household registration policy reforms in 1997. The reform relaxed migration requirements from rural to urban areas in minor cities, and can be viewed as the starting point when China allowed citizens to change their household registered locations.[8] Further, the year 2019 was the year with latest available data at the time of writing this study. We exclude Xinjiang, Tibet, Qinghai, and Hainan provinces from our sample to reduce heterogeneity across cities. Xinjiang is known to have much stricter migration policy controls, Qinghai and Tibet have significantly different climates from the rest of China due to their much higher altitudes, and Hainan's administrative structure differs much from that for other provinces.[9] We further excluded prefecture-level municipalities because they are usually much less developed. This leaves us with a total of 282 urban municipalities in the sample.

5.1 Migration Rates

Our main variable of interest is migration rates. Similar to other developing countries, China has yet to establish granular city-level migration data (Mu et al., 2021). However, the household registered population data are well-recorded under the Hukou system at the urban district level. Furthermore, although China City Statistic Yearbooks do not provide migration data, they report household registered urban population, and birth and death rates yearly. Therefore, we use the method employed by Zhang and Song (2003) to calculate migration rates. We subtract estimated population change with birth and death rates from actual population change to get net migration each year. Then, we divide the net migration by the urban population to get the migration rates.

However, the calculated migration rates suffer from outlier problems due to constant administrative changes at city levels over the sample period. An urban district that expands by absorbing nearby municipalities or contracts by ceding certain areas to other municipalities would result in a sudden increase or decrease in urban population, thereby leading to abnormally high or low migration rates. In addition, in a few cases, a city is entirely merged into another city during our sample period and no longer reported thereafter.[10] To deal with such merging issues, we follow the following method: when a city is completely merged into another city, we compare the urban district population of the target city before and after the merger. If the urban population

[8] *Xiao Chengzhen Huji Guanli Zhidu Gaige Shidian Fang'an.*

[9] Prefecture-level municipalities in Hainan are directly governed by the province, while nearby city-level municipalities usually govern those in other provinces.

[10] For example, Laiwu was merged into Jinan city in 2018, and thus, did not have 2019 data.

substantially changes, we consider the merged city as part of the urban district of the target city and combine their urban statistics; otherwise, we keep both cities' data and consider the merged city's data missing after the merger. Then, we drop the top and bottom 5% of the migration rate data as outliers. The average annual migration rates are shown in Figure 1.

(Figure 1)

5.2 Determinants of Migration

Migration decisions are influenced by individual and household characteristics, and regional differences (Greenwood, 1997). Studies show that China's population distribution patterns, along with Hukou transfer decisions, are formed due to the combination of environmental and socioeconomic conditions (Fan and Xiang, 2020; Lao and Gu, 2020; Zhang et al., 2020). Drawing on the push-pull framework, we retrieve the following regional characteristics as our control variables.

Income: Income is one of the most important economic factors that affects migration decisions. Both micro-level surveys and macro-level economic models have identified income's significant impacts on migration (Zhao, 2004; Kondo and Okubo, 2015). We use urban wage to proxy income, following Murayama et al. (2022). Urban wage data are collected from local firm surveys and measure the average wage of the employees hired by firms in urban areas. Higher wage provides more incentives for migrants to work in the city and offsets the economic burden of settling down permanently.

Housing: Over the past decades, China has experienced enormous increases in residential housing prices. This has become a social problem and the primary concern for young generations to live in cities. The rise in housing prices has also placed severe burdens on migration, as housing costs have gradually become the most significant obstacle to settling in cities (Zhou and Chi-Man Hui, 2022). While studies typically use housing prices, the China City Statistic Yearbooks only contain housing prices from 2017 to 2019. Meanwhile, other data sources that contain housing prices throughout our sample period, such as National Statistic Yearbooks, only cover prices in major cities. Therefore, we use real estate investments in China City Statistic Yearbooks to proxy housing market supply. We expect a higher real estate investment (per capita) to lower housing prices and increase migration inflows.

Economy structure: As implied by Harris and Todaro (1970), rural-urban migration is accompanied by the reallocation of the labor force from agricultural to the manufacturing and service industries. Most firms reallocating into SEZs are manufacturing firms or producer service providers. Therefore, the economic structure of host urban regions is another important factor affecting migration. We use the employment share of the tertiary industries to proxy the economic structure. A higher share of tertiary industry employment will likely provide better incentives for migrants to settle down.

Infrastructure: Road infrastructure facilitates not only the movement of traded goods but also that of labor (Wang et al., 2022b). Better road infrastructure can significantly reduce the costs of migration, especially for migrants who need to constantly visit older parents left in their origin village, which is a common phenomenon in China. Due to data limitations, we do not have a reliable measurement of the length of roads within each urban region, which is often employed by other studies (Wang, 2013). Therefore, we use the number of passengers traveling in and out of urban regions as our measurement for road infrastructure. We expect a positive relationship between the number of passengers and migration rates.

Unemployment: Another common variable that captures the potential economic risks of migration is the unemployment rate. However, unemployment data in China normally suffer from poor quality. The yearbooks report registered unemployment data, which require individuals to self-claim their unemployment statuses to be recorded. In practice, however, social security for the unemployed does not motivate many unemployed residents to complete the self-claiming process. Therefore, the registered unemployment data are widely believed to understate the true unemployment rates (Giles et al., 2005).

Local amenities: As suggested by Roback (1982), local amenities play important roles in shaping local labor markets. Green area coverage and climate are commonly used to proxy local amenities (Huang et al., 2015). High green area coverage and suitable climate improve living quality and attract migrants to settle permanently. Due to a lack of reliable regional data on climate, we use green area coverage to proxy local natural amenities. The data come from China City Statistic Yearbooks and this metric is calculated as a percentage of green areas in urban regions. A higher green area coverage indicates more parks or grasslands. These can provide better recreation opportunities to citizens, and therefore, increase migrant inflows.

Population and GDP: The gravity model (Zipf, 1946) indicates that population directly impacts migration flows. Meanwhile, GDP per capita is commonly employed as a control variable to proxy economic activities (Kondo and Okubo, 2015).

Government expenditure: Researchers have found the importance of social security in attracting migrants (Bairoliya and Miller, 2021), which is reflected in local government expenditure (Yip et al., 2012). Under the Hukou system, the quality of social security is strictly tied to migrants' registered Hukou location. Gaining access to better social insurance could incentivize them to transfer their Hukou. We use government expenditure per capita to measure the public expenses of each resident.

Education and healthcare: Multiple studies have identified the importance of child education in household migration decisions (Liao et al., 2022). Migrants who bring their children with them are more encouraged to settle down because transferring Hukou allows them access to local schools, which usually provide better education than those in migrants' original residence areas. We use the number of high school teachers (per capita) to proxy education. Because of the Gaokao system, high school is considered the most important part of children's education; a higher number of high school teachers indicate better education, which could attract migrants to settle down. Another important reason migrants settle down in urban regions is gaining access to better healthcare. We use the number of hospital beds (per capita) to proxy local healthcare.

Since migration decision involves comparing the origin and destination, finding the gap in factors between the two regions is common practice. However, as described earlier, we do not have information on migrants' origins. Therefore, we use the provincial average to proxy the origins of migrants; subtracting it from each urban region's data will give us the relative advantage a city holds against other regions of the same province. As most migrants move into nearby cities rather than across provinces (Mu et al., 2021), this method allows us to measure the relative strength of a city against migrants' original residence locations.

