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# Reverse Effects of Outward FDIs: Panel Data Evidence from Chinese City-Regions

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## Abstract

This paper investigates whether outward foreign direct investments (OFDIs) from Chinese city-regions have a positive impact on home-location income levels. The mechanism that links investment activity with economic development at home is associated with reverse regional spillovers derived from foreign knowledge and market access. We undertake ordinary-least-square (OLS) panel regressions from 2003 through 2016 to show that OFDIs can lead to localized multiplier effects and income increases in the home city-region. To capture the regional growth dynamics in China, we consider minimum-threshold levels of investment activity and different time horizons of such effects and control for a number of influences, such as the growth rate of the gross regional product (GRP) and city size. Our results show first that, when there is a sufficient number of investment projects, OFDIs have significant effects on per-capita income changes in the home city-regions and second that city-regions with a strong capacity to assimilate and internalize knowledge related to prior inward foreign direct investments (IFDIs) achieve the largest benefits from reverse spillover effects.


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## 1 Introduction

The importance of foreign direct investments (FDIs) in the global economy has grown substantially over the past few decades, and their potential effects have attracted attention from scholars and policymakers. Inward FDIs (IFDIs) are well-recognized as important contributors to economic development in emerging economies as these investments often go along with technology transfers to the target regions (e.g. Buckley et al., 2002). Outward FDIs (OFDIs), in contrast, are often viewed as compromising economic development, especially in developed contexts, as they shift resources and production away from home economies (Elia et al., 2009). Empirical evidence, however, for any of these investment effects is ambivalent.

In the past decade, academic scholarship in economic geography and international business has increasingly focused on investigating the *reverse* effects of OFDIs. Findings reveal that OFDIs do not simply shift resources away to different countries and regions but have a positive impact at home. Empirical investigations mainly explore corresponding national effects on employment and innovation (e.g., Elia et al., 2009; Li, et al., 2016), alongside their impacts on firm-level productivity (e.g., Li et al., 2017; Hejazi et al., 2021). Only in recent years have there been intensified efforts to identify the reverse regional impacts of OFDIs on the *home region*, with studies across different contexts yielding varied results (Crescenzi & Iammarino, 2017; Bathelt & Buchholz, 2019; Gagliardi et al., 2021; Crescenzi et al., 2022).

Although these studies present an interesting new perspective for policymakers, empirical evidence remains largely confined to a few highly developed economies, with little emphasis on emerging and developing economies. Nonetheless, if OFDIs do indeed exert a positive impact on regional development, even in emerging and developing economies, this bears significant implications for regional growth with wide-ranging impacts. It prompts policymakers to reconsider strategies that try to minimize such international investments and focus on domestic trade instead.

Using a panel setting with lagged effects and extensive controls, this paper aims to contribute to this discourse by providing evidence that OFDIs are positively correlated with per-capita income growth in the home city-region, particularly in emerging contexts. Dunning (1981) has explored the relationship between OFDIs and home-economy development in his investment development path (IDP) model, which suggests that OFDI and IFDI flows depend on a country's level of economic development. Accordingly, IFDIs dominate in early development stages, while OFDIs impact economic development in later stages. While this model has been investigated in the historical context of developed economies, it is much less clear whether it also applies to the emerging context of China's urban system, where OFDIs have grown exponentially since the 2000s (Yang & Bathelt, 2022). This paper hypothesizes that outward investments have a positive income effect not only in the home country but also in the home city-region and that this may equally apply to developing and emerging economies.

Using a database that merges data on OFDIs with city-level information, we investigate whether OFDIs positively and significantly affect per-capita income in home locations, which carry out these investments. This is analyzed through ordinary-least-square (OLS) panel regressions across 273 Chinese city-regions from 2003 through 2016. In contrast to the IDP approach that argues OFDIs become significant only at later stages of development, our

results suggest that a positive income effect on home locations may already occur during emerging stages of economic development.

Initially, we identify adverse income effects of OFDIs for the period 2003–2009 when China was still in an early developing stage. This seems to confirm the conventional view of OFDIs, suggesting that increasing OFDIs have a negative impact on income levels at home. We then undertake a more in-depth investigation by considering China's specific growth process and the role of inward investments. Our investigation reveals that, after a stage of growing regional disparities following the country's opening policies, less developed city-regions—particularly inland regions—without OFDIs benefited most from robust growth during the 2000s, driven by high demand for simple, low-cost products and supported by regional development strategies. Under these conditions, it was expected that it would require a sufficient number of investment projects, as well as some time, before the reverse effects of OFDIs could significantly impact income development in city-regions. This is supported by our analysis.

The remainder of the paper is divided into five sections. Section 2 investigates the specific context of regional development in China and the role of OFDIs since the early 2000s. Next, Section 3 conceptualizes the reverse effects of OFDIs in the home location and the moderating role of IFDIs and develops propositions. The database and methodology of the analysis are described in Section 4. Section 5 tests the relationship between OFDI activity and per-capita income in home city-regions. Concluding remarks are offered in Section 6.