Liu and Wang (2020), Wang et al. (2022a), and Zhang et al. (2018) also reveal that the administrative level or "tier" of a city can strongly influence migrants' settlement intentions.[11] To capture and compare disparities across cities, we categorize our cities into three sub-groups based on urban population in 2011. Cities with an urban population over 2 million, over 1 million

[11]Zhang et al. (2018) find that cities have different preferences over workers eligible for local Hukou. Furthermore, a more recent study on the impacts of high-speed rail on spatial structures in central China cities (Wang et al., 2022b) also indicates that spatial structure characteristics vary across urban regions.

but less than 2 million, and the rest are tier 1, 2, and 3 cities, respectively. A full list of sampled cities by city tiers is provided in Appendix B.

6 Empirical Results

6.1 Background Information

A comprehensive list of state- and provincial-level SEZs in China can be found in China's SEZs Audit Announcement (2018 edition). It was co-published by multiple ministries belonging to China's central government to regulate SEZs nationwide. The list includes each SEZ's name, location, geographic scale, and designated industrial focus. To the best our knowledge, ours is the first study to focus on an SEZ is established in each city. However, the SEZ list does not include the most widely acknowledged Open Economic Areas, since Open Economic status in China is granted to a larger geographic area that usually covers the entire city, while SEZs are located within certain suburban zones of the city. Nonetheless, some researchers (Wang, 2013) treat both as identical; hence, we do not consider acquiring Open Economic status. All cities with open economic status have established at least one state-level SEZ before 1998, the starting time of our sample period. Therefore, they belong to the same treatment group in our analysis.[12]

Our research focuses on state-level SEZs to reduce the heterogeneity across SEZ levels. State-level SEZs tend to attract more policy attention, and thus, account for a more fundamental influence on the urban population. Figure 2 shows the number of state-level SEZs established each year. Among the 282 cities in our sample, 202 cities have at least one SEZ by the end of 2018. We consider the establishment year of the very first state-level SEZ in a city as the timing of the policy treatment for a city.

(Figure 2)

Inspired by Xie et al. (2018), we build a map to illustrate the geographic relationship between SEZs and urban population (Figure 3). We exclude Xinjiang, Tibet, Qinghai, and Hainan provinces from our sample because urban municipalities in these provinces tend to be much smaller. We also exclude prefecture-level (*Xianji Shi*) municipalities because their administrative structures are much different from city-level municipalities (*Diji Shi*). The excluded municipali-

[12]These cities are Dalian, Qinhuangdao, Tianjin, Yantai, Qingdao, Lianyungang, Nantong, Shanghai, Ningbo, Wenzhou, Fuzhou, Guangzhou, Zhanjiang, Beihai, Xiamen, Shantou, Shenzhen, and Zhuhai.

ties are colored yellow on our map. Then, we use the 2010 SEZ and 2015 urban population data to show the differences in urban population between municipalities with at least one state-level SEZ for a minimum of five years and those without one. Municipalities with at least one SEZ by 2010 are marked with a black triangle. The urban population is indicated with a blue color; a darkened color indicates a higher urban population in Figure 3. Notably, municipalities with at least one SEZ are likely to have more urban population in five years.

(Figure 3)

The correlation matrix of our control variables is presented in Table 2. Several variables have high correlation, which may imply a potential multi-collinearity problem. To further examine this issue, we conduct a Variance Inflation Factor (VIF) test to measure how much each variable is affected by multi-collinearity issues and exclude variables that receive a VIF score of 10 or more. The test results are shown in Table 3. All selected variables fall under a VIF score of 10, suggesting that our estimations do not suffer from multi-collinearity problems.

(Table 2) (Table 3)

6.2 Two-way Fixed Effect DID Results

Table 4 reports the estimates of Equation (7) without control variables. Model (1) is estimated with all sample cities, and Models (2) through (4) are estimated with sub-samples of tier 1 to 3 cities, respectively. Table 5 shows estimates with control variables. All eight models include both provincial and year-fixed effects.

(Table 4) (Table 5)

Our DID variable (D) coefficients are significant and positive in all models, consistent with our hypothesis that establishing SEZs positively impacts inward urban migration flows. Model (5) suggests that, on average, establishing the state-level SEZ can increase the host urban region's inward migration rate by approximately 0.2%. In addition, results from different city tiers suggest that the significant positive impact of SEZs on urban migration is consistent across city levels. The coefficients of the DID variable decrease from Models (2) to (4), indicating that the impacts of SEZs on urban migration are less effective in smaller cities than those in larger cities. The same pattern appears in Models (6) through (8) with control variables.

SEZs' effects over time estimated with the event study DID are presented in Figures 4 and

5. Figure 4 is estimated with only event study DID variables and fixed effects, while Figure 5 includes control variables. In our event study models, the base year for comparison is one year before SEZs are established ($t = -1$). A non-significant coefficient for a specific year indicates that the migration rate remains relatively consistent compared to the year immediately preceding the establishment of SEZs. Both figures show that while the impacts from SEZs are not significant within seven years, positive and significant effects emerge starting from the eighth year after the establishment of SEZs. Furthermore, the non-significant coefficients observed before the establishment suggest that all urban regions exhibit consistent migration rates before implementation, thus satisfying the parallel trends assumption. Overall, the event study DID results support our second hypothesis.

(Figure 4) (Figure 5)

6.3 Robust DID Approaches

Multiple studies have provided insightful critiques on the traditional DID approach (Butts and Gardner, 2022; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021). By decomposing the DID estimator, they suggest that this approach may lead to biased estimates. Consider estimating the traditional DID model by decomposing our sample and using g to denote the group a unit is in and t to denote time.[13] The treatment effects implicitly estimating are:

$$E[\hat{\beta}_{fe}] = E[\sum_{(g,t):D_{gt}\neq 0} W_{g,t}TE_{g,t}] \tag{9}$$

where $\hat{\beta}_{fe}$ is the estimate of the covariate of our DID variable (i.e., estimate of our treatment effects). $TE_{g,t}$ is the true treatment effect of group g at time t, and can be described as follows:

$$TE_{g,t} = Y_{g,t}(1) - Y_{g,t}(0) \tag{10}$$

where $Y_{g,t}(1)$ is the outcome variable of the treated group, and $Y_{g,t}(0)$ denotes the anticipated outcome variable of the same group g at the same time t in the absence of the treatment. Back to Equation (9), the weighted factor added implicitly by the traditional DID here is $W_{g,t}$; its sum

[13]Units that receive treatment simultaneously are considered within the same group.

equals 1 and it is proportional to:

$$N_{g,t}(DID_{g,t} - DID_{g,.} - DID_{.,t} + DID_{.,.}) \tag{11}$$

where $N_{g,t}$ is the number of observations, $DID_{g,t}$ is the average treatment effect of group g at time t, $DID_{g,.}$ is the average treatment effect of group g over all periods, $DID_{.,t}$ is the average treatment effect at time t of all groups, and $DID_{.,.}$ is the average treatment effect of all groups over whole periods. With heterogeneous treatment points in time, we clearly know that $(DID_{g,t} - DID_{g,.} - DID_{.,t} + DID_{.,.})$ is not constant for all groups. Thus, the estimated treatment effect $\hat{\beta}_{fe}$ is biased from the true effect $TE_{g,t}$. Hence, we face a weighting problem while employing the traditional DID approach. A more detailed example using insights sparked by Borusyak et al. (2022) is provided in Appendix A.

Therefore, we follow the two-stage DID approach to rule out the possible weighting problem in the traditional DID approach (Butts and Gardner, 2022). Assuming that the trend of the outcome variable is estimated from the not-yet-treated group, they pre-exclude fixed effects from the estimation using sub-samples of not-yet-treated units. Specifically, the two-stage DID model begins with the first stage which estimates the following model with observations that satisfy $D_{it} = 0$:

$$Y_{igt} = v_g \mathbf{B} + \mu_t \mathbf{T} + \theta Z_{igt} + u_{igt} \tag{12}$$

where g denotes groups with units that receive treatment simultaneously. $\mathbf{B}$ and $\mathbf{T}$ are vectors of group and time dummy variables that account for group and time-fixed effects, respectively. Estimating model (12) gives us the estimated group and time fixed effects v_g and μ, respectively, denoted as $\hat{v_g}$ and $\hat{\mu}$. Then, we can use the fixed effects to form the adjusted outcomes with:

$$\tilde{Y}_{igt} = Y_{igt} - \hat{v_g} - \hat{\mu} \tag{13}$$

where $\tilde{Y}_{igt}$ is the adjusted outcomes. With the adjusted outcomes, we move to the second stage and regress the adjusted outcome on treatment status in the full sample to get the treatment effects. We use the following model:

$$\tilde{Y}_{igt} = \tau D_{igt} + u_{igt} \tag{14}$$

The same procedure applies to the event study model where τ is the treatment effect.

The static two-stage DID results are presented in Table 6. Both results are estimated with the full sample. Model (9) is estimated with no control variables, and Model (10) includes the same control variables as those in Table 5. The coefficients of control variables are omitted because they are estimated only in the first stage with a sub-sample of not-yet-treated observations. Both results are consistent with those from the traditional DID approach, demonstrating the robustness of our results.

(Table 6)

The event study two-stage DID results are shown in Figures 6 and 7. Figure 6 is estimated with only fixed effects and no control variables, while Figure 7 considers control variables. Overall, these results are consistent with those estimated with the traditional DID approach shown in Figures 4 and 5. However, significant positive impacts emerge in the seventh year rather than the eighth. Notably, the coefficients from the two-stage DID approach are slightly larger than those from the traditional DID approach in both the static and event study results. This demonstrates that the negative weighting problem in the traditional DID approach negatively affects our estimations.

(Figure 6) (Figure 7)

We further employ the local projection DID (LP-DID) (Dube et al., 2023) to examine our event study results. Contrary to the conventional event study approaches, the LP-DID considers heterogeneous treatment effects, acknowledging that implementing the same policy at different times may yield varied impacts. The LP-DID approach implements a "clean control" condition where only never-treated observations are used as a control group to estimate policy impacts. The estimation model is expressed as:

$$Y_{i,t+h} - Y_{i,t-1} = \delta_t^h + \beta_h^{LP} \Delta D_{it} + \epsilon_{it}^h; \; for \; h = 0, 1, ..., H \tag{15}$$

where h denotes each period, and a different regression is needed for each h. For unit i that receives the policy treatment at time s, ΔD_{it} equals 1 if $t = s$, and 0 otherwise. The results are shown in Figures 8 and 9. Figure 8 is estimated with only fixed effects, and the results in Figure 9 further incorporate control variables.

(Figure 8) (Figure 9)

The outcomes from the LP-DID approach align with those from other event study methodologies, affirming the satisfaction of the parallel trends assumption, as evidenced by the non-significant pre-treatment coefficients. Nevertheless, the timing at which the impacts from establishing SEZs become significant is slightly earlier than previously estimated. According to the LP-DID approach, the effects occur within five to six years. This implies that, on average, the impacts of SEZs on permanent migration manifest earlier when accounting for heterogeneous treatment effects.

The results from all our DID models show significant positive impacts of establishing SEZs on urban migration. On average, establishing SEZs can increase migration rates in host urban regions by 0.2 percentage points. While the increase is marginal compared to other factors, it provides valuable support to our theory that economic policies could also affect regional migration.[14] Our results are consistent with Xie et al. (2018), who reveal the geographic correlation between SEZ locations and urban population distribution. Our study suggests that SEZs' impacts on urban migration are the reason behind this geographic correlation. In addition, our results are consistent with Cerqua et al. (2022), who reveal the positive impacts of regional economic policies on migration in the European Union, and Xu and Wang (2020), who find that African SEZs can attract migrants.

While the literature on SEZs in China has focused on their impacts on economic development (Wang, 2013; Lu et al., 2019; Gao et al., 2021), our results suggest that SEZs also affect the local population. Within the push-pull framework, our findings show that the economic benefits from establishing SEZs could act as pull factors to influence migrants' settlement intentions. Given the context of the Hukou system in China, we show that SEZs encourage migrants to settle down in urban regions permanently.

Recent studies reveal that trade liberalization leads to less restriction on the Hukou system (Tian, 2022). Given that SEZs are important components of China's economic reform practices, establishing SEZs indicates that host cities are more willing to accept migrants. This provides an institutional encouragement other than economic benefits to attract migrants. Furthermore, the estimation results imply that the impacts of SEZs on urban migration are heterogeneous across city tiers. Cities in higher tiers receive larger impacts from SEZs. This is consistent with Wang et al. (2023), who suggest that administrative levels of cities impact migrants' settlement intentions. Meanwhile, we also show that city scales play a role in regional economic policies'

[14] For example, Davis et al. (2021) finds that TFP accounts for 77 % of migration in the United States.

influence on migration. Economic policies implemented in larger cities tend to have stronger effects on urban migration.

Our event study results in Figures 4 through 9 reveal no significant change during the pre-treatment period. This observation indicates that our DID models adhere to the parallel trends assumption, providing confidence about the validity of our methodology. Migration rates of all urban regions in our sample share the same trend when SEZs are absent. Moreover, the coefficients in the post-treatment periods estimated by our event study results suggest that SEZs' effects may take up to five to eight years to become significant. Research shows that the interactive relationship between SEZs and their host cities plays out over time (Luo et al., 2015). During the initial stages of SEZs' development, reliance on preferential policies can create a polarization effect, diverting developmental resources from host cities. As SEZs mature, their advantages begin to spill over, benefiting and influencing the development of surrounding regions. The establishment of SEZs triggers an immediate response in certain economic factors, such as GDP and FDI (Wang, 2013; Gao et al., 2021), owing to their direct influence via capital accumulation and policy preferences. However, for permanent migration, the materialization of attractive characteristics requires more time. The unique features of the Hukou system in China add an extra layer of complexity to the migration process. Studies on the Hukou system, such as Liu and Shi (2020), argue that it takes years before migrants can acquire local Hukou after moving into urban regions. Thus, migrants attracted to the urban regions by SEZs do not immediately settle down. Instead, after spotting the economic benefit of SEZs and moving into the urban region, it takes years for them to transfer their Hukou to the urban region for economic or non-economic reasons. In practice, many migrants maximize family resources by earning in urban regions and spending in rural regions (Liu and Wang, 2020).