# 2 Context: China's Regional Growth Pathway

Over the past 45 years, China's economy has undergone a radical transformation from an agricultural economy to the "world's manufacturing plant" and evolved from a developing into an emerging economy.[1] This development went along with growing inter-regional disparities – especially between urban coastal areas and inland locations (Fan & Sun, 2008; Cheong & Wu, 2014). Disparities surged in the 1980s and 1990s, and only since the 2000s some convergence tendencies have occurred as initially lagging city-regions experienced faster growth than coastal regions (Fan & Sun, 2008). This section traces the growth pathways of coastal and inland regions and draws implications about the effects on the link between OFDIs and home-region economic development.

At the onset of economic reforms in the late 1970s, China's regional policy heavily favored coastal regions and produced unbalanced growth (Wei, 1999). This development strategy – supported by an already well-developed industrial infrastructure and environment of higher-education – led to growth in inward investments and exports of standardized commodities (Zhang & Zhang, 2003). Foreign firms began establishing subsidiaries within China, facilitating knowledge transfer, and enabling Chinese firms to build extensive relationships with foreign partners. These inward FDIs (IFDIs) were predominantly concentrated in coastal regions (Hao & Wang, 2010), propelling them to the forefront of China's industrialization and economic development, while interior regions were left behind.

[1]/. Although China may soon be viewed as a medium-income developed economy (World Bank, 2023), with an observation period from 2003 until 2016, this study considers China's economic development as a transition from a developing to an emerging economy, with sustained international market access and strong and stable economic growth that resemble those of advanced economies.

In the 2000s, the implementation of the "Go Global" strategy led to a dramatic increase in Chinese OFDIs. Like IFDIs, China's rapid integration into the global market through OFDIs was manifested as a regional phenomenon. As shown in Figure 1, the majority of OFDIs (as well as IFDIs) from 2003 to 2016 was concentrated in coastal city-regions (albeit not with a perfect correlation[2] between both types of investment), with technological triggers from FDIs likely being captured mainly by these city-regions. In the meantime, a series of regional strategies were implemented to support economic development in Western regions, such as the Great Development of Western China and Rise of Central China policy programs (Qi et al., 2013). The goal was to support a more balanced regional development through inter-governmental fiscal transfers, reduced corporate taxes, large-scale infrastructure projects and changes in institutional settings (Ouyang & Yao, 2017).