7 Conclusion

This study examines the roles of SEZs in shaping urban migration using data between 1998 and 2019 on the urban regions of 282 cities in China. Employing static and event study DID models to examine the impacts of establishing state-level SEZs on migration to urban areas, we report two main findings.

First, establishing SEZs positively impacts the migration to host urban regions. Compared with urban regions with no or not-yet-established SEZs, urban regions with SEZs have significantly higher migration rates on average. This finding is consistent with a few studies that link regional policies with migration, such as Cerqua et al. (2022), who demonstrate that European public funding positively impacts migration. Regional economic policies that promote local economic development also impact the local population. As pointed out by Fan et al. (2015), reduced labor mobility in China has hindered urban regions' sustainable development against the declining population trends; therefore, local governors need to reevaluate their economic policies to attract migrants from rural regions. In addition, the Hukou system differentiates migration in China than that in Western countries. Since substantial social welfare benefits in China are tied to the Hukou location, allowing migrants with Hukou in urban regions can significantly increase their social welfare. Thus, we suggest that besides improving local economic performance, SEZs in China can further improve social welfare by allocating more Hukou to non-Hukou residents.

Second, our event study model reveals that SEZs have significant impacts on urban migration after urban regions have been exposed to SEZ treatments for more than seven years. Thus, regional economic policies have time-lagged effects on permanent migration. Together with the improved social welfare from granting Hukou to migrants, our finding indicates that SEZs' impacts on the local population emerge slowly. To the best of our knowledge, no studies have shown the lagged impacts of SEZs. As such, our results address the importance of long-term planning during economic policy design processes. As population aging is becoming more prominent in China, the impacts of current economic policies on future populations must be carefully evaluated. Moreover, local governors should be prepared that their economic policies to increase the local population may not yield immediate results.

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Appendix A
An Example of the Weighting Problem in the Traditional DID Approach

Here, we provide a simple example to demonstrate the weighting problem that arose from the traditional DID approach, following the insights provided by Borusyak et al. (2022).

Suppose we have two groups (a and b) and three periods ($T = \{1, 2, 3\}$). Furthermore, assume group a is treated at the beginning of the second period when $T = 2$, and group b is treated at the beginning of the third period when $T = 3$. Denote $DID_{g,g',t,t'}$ as DID treatment effect comparing treatment g and control groups g' from period t to t'. By definition, the estimate of the traditional DID parameter $\hat{\beta}$ follows:

$$\hat{\beta} = (DID_{a,b,1,2} + DID_{b,a,2,3})/2 \tag{16}$$

The estimate is the average treatment effect of group a using group b as a comparison from the first to the second period, and that of group b using group a as a comparison from the second to the third period.

We denote $Y_{g,t}$ as the outcome variable of group g at time t. Assuming that our outcome satisfies the parallel trends assumption, we have:

$$DID_{a,b,1,2} = Y_{a,2} - Y_{a,1} - (Y_{b,2} - Y_{b,1}) \tag{17}$$

and

$$DID_{b,a,2,3} = Y_{b,3} - Y_{b,2} - (Y_{a,3} - Y_{a,2}) \tag{18}$$

Using $TE_{g,t}$ to denote the true treatment effect and $Y_{g,t}(0)$ for the anticipated outcome in the absence of treatment for group g that received treatment in time t, we get:

$$Y_{g,t} = Y_{g,t}(0) + TE_{g,t} \tag{19}$$

and we have:

$$Y_{a,3} - Y_{a,2} = Y_{a,3}(0) + TE_{a,3} - (Y_{a,2}(0) + TE_{a,2}) \tag{20}$$

and

$$Y_{b,3} - Y_{b,2} = Y_{b,3}(0) + TE_{b,3} - Y_{b,2}(0) \tag{21}$$

By inserting Equations (20) and (21) into Equation (18), we have:

$$DID_{b,a,2,3} = Y_{b,3}(0) + TE_{b,3} - Y_{b,2}(0) - (Y_{a,3}(0) + TE_{a,3} - (Y_{a,2}(0) + TE_{a,2})) \tag{22}$$

Under the parallel trends assumption, we know:

$$Y_{a,3}(0) - Y_{a,2}(0) = Y_{b,3}(0) - Y_{b,2}(0) \tag{23}$$

Therefore, Equation (22) can be rewritten as:

$$E[DID_{b,a,2,3}] = E[TE_{b,3} - TE_{a,3} + TE_{a,2}] \tag{24}$$

Similarly albeit in a more simplified manner, Equation (17) can be expressed as:

$$E[DID_{a,b,1,2}] = E[TE_{a,2}] \tag{25}$$

Combining Equations (24) and (25) with (16), we find:

$$E[\hat{\beta}] = E[\frac{1}{2}TE_{b,3} - \frac{1}{2}TE_{a,3} + TE_{a,2}] \tag{26}$$

This shows that the estimated treatment effect from the traditional model is the weighted average of each group's treatment effects from various periods, with some of them even taking negative weights, leading to severe bias issues.