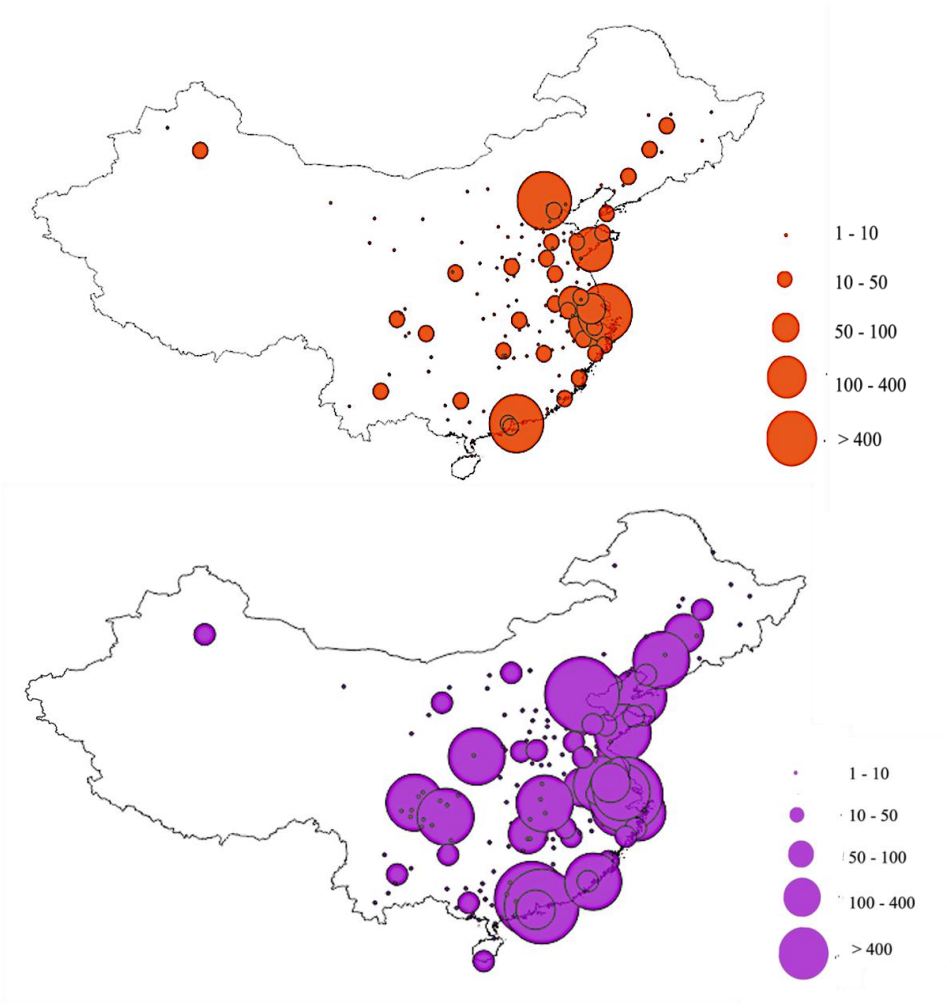
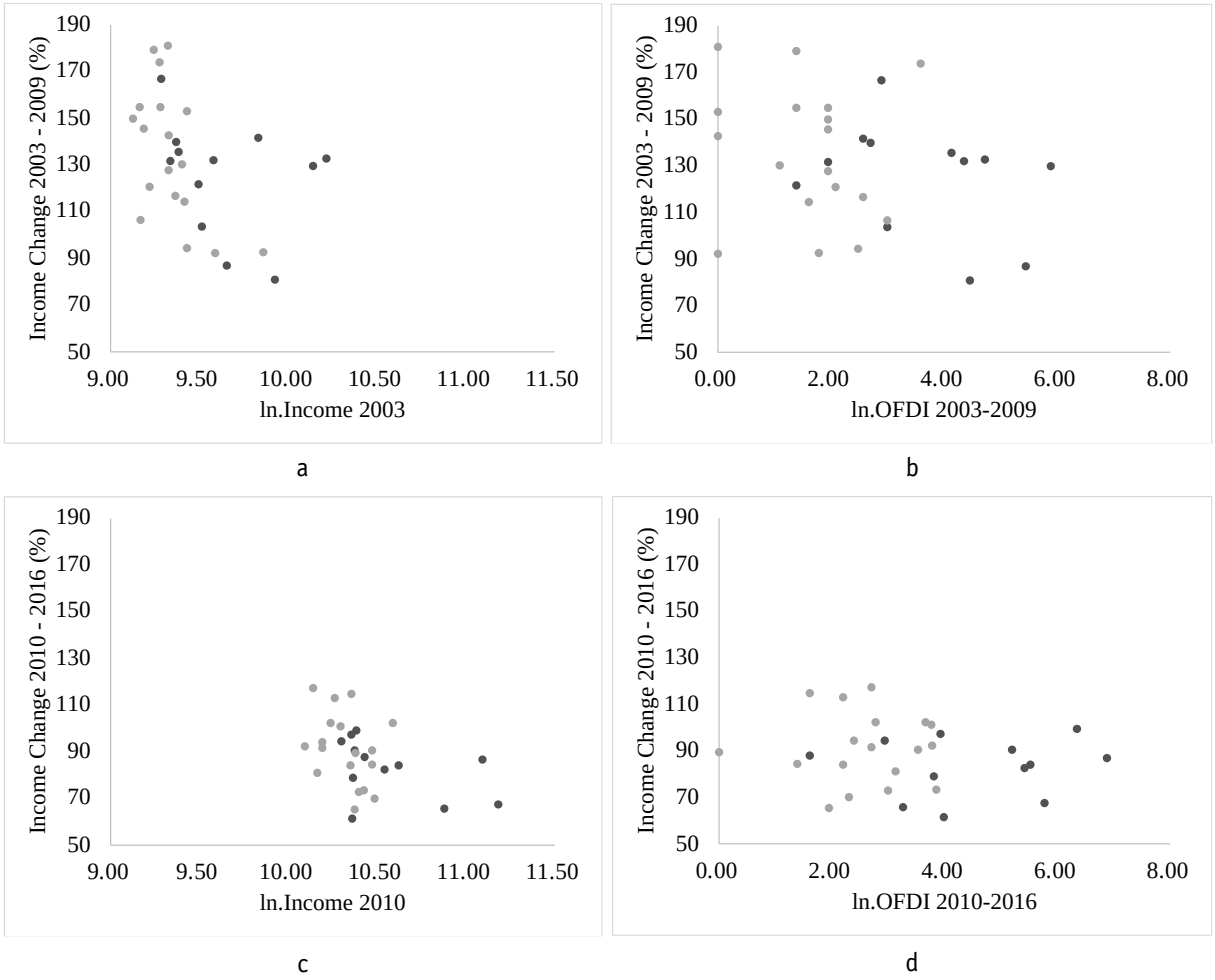



**Figure 1:** *Number of Chinese Greenfield Outward FDIs (Top) and Inward FDIs (Bottom) by Investing City-Regions, 2003-2016 (Data source: Financial Times, 2017 (fDi))*

Inland locations also received growth impulses through strong economic linkages with coastal regions. Overall, these lagging city-regions benefited from high demand for standardized, low-technology and labor-intensive final and intermediate products in manufacturing industries (Ouyang & Fu, 2012). Through backward and forward linkages, coastal regions enabled inland regions to achieve scale economies and productivity increases (Brun et al., 2002).

[2]/. The correlation coefficient between cumulated OFDIs and IFDIs is 0.6264 and for OFDIs and IFDIs per 10,000 residents it is 0,6498.




Note: Coastal provinces are colored in dark and inland provinces in light grey.