Appendix B
List of Cities of Each Tier

Sample cities by each tier

Tier 1 Cities	Tier 2 Cities		Tier 3 Cities			
Beijing	Ankang	Nanyang	Anqing	Huangshan	Pu'er	Xuancheng
Changchun	Anshan	Neijiang	Anshun	Huangshi	Puyang	Xuchang
Changsha	Anyang	Pingdingshan	Baicheng	Huludao	Qingyang	Ya'an
Changzhou	Baoding	Qinzhou	Baise	Hulunbuir	Qingyuan	Yan'an
Chengdu	Baoji	Qiqihar	Baishan	Jiamusi	Qinhuangdao	Yangjiang
Chongqing	Baotou	Quanzhou	Baiyin	Ji'an	Qitaihe	Yangquan
Dalian	Bazhong	Rizhao	Baoshan	Jiaozuo	Qujing	Yichun
Foshan	Bijie	Shangqiu	Bayannur	Jiaxing	Quzhou	Yinchuan
Fuyang	Bozhou	Suining	Beihai	Jiayuguan	Sanmenxia	Yingkou
Guangzhou	Changde	Suqian	Bengbu	Jieyang	Sanming	Yingtan
Guiyang	Chifeng	Suzhou	Benxi	Jinchang	Shangluo	Yulin
Hangzhou	Daqing	Tai'an	Binzhou	Jincheng	Shangrao	Yuncheng
Harbin	Datong	Taizhou	Cangzhou	Jingdezhen	Shanwei	Yunfu
Hefei	Dongguan	Tianshui	Changzhi	Jingmen	Shaoguan	Yuxi
Huai'an	Ezhou	Wei fang	Chaoyang	Jinhua	Shaoxing	Zhangjiajie
Jinan	Fushun	Wenzhou	Chaozhou	Jinzhong	Shaoyang	Zhangjiakou
Kunming	Fuzhou	Wuhu	Chengde	Jinzhou	Shiyan	Zhangye
Lanzhou	Fuzhou	Wuwei	Chenzhou	Jiujiang	Shizuishan	Zhangzhou
Linyi	Guang'an	Xiamen	Chizhou	Jiuquan	Shuangyashan	Zhaoqing
Nanchang	Guigang	Xinxiang	Chongzuo	Jixi	Shuozhou	Zhaotong
Nanjing	Handan	Xinyang	Chuzhou	Kaifeng	Siping	Zhongwei
Nanning	Heze	Yancheng	Dandong	Langfang	Songyuan	Zhoukou
Nantong	Hezhou	Yantai	Dazhou	Lianyungang	Suihua	Zhoushan
Ningbo	Hohhot	Yibin	Deyang	Liaoyang	Suizhou	Zhumadian
Putian	Huaibei	Yichang	Dezhou	Liaoyuan	Taizhou	Zhuzhou
Qingdao	Huainan	Yichun	Dingxi	Lijiang	Tieling	Zunyi
Shanghai	Huizhou	Yiyang	Dongying	Lincang	Tongchuan	
Shantou	Huzhou	Yongzhou	Erdos	Linfen	Tonghua	
Shenyang	Jiangmen	Yueyang	Fangchenggang	Lishui	Tongliao	
Shenzhen	Jilin	Yulin	Fuxin	Liupanshui	Tongling	
Shijiazhuang	Jingzhou	Zhanjiang	Ganzhou	Longnan	Tongren	
Suzhou	Jining	Zhenjiang	Guangyuan	Longyan	Ulanqab	
Taiyuan	Laibin	Zhongshan	Guilin	Loudi	Weihai	
Tangshan	Laiwu	Zhuhai	Guyuan	Lvliang	Weinan	
Tianjin	Leshan	Zigong	Hanzhong	Maanshan	Wuhai	
Wuhan	Liaocheng	Ziyang	Hebi	Meishan	Wuzhong	
Wuxi	Liu'an		Hechi	Meizhou	Wuzhou	
Xi'an	Liuzhou		Hegang	Mudanjiang	Xiangtan	
Xiangyang	Luohe		Heihe	Nanping	Xianning	
Xuzhou	Luoyang		Hengshui	Ningde	Xianyang	
Yangzhou	Luzhou		Hengyang	Panjin	Xiaogan	
Zaozhuang	Maoming		Heyuan	Panzhihua	Xingtai	
Zhengzhou	Mianyang		Huaihua	Pingliang	Xinyu	
Zibo	Nanchong		Huanggang	Pingxiang	Xinzhou	

Table 1: DID Variable

DID	$D_i = 0$	$D_i = 1$
$T = 0$	0	0
$T = 1$	0	1

Table 2: Correlation Matrix

	GDP	Wage	Population	Traffic	Real Estate Investment	Education	FDI	Health	Government Expenditure	Unemployment Rate	Green
GDP	1.000										
Wage	0.608	1.000									
Population	0.299	0.240	1.000								
Traffic	0.060	-0.015	-0.193	1.000							
Real Estate Investment	0.758	0.599	0.317	0.057	1.000						
Education	0.331	0.193	-0.200	0.136	0.226	1.000					
FDI	0.652	0.373	0.288	0.108	0.595	0.167	1.000				
Health	0.493	0.445	-0.026	0.132	0.489	0.338	0.261	1.000			
Government Expenditure	0.801	0.648	0.190	0.037	0.674	0.288	0.594	0.475	1.000		
Unemployment Rate	0.110	-0.039	-0.022	0.001	0.060	0.049	0.081	0.308	0.101	1.000	
Green	0.385	0.426	0.197	0.010	0.355	0.119	0.274	0.290	0.360	0.124	1.000
Employment Structure	-0.183	0.045	-0.094	0.034	-0.053	-0.057	-0.166	-0.123	-0.057	-0.231	-0.182

Table 3: VIF Test Results

Variable	VIF	1/VIF
did	1.63	0.615
GDP	5.18	0.193
Government Expenditure	4.98	0.201
Real Estate Investment	3.31	0.302
Wage	3.21	0.311
Healthcare	1.72	0.580
FDI	1.72	0.582
Population	1.53	0.655
Green	1.28	0.780
Education	1.21	0.826
Employment Structure	1.20	0.834
Unemployment Rate	1.20	0.834
Traffic	1.14	0.874
Mean VIF	2.25	

Table 4: Static TWFE DID Results

Model	(1) All Cities	(2) Tier 1 Cities	(3) Tier 2 Cities	(4) Tier 3 Cities
Dependent Variable	Migration Rates	Migration Rates	Migration Rates	Migration Rates
D	0.414***	0.617***	0.352***	0.151***
	(0.0224)	(0.0870)	(0.0408)	(0.0341)
cons	0.24***	0.328***	0.221***	0.267***
	(0.0138)	(0.0814)	(0.0241)	(0.0164)
Fixed Effects	Yes	Yes	Yes	Yes
N	6165	968	1751	3446
adj. R-sq	0.181	0.358	0.261	0.148

Data source: China City Statistic Year Books. See Appendix B for a list of cities of each city tier
standard error in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 5: Static TWFE DID Results with Relative Controls

Model	(5) All Cities	(6) Tier 1 Cities	(7) Tier 2 Cities	(8) Tier 3 Cities
Dependent Variable	Migration Rates	Migration Rates	Migration Rates	Migration Rates
D	0.183***	0.327***	0.210***	0.111***
	(0.0248)	(0.0878)	(0.0432)	(0.0350)
GDP	9.60e-07**	2.95e-06**	1.96e-06**	-8.66e-07
	(4.87e-07)	(1.42e-06)	(8.35e-07)	(8.41e-07)
Wage	1.94e-06*	-6.09e-06	-1.07e-06	9.14e-06***
	(1.10e-06)	(3.71e-06)	(1.22e-06)	(2.46e-06)
Population	.0733***	.146*	-.159**	-.178***
	(.0178)	(.0759)	(.0719)	(.038)
Traffic	.000487***	.000314	-.000836***	.000594***
	(.00012)	(.000514)	(.000301)	(.000138)
Real Estate Investment	.000021***	7.27e-07	.0000138***	.0000165***
	(2.27e-06)	(4.63e-06)	(4.66e-06)	(3.73e-06)
Education	.00499***	-.00415	.00602***	.00433***
	(.00098)	(.00431)	(.00227)	(.00116)
FDI	.000252***	.000391***	.000176***	.000298***
	(.0000388)	(.0000918)	(.0000508)	(.0000838)
Healthcare	.000884*	.00703***	-.000769	-.000636
	(.000524)	(.00187)	(.00119)	(.00066)
Government	3.19e-07	-1.33e-06	4.22e-06	-5.88e-06
	(2.67e-06)	(6.92e-06)	(3.93e-06)	(4.71e-06)
Unemployment Rate	-.0102	-.0321	.0524*	-.0111
	(.0136)	(.0486)	(.0315)	(.0162)
Green	.00272**	.0154***	.00179	.00249
	(.0013)	(.00502)	(.00263)	(.00162)
Employment Structure	.0004	.00508	.000984	-.00164
	(.00079)	(.00346)	(.00157)	(.00102)
cons	0.340***	0.290***	0.339***	.233***
	(.0143)	(.0936)	(.0311)	(.0236)
Fixed Effects	Yes	Yes	Yes	Yes
N	6137	961	1751	3425
adj. R-sq	0.260	0.466	0.312	0.188

Data source: China City Statistic Year Books. GDP, Traffic, Real Estate Investment, Eductaion, FDI, Health, and Government Expenditure are per capita data.
All control variables are in relative to provincial average
See Appendix B for a list of cities of each city tier
standard error in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 6: Static Two-Stage DID Results