**Figure 2:** *Scatterplots of Per-Capita Income Growth over Income/OFDI Levels by Chinese Province for the Periods 2003–2009 (Top) and 2010–2016 (Bottom) (Data source: National Bureau of Statistics of China, 2019 (CCSY), Financial Times, 2017 (fDi))*

This is supported by the scatterplots in Figure 2, which show income growth in each Chinese province for the two periods 2003–2009 (top plots) and 2010–2016 (bottom plots), over per-capita income levels in the respective base year (plots a and c) and over the cumulative number of OFDIs (plots b and d), both in logarithmic form. The figure indicates two important trends: First, inter-provincial disparities in income growth were much larger in the first decade of the 2000s with increases ranging from 80 to 180%, compared to the 2010s with values between 60 and 120% (top vs. bottom plots). In each of these periods, inland provinces, characterized by lower per-capita incomes, had on average higher income growth than coastal provinces (Feng & Zhang, 2011).

Second, the figure seems to point to a negative relationship between income changes and per-capita income at the beginning of each period (Figures 2a and 2c) and between income changes and OFDI activity (Figures 2b and 2d). Provinces with low per-capita income and those with a smaller number of OFDI projects tended to have relatively higher income changes during both periods, while provinces with high OFDI activity and high per-capita income values experienced lower income growth. However, when differentiating between different types of provinces, this tendency is less clear and could be questioned. In the period 2010–2016, only a slightly negative relationship between income growth and OFDI levels can be identified for inland provinces, and even a slightly positive one for coastal regions (Figure 2d).

This demonstrates that inland and coastal regions developed along different trajectories and that low-income inland provinces benefited most from the growth of the Chinese economy in the 2000s. In contrast, coastal provinces were able to develop the skills and capabilities necessary to conduct ongoing OFDIs and began to benefit from related multiplier effects, especially in the 2010s (Yang & Bathelt, 2023).

# 3 Theoretical Background and Proposition Development

Having discussed the specific growth trajectories of Chinese regions, this section develops the main propositions to be tested in our analysis.

## 3.1 Reverse Income Effects of OFDIs through Knowledge Spillovers and Multipliers

In today's knowledge economy, firms' internal knowledge stock no longer satisfies all knowledge requirements to be competitive in national and international markets. For many firms, it requires looking beyond their regional and even national environment to find external knowledge inputs and expertise (Contractor et al., 2010). This creates a challenge, especially for firms in emerging contexts that do not have traditional resource-based advantages (unlike their advanced-economy counterparts) that could be exploited in knowledge-seeking processes in a global setting (Mathews, 2002).

For emerging multinational enterprises (MNEs), internationalization through OFDIs can be a means for acquiring required knowledge from diverse industrial knowledge pools or clusters that are not available at home and getting access to markets (Iammarino & McCann, 2013; Poon et al., 2006; Schaefer, 2020). Through OFDIs, emerging MNEs gain access to information channels in the host location and can source location-specific knowledge to the parent firm at home (Hsu et al., 2008; Bathelt et al., 2018; Fu et al., 2018). After being transferred to the parent location, the acquired knowledge extends the firms' knowledge reservoir and triggers adjustments in production and innovation – if successfully applied (Poon & MacPherson, 2005; Bathelt & Li, 2020). The acquired knowledge and associated growth triggers are also transmitted to other regional partner firms, such as suppliers (Maskell & Malmberg, 1999; Bathelt & Glückler, 2011), feeding a regional multiplier process and resulting in income increases overall.[3]

The city of Shenzhen illustrates how OFDIs can lead to reverse knowledge spillovers and cause economic growth. Shenzhen is home to many renowned Chinese MNEs, such as Huawei, Tencent and ZTE, which together conducted 586 OFDI projects from 2003 through 2016, accounting for 14% of China's total greenfield OFDIs (Financial Times, 2017). Shenzhen's MNEs have acquired sophisticated knowledge about foreign locations by investing abroad. According to Fu et al. (2018) and Schaefer (2020), for instance, Huawei strategically used OFDIs to access international knowledge pools and applied these internally to become a global innovation leader. ZTE similarly learned about advanced strategic management concepts through its European subsidiaries that were then applied in Shenzhen. The knowledge acquired through OFDIs also spilled over to other firms in Shenzhen, contributed to their growth and triggered the city-region's income development (Yang, 2023). This logic about reverse OFDI effects leads to our main proposition:

[3]/. There are also other forms of knowledge spillovers that benefit the home region, such as related to the role of "New Argonauts" (Saxenian & Sabel, 2009).

***Proposition 1a:*** *Growing OFDI activity in Chinese city-regions stimulates increasing home-location income levels.*

While some may argue that the relationship between OFDIs and home regional income could also go in the opposite direction, we believe that, from a firm perspective, it will be difficult to develop a convincing chain of arguments to suggest that high-income levels lead to growing OFDI activity. However, from a co-evolutionary perspective, OFDIs (also IFDIs) may stimulate the development of highly-skilled labor markets with transnational capabilities, leading to higher income levels and higher capabilities to conduct future investments (Bathelt et al., 2023). Therefore, showing that a positive relationship can be assumed between OFDI activity and home-region income levels does not rule out the existence of other linkages.

The specific regional development dynamic of the Chinese economy, discussed before, suggests considering a minimum-threshold level of OFDIs before significant income effects can be expected. This threshold reflects a city-region's experience, local supplier capability and skill base to trigger significant growth. Chinese MNEs, as latecomers to the global market, initially lacked external business networks and knowledge to exploit growth triggers from foreign locations (Mathews, 2002). With increasing number of OFDIs, however, headquarters of MNEs develop experience in internationalization, skills and capabilities to apply knowledge and growth triggers from abroad (Chen et al., 2012), also in the local (and non-local) supplier sector (Lane et al., 2006). The importance of having a minimum number of OFDIs leads to the following proposition:

***Proposition 1b:*** *Because of a lack of experience, there needs to be a minimum number of OFDIs in a Chinese city-region in order to stimulate increasing home-location income levels.*

When investigating the relationship between OFDIs and home-location income levels in an emerging context, such as China, it cannot be expected that there are immediate effects. In addition to the need to have sufficient investments, we should expect time lags before a significant impact will occur. After an OFDI project is completed, it will immediately change and shift the existing activities and operations within the respective corporation (Crescenzi et al., 2022). However, regional effects will not materialize before adjustments have been made, upgrading of firms has occurred, and learning processes have been completed, especially in the local supplier sector. It may therefore take one or several years before MNEs establish relationships with other firms in the host locations and are able to acquire knowledge and sales contracts. It may also take time for the foreign affiliate to translate and transfer knowledge to the parent firm, generate localized spillovers in the home city-region and eventually induce positive effects in the home location (Castellani & Pierri, 2013). Thus, it is important to consider time lags in reverse effects of OFDIs, which leads to our next proposition:

***Proposition 1c:*** *In the emerging context of Chinese city-regions, reverse effects of OFDIs on home-location income levels require one or several years before they unfold.*

## 3.2 Moderating Role of IFDIs in Generating Absorptive Capacity

In Propositions 1b and 1c, we suggested that the effects of OFDIs on income growth may require a minimum number of investments and take some time to be realized. Both propositions imply that firms in city-regions need to acquire sufficient capabilities and skill levels to benefit from reverse effects of OFDIs. As Cohen and Levinthal (1990: 128) argue, firms need sufficient absorptive capacity "to recognize the value of new information, assimilate it, and apply it to commercial ends." Therefore, it can be assumed that firms' absorptive capacity in the home region determines the extent to which the reverse effects of OFDIs can be realized.

The notion of absorptive capacity also applies to the aggregate level of city-regions as broader regional development effects require regional firms, specifically suppliers, and labor markets to be able to absorb and internalize external knowledge effectively and to flexibly adjust production arrangements to new demands (Miguélez & Moreno, 2015). Part of this absorptive capacity is already considered in Propositions 1b and 1c, which suggest that previous OFDI activity and sufficient time enable regional firms to develop corresponding skills and capabilities. In recent research, the role of IFDIs has been emphasized in this respect (Li & Cantwell, 2018). Firms (and city-regions) that are exposed to IFDIs develop knowledge about business practices, management structures and technologies abroad when engaging in inter-firm relations with foreign subsidiaries. From this, firms can learn and develop capabilities that enable them to manage external knowledge more effectively and achieve higher economies of scale and productivity levels, thus helping them go abroad. As such, past IFDIs in a city-region may improve the local knowledge infrastructure, support internationalization processes and contribute to increasing the city-region's absorptive capacity. This leads to our final proposition:

***Proposition 2:*** *In the emerging context of Chinese city-regions, exposure to IFDIs strengthens reverse home-location income effects of OFDIs by increasing local firms' absorptive capacity.*

# 4 Data and Methodology

## 4.1 Database

Our empirical analysis used data from 269 prefectural city-regions and 4 municipality cities to test our propositions. These city-regions comprise central cities and their surrounding communities and form regional administrative units to implement national and regional development policies (Qi et al., 2013). The city-regions are similar to integrated urban-industrial regions and their labor markets, providing an adequate basis to measure reverse spillovers of OFDI activity (Maskell & Malmberg, 1999). Using prefectural cities and municipalities also creates a sample size large enough to control for unobserved location-specific factors that affect income growth. It thus reduces potential measurement errors (Ouyang & Fu, 2012).

Data about regional attributes, such as income, employment shares and city size, were taken from the China City Statistical Yearbook (National Bureau of Statistics of China, 2019). Information about Chinese foreign investment activity was derived from the fDi Markets database, which provides data on the number of greenfield FDIs[4] at the city-region level (Financial Times, 2017). Our study begins with the availability of investment data in 2003 and ends in the year 2016, which coincided with important changes in the global political and economic landscape, especially the election of Donald Trump as U.S. president, rising anti-globalization politics and a decrease in Chinese OFDI activity. Over the entire period from 2003 through 2016, the database lists 4,381 OFDI projects of Chinese firms.[5]

[4]/. We used the number of OFDI projects as an indicator of investment activity in our study (rather than their value) because it provides a better representation of overall investment dynamics. Using investment values instead would produce a bias toward sectors with high sunk costs (Yang & Bathelt, 2022).

[5]/. These are not small projects but present sizable investments, with 91 percent exceeding 1 million US-$. Of these, 44 percent are above 100 million US-$ and 11.5 percent over 1 billion US-$ (computed from Financial Times, 2017). It can be expected that these investments have a considerable reverse impact on the home region.