Model	(9)	(10)
Dependent Variable	Migration Rates	Migration Rates
D	0.345***	0.280***
	(0.0733)	(0.0745)
Fixed Effects	Yes	Yes
N	6165	6137
adj. R-sq	0.260	0.312

Estimated with Two-Stage DID proposed by Butts and Gardner (2022)
standard error in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Figure 1: Average Migration Rates

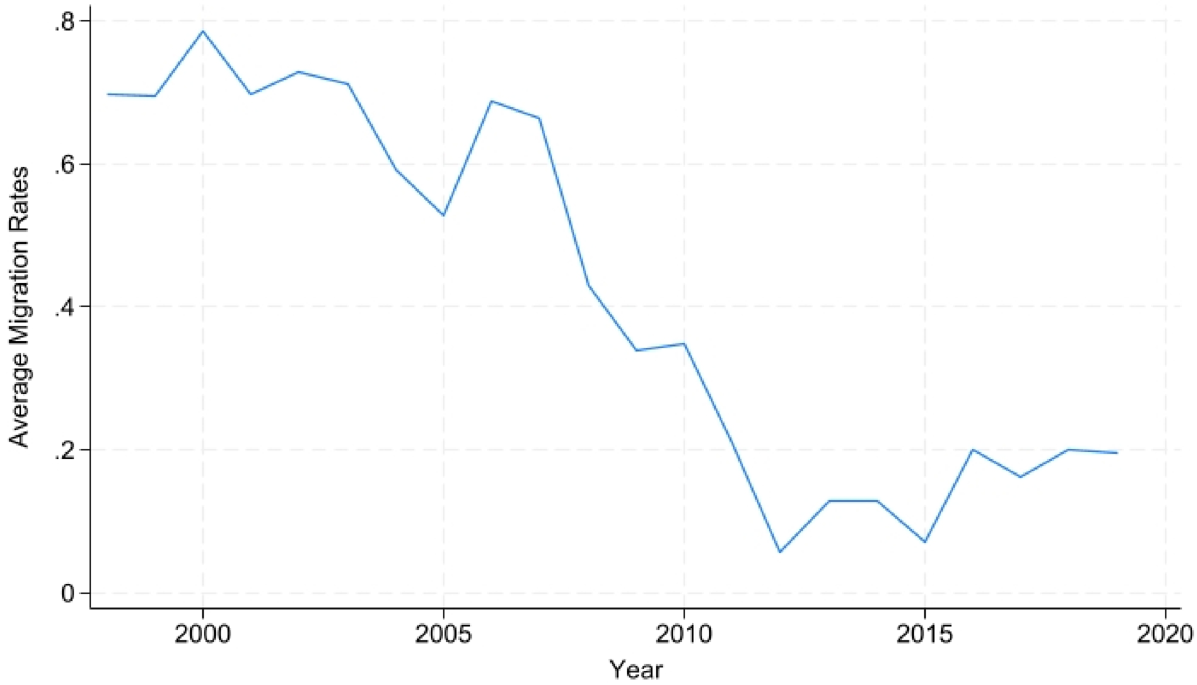


Figure 2: Number of state-level SEZs established each year

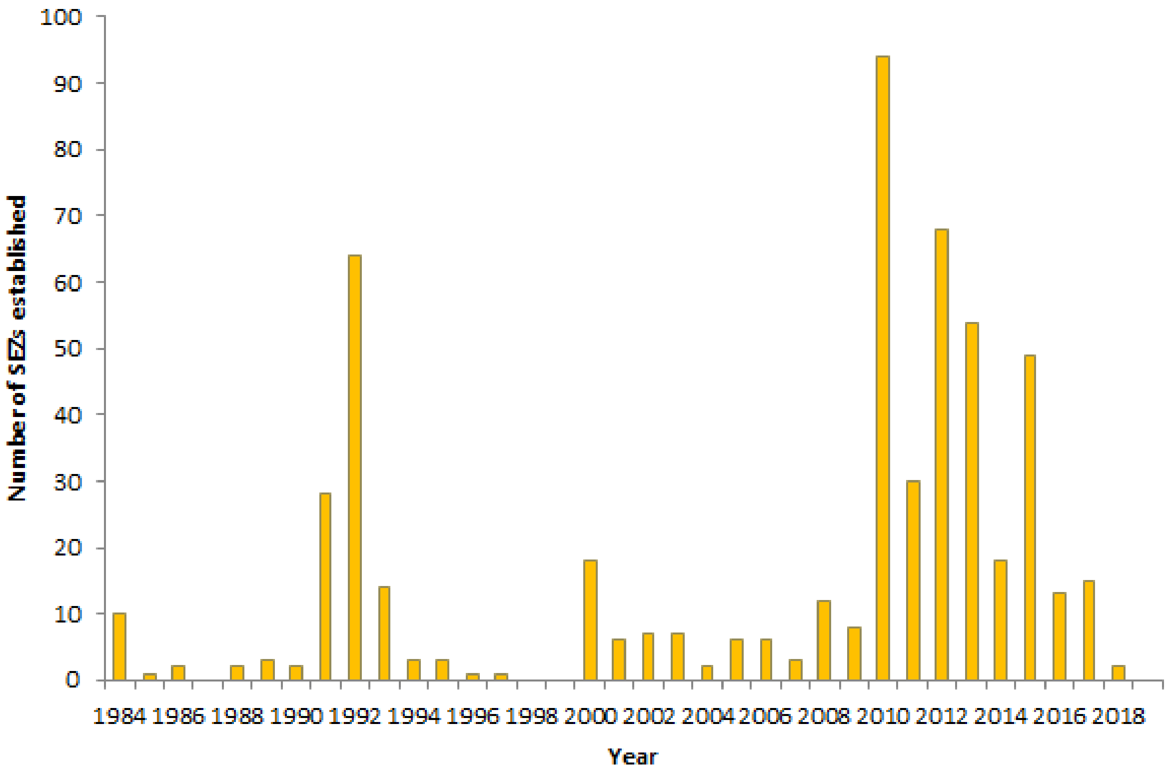
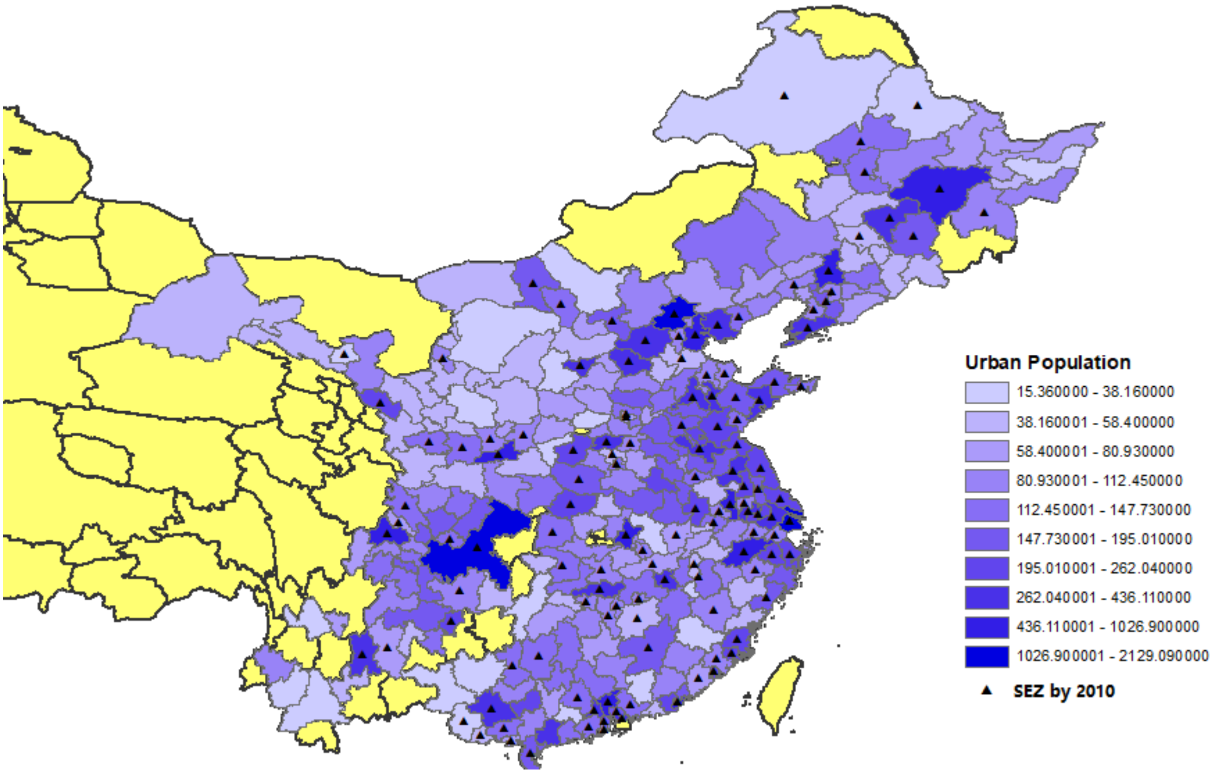
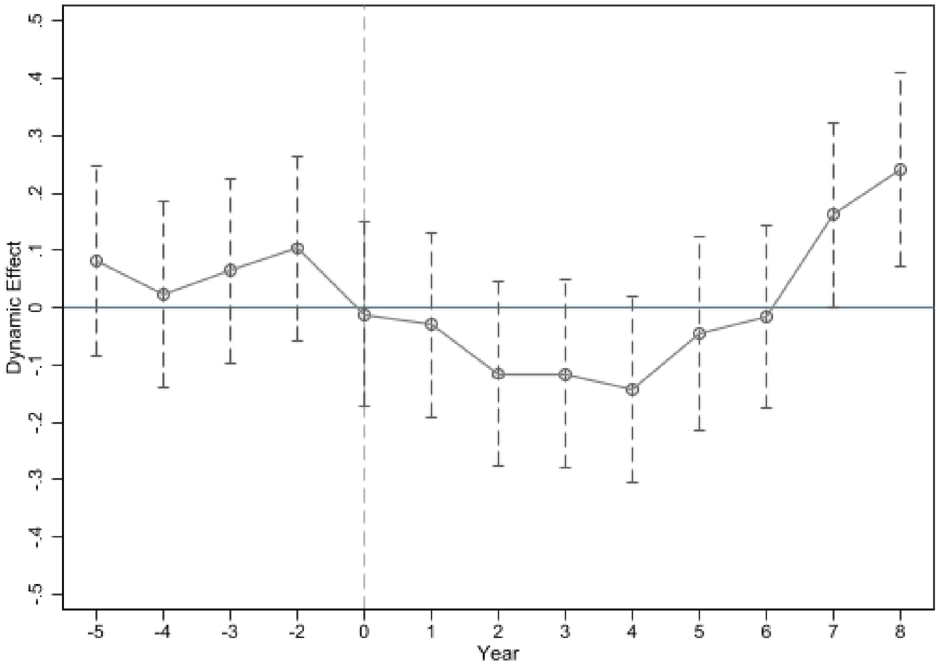