## 4.2 Variables

*Dependent variable.* To proxy a city-region's economic development, we used the annual per-capita income in logarithmic form (*ln.Income*). Per-capita income is a crucial indicator of economic development, as it directly measures the prosperity level of a city-region's population and excludes government transfers (Bathelt & Buchholz, 2019). It also corresponds well with other regional development indicators in China, such as the per-capita gross regional product (GRP) (Yang & Bathelt, 2023).

*Independent variables*. Our independent variables included attributes about city-regions' OFDI activity and regional attributes that impact income. *OFDIper10000* was our key independent variable, defined as the number of OFDI projects per 10,000 residents in a city-region and given year.[6] According to proposition 1a, we expected *OFDIper10000* to be positively associated with *ln.Income*. As explained in Section 2, it is important, however, to consider the specific regional growth context of Chinese city-regions in the 2000s, with economic growth being strongest in inland regions with both low income levels and OFDI activity. We therefore expected that city-regions required a minimum threshold of OFDIs for reverse income effects to materialize. Using a minimum threshold of OFDI projects per city-region also took into consideration that city-regions needed to have sufficient internationalization experience to benefit from reverse income effects of OFDIs (Li & Cantwell, 2018). Our model used dummy variables to represent different minimum-threshold levels: *OFDIPresence3, OFDIPresence5* and *OFDIPresence7*, which had a value of "1" for city-regions with at least 3, 5 and 7 OFDIs in a given year, respectively; and "0" otherwise. We then interacted these minimum-threshold variables with *OFDIper10000.* According to Proposition 1b, we anticipated that the interaction terms *OFDIper10000*OFDIPresence3*, *OFDIper10000*OFDIPresence5* and *OFDIper10000*OFDIPresence7* would have a positive association with *ln.Income*.

Our model also included five additional independent variables that measure other attributes of the regional economy that might affect income levels. *HighTechBSLaborShare* corresponds with the share of labor in advanced and knowledge-intensive sectors (factored by 100). Scholars have argued that jobs in knowledge-intensive sectors (i.e. computer science, engineering and business/financial operations) positively impact economic development and are associated with higher income levels compared to other sectors (Florida et al., 2008). We therefore expected that *HighTechBSLaborShare* is positively associated with regional per-capita income. Another occupational variable used was *AgriMiningLaborShare*, measured as the share of jobs in agricultural and mining sectors (factored by 100). We assumed that cities with a large agricultural and mining sector were characterized by lower income levels and that this variable had a negative effect.

The third independent variable was *HigherEduEnrollment*, defined as the share of residents enrolled in higher-education programs at the college level or higher (factored by 100). As human capital plays an important role in enhancing productivity and generating economic growth, we expected that *HigherEduEnrollment* to have a positive impact on regional income levels.

We also used *LargeFirmsper100,000* as an independent variable, corresponding with the number of industrial firms with annual revenues over RMB 5 million in 2003–2010 and over RMB 20 million thereafter per 100,000 residents. We expected this variable to be positively associated with city-region income for two reasons. First, compared to smaller firms, employees in large firms are more productive and may earn higher wages in a competitive labor market (Idson & Oi, 1999). Second, large firms collaborate with a large number of local partners,

[6]/. As a robustness check, we also used the value of OFDI projects per 10,000 residents as our key independent variable, with the results remaining fully consistent. This is due the fact that our investment database overwhelmingly includes very large investment projects.

are involved in many localized knowledge exchanges and innovation networks and likely contribute to higher regional prosperity levels (Cooke et al., 2005).

*Urbanization* was our final region-specific independent variable, reflecting the proportion of a city-region's population residing in urban core areas[7] (Gross & Ouyang, 2021). Greater urbanization may provide a favorable environment for knowledge spillovers and to realize agglomeration economies that are conducive to learning and innovation (Chen et al., 2014). We expected *Urbanization* to affect city-region income levels positively.

*Control variables*. We used *GRPGrowthRate* as a control variable, measured as the growth factor of the GRP (factored by 100). Controlling for GRP growth was necessary, as it considered different trajectories of Chinese city-regions and reflected changes in the monetary value of all finished goods and services (Yang & Bathelt, 2023). We also controlled for city size (*CitySize*) as synergies from a large agglomeration of economic activity may be important drivers of regional economic growth. Indeed, Frick and Rodríguez-Pose (2008) argued that agglomerations of people and firms increase economic productivity in a region and contribute to higher growth through forward and backward linkages between local firms and pooled-labor-market effects. Overall, we expected that both controls would positively affect per-capita income.

*Moderating variable*. Furthermore, our conceptualization suggests that not all city-regions can utilize and exploit the potential reverse impacts of OFDIs and realize income effects in the same way. Rather, the effect size depends on a city-region's ability of local actors to recognize the value of newly acquired knowledge, apply it to its production and distribute new or modified products to markets. In other words, this varies with a city-region's absorptive capacity. Unfortunately, available data did not allow us to measure regional absorptive capacity of Chinese city-regions through research and development indicators for each of the years from 2003 to 2016. Instead, we used *IFDIper10000*, defined as the number of greenfield IFDIs for every 10,000 residents, as both a control variable and an indicator to measure regional absorptive capacity indirectly. On the one hand, this variable helps us reject counter-arguments claiming that income effects are primarily caused by inward (as opposed to outward) investments, even though studies have raised questions as to whether IFDIs automatically have positive impacts in target regions (Konings, 2003).

[7]/. The urban core includes urban and suburban areas but excludes surrounding counties (National Bureau of Statistics of China, 2019). Key criteria of the urban core are an employment share of non-agricultural workers above 70% and an industrial-output share of secondary and tertiary activities above 75% (First City, 2023).

**Table 1:** *Variable definitions and data sources*

| Variables | Variable definition | Variable type | Data source |
|---|---|---|---|
| ln.Income | Average annual salary of employees at the city-region level | Dependent | CCSY |
| OFDIper10000 | Number of outward foreign direct investments (OFDIs) per 10,000 residents | Explanatory | fDi |
| HighTechBSLaborShare | Share of labor in high-tech and business service sectors (factored by 100) | Explanatory | CCSY |
| AgriMiningLaborShare | Share of labor in agricultural and mining sectors (factored by 100) | Explanatory | CCSY |
| HigherEduShare | Share of residents enrolled in college or higher education (factored by 100) | Explanatory | CCSY |
| LargeFirmsper100000 | Number of firms with an annual revenue above RMB 5 million in the period 2003–2010, and above RMB 20 million thereafter, for every 100,000 residents. | Explanatory | CCSY |
| Urbanization | Percentage of the population residing in the urban core area of a city-region (factored by 100). Key criteria of this core area are a share of non-agricultural labor above 70% of total labor and a share of secondary and tertiary sectoral output above 75% of total industrial output. | Explanatory | CCSY |
| GRPGrowthRate | Growth factor of the gross regional product (GRP) (factored by 100) | Control | CCSY |
| CitySize | Population size (registered residents in ten million) | Control | CCSY |
| IFDIper10000 | Number of inward foreign direct investments (IFDIs) per 10,000 residents | Moderating | fDi |
| OFDIPresence3 | "1" if the number of OFDIs is greater or equal "3", and "0" otherwise. | OFDI dummy | fDi |
| OFDIPresence5 | "1" if the number of OFDIs is greater or equal "5", and "0" otherwise. | OFDI dummy | fDi |
| OFDIPresence7 | "1" if the number of OFDIs is greater or equal "7" and "0" otherwise. | OFDI dummy | fDi |

On the other hand, the inclusion of IFDIs supports the argument that IFDIs capture important aspects of regional absorptive capacity when time lags are used. Foreign investments in a city-region can contribute to technological progress and increased innovation capacity (Chen et al., 2020), generate experiential knowledge for local firms and support firms' internationalization efforts (Li & Cantwell, 2018). Recipients will benefit from having prior experience with foreign partners when conducting investments that help absorb and integrate new knowledge and market triggers locally (Lane et al., 2006).[8] Consequently, past IFDIs in a city-region can enhance the region's absorptive capacity. The knowledge that firms in a city-region gain from foreign subsidiaries may include specifics about intellectual property protection, training requirements, and norms about the use of technologies (Potter et al., 2002; Yeung et al., 2006).

[8]/. For example, in an analysis of interaction patterns between foreign MNEs and firms in a leading ICT cluster in Beijing, Zhou and Xin (2009) found that the learning capacity of local firms vastly improved.

We applied different time lags for our moderating variable *IFDIper10000* to allow sufficient time to pass before unfolding moderating effects. We expected IFDIs to positively moderate the causal relationship between OFDIs and regional income levels after one or few years. As a corollary, Table 1 lists the precise definitions and data sources of all variables.

## 4.3 Estimation Method

We began the estimation process by conducting OLS panel regressions for our base model representing the key relationship between home city-region income and OFDI activity. Conducting a Hausman specification test supported using a fixed-effects model (Hausman, 1978), which allowed us to estimate different intercepts for each city-region (Wooldridge, 2016). Our fixed-effects base model was specified as follows:

$$\begin{aligned}\ln(\boldsymbol{Income})_{jt} = {} & \beta_1 \boldsymbol{OFDIper10000}_{jt} + \beta_2 \boldsymbol{HighTechBSLaborShare}_{jt} + \\ & \beta_3 \boldsymbol{AgriMiningLaborShare}_{jt} + \beta_4 \boldsymbol{HigherEduShare}_{jt} + \\ & \beta_5 \boldsymbol{LargeFirmsper100000}_{jt} + \beta_6 \boldsymbol{Urbanization}_{jt} + \beta_7 \boldsymbol{GRPGrowthRate}_{jt} + \\ & \beta_8 \boldsymbol{CitySize}_{jt} + \boldsymbol{\psi_j} + \boldsymbol{\psi_t} + \varepsilon_{jt},\end{aligned}$$

where $\ln(Income)_{jt}$ refers to the natural logarithm of per-capita income in city-region j at time t. $HighTechBSLaborShare_{jt}$, $AgriMiningLaborShare_{jt}$, $HigherEduShare_{jt}$, $LargeFirmsper100000_{jt}$ and $Urbanization_{jt}$ are independent variables of regional attributes in city j at time t. $GRPGrowthRate_{jt}$ and $CitySize_{jt}$ are control variables that consider the regional growth and city size in city j at time t. Parameters $\psi_j$ and $\psi_t$ measure fixed effects: $\psi_j$ accounts for the unique differences across city-regions that affect income but do not change over time, and $\psi_t$ denotes time-specific influences from year to year. $\varepsilon_{jt}$ is an idiosyncratic error that reflects unobserved factors in specific city-regions that change over time.