Figure 3: Urban Population Distribution as of 2015



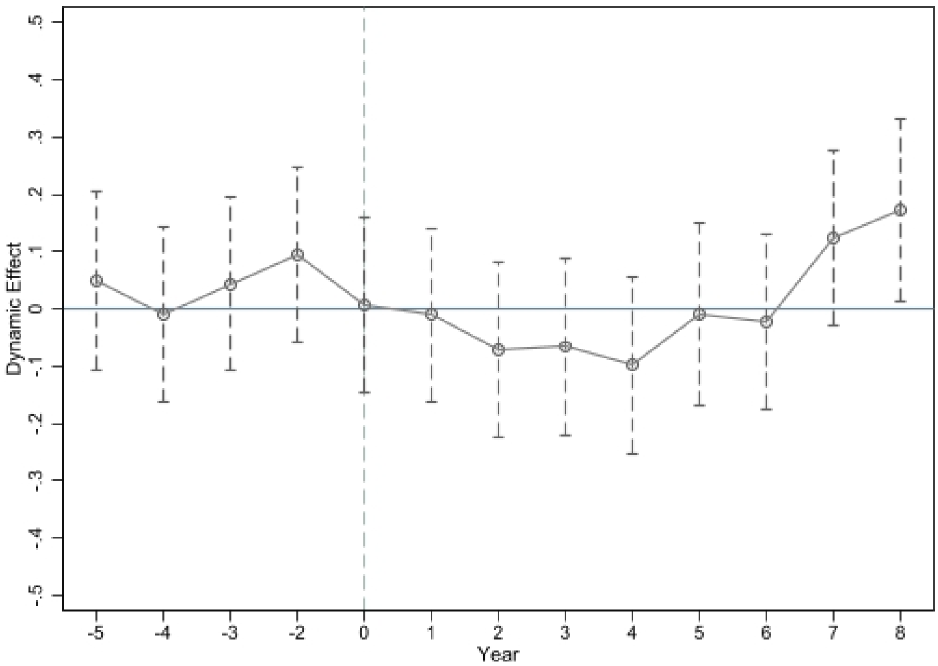
Data source: China City Statistic Yearbook 2015, the authors created the map with ArcGIS.

Figure 4: Event Study Results without Controls



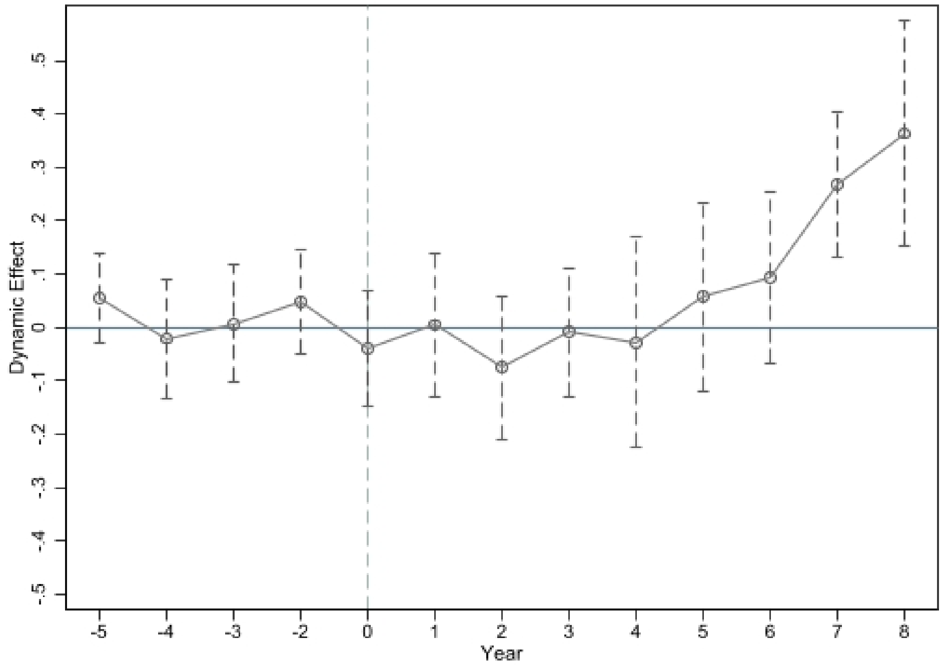
Data source: China City Statistic Year Books.

Figure 5: Event Study Results with Controls



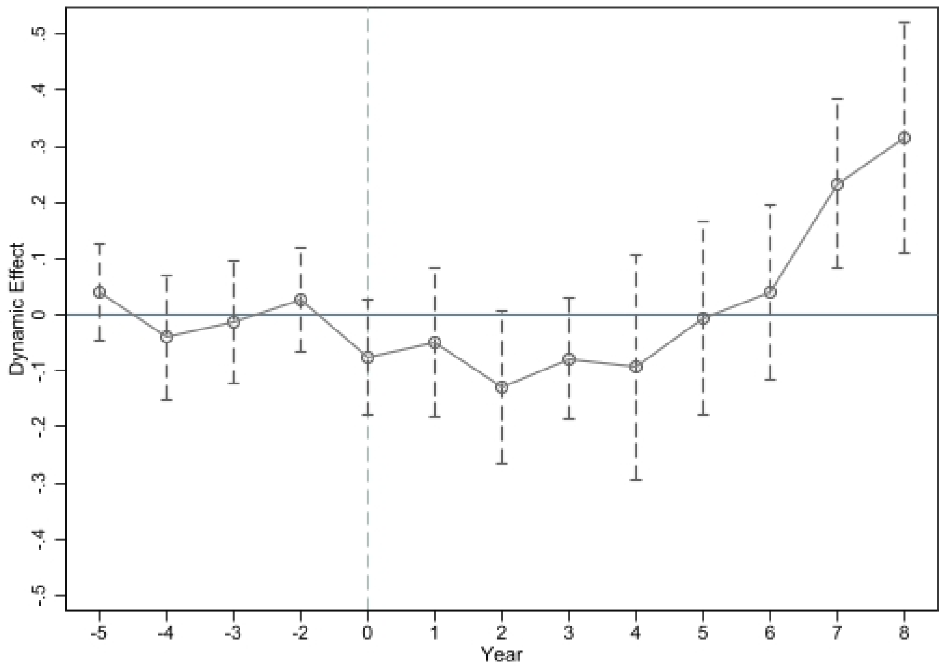
Data source: China City Statistic Year Books. Control variables and sample range are the same with model (5) in Table 5

Figure 6: Event Study Results Using Two-Stage DID Model



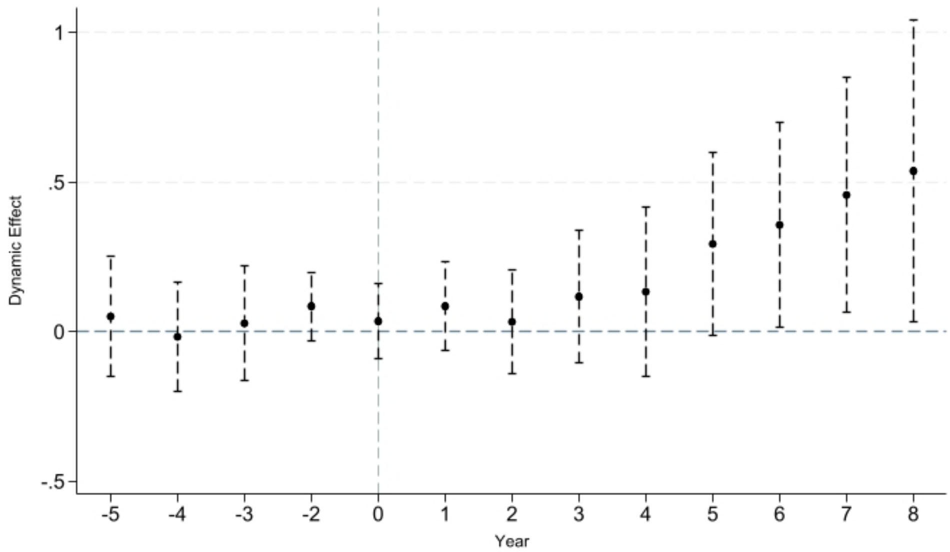
Estimated with Two-Stage DID proposed by Butts and Gardner (2022).

Figure 7: Event Study Results Using Two-Stage DID Model with Controls



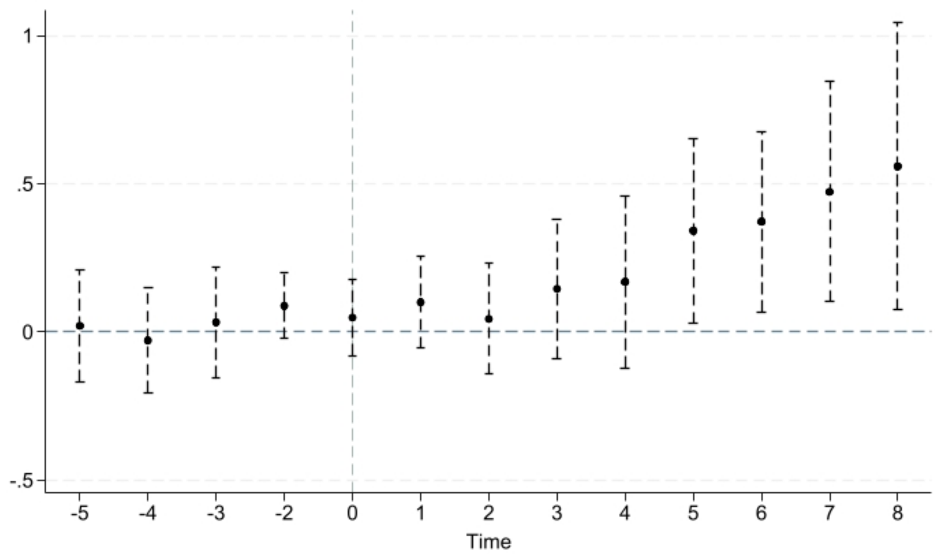
Estimated with Two-Stage DID proposed by Butts and Gardner (2022), control variables and sample range are the same with Model (5) in Table 5.

Figure 8: Event Study Results Using LP-DID



Estimated with LP-DID proposed by Dube et al. (2023), control variables and sample range are the same with Model (1) in Table 4.

Figure 9: Event Study Results Using LP-DID with Controls



Estimated with LP-DID proposed by Dube et al. (2023), control variables and sample range are the same with Model (5) in Table 5.