To test our key variable, *OFDIper10000*, we split our analysis into two time periods: 2003–2009 and 2010–2016. We did so because we expected that the reverse effects of OFDIs would change over time. We held this belief as OFDI levels of Chinese regions have drastically increased since 2000, and China moved from a developing stage (i.e. pre-financial crisis) to an emerging stage (i.e. post-financial crisis) of development (World Bank, 2023). Next, we included interactions with minimum-threshold OFDI variables and lag effects before testing for the moderating impact of past IFDI activity. Finally, we investigated the robustness of our findings concerning the impact of OFDIs on home-location income levels.

# 5 Results and Discussion

## 5.1 Main Effects of OFDIs

Table 2 presents the descriptive statistics and correlations for the model variables. As shown in the table, the variance inflation factors (VIFs) were well below the acceptable threshold of 10, indicating that our data did not suffer from multicollinearity problems.

**Table 2:** *Descriptive statistics and correlation matric with variance inflation factors*

| *Variables* | *Mean* | *S.D.* | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* | *(8)* | *VIFs* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) ln.Income | 10.224 | 0.564 | | | | | | | | | |
| (2) OFDIper10000 | 0.010 | 0.066 | 0.144 | | | | | | | | 1.454 |
| (3) HighTechBSLaborShare | 7.531 | 2.879 | 0.196 | 0.347 | | | | | | | 2.131 |
| (4) AgriMiningLaborShare | 44.929 | 13.619 | 0.079 | 0.078 | -0.361 | | | | | | 1.849 |
| (5) HigherEduShare | 1.575 | 2.156 | 0.197 | 0.175 | 0.495 | 0.089 | | | | | 1.857 |
| (6) LargeFirmsper100000 | 0.280 | 0.359 | 0.211 | 0.464 | 0.140 | 0.423 | 0.206 | | | | 1.705 |
| (7) Urbanization | 34.626 | 24.058 | 0.202 | 0.317 | 0.309 | 0.317 | 0.526 | 0.425 | | | 1.918 |
| (8) GRPGrowthRate | 112.05 | 4.216 | 0.023 | -0.013 | -0.049 | 0.008 | 0.107 | 0.060 | 0.033 | | 1.044 |
| (9) CitySize | 433.48 | 308.11 | 0.026 | 0.068 | 0.169 | -0.112 | 0.136 | -0.010 | -0.158 | -0.062 | 1.140 |

Note: S.D. = standard deviation. VIF = variance inflation factor. | Data sources: National Bureau of Statistics of China (2019) (CCSY), Financial Times (2017) (fDi)

Table 3 shows the fixed-effects estimates of our base model, which measures the impact of OFDIs on home-region income levels when controlling for city-region and time-specific influences. We also included different minimum-threshold levels for OFDIs in consecutive models. Models (1) to (4) display the results for the first period 2003–2009. As shown in Model (1), *GRPGrowthRate* was positively and significantly related to income, as expected, suggesting that city-regions with high growth rates in production had higher income levels than other city-regions. The coefficient of *CitySize* was negative but not significant, suggesting that a city's size did not add to income increases.

**Table 3:** *Effects of OFDIs on regional per-capita income in Chinese city-regions | two-way fixed-effects panel OLS estimates by time period, 2003–2009 and 2010–2016*

| | 2003 - 2009 | | | | 2010 - 2016 | | | |
|---|---|---|---|---|---|---|---|---|
| *Variables* | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* | *(8)* |
| GRPGrowthRate | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.003** | 0.002** | 0.002** | 0.002** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| CitySize | -0.000 | -0.000 | -0.004 | -0.004 | -0.004 | -0.004 | -0.004 | -0.004 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| OFDIper10000 | -0.438*** | -1.942 | -2.750 | -2.860* | 0.004 | -1.901* | -3.132*** | -1.541** |
| | (0.102) | (1.441) | (1.780) | (1.491) | (0.071) | (0.983) | (0.965) | (0.921) |
| OFDIPresence3 | | -0.041*** | | | | -0.015 | | |
| | | (0.016) | | | | (0.015) | | |
| OFDIPresence5 | | | -0.036** | | | | -0.024 | |
| | | | (0.017) | | | | (0.018) | |
| OFDIPresence7 | | | | -0.039** | | | | -0.012 |
| | | | | (0.020) | | | | (0.021) |
| HighTechBSLaborShare | 0.003 | 0.002 | 0.002 | 0.002 | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| AgriMiningLaborShare | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| HigherEduShare | -0.010 | -0.010 | -0.011 | -0.010 | 0.003 | 0.004 | 0.004 | 0.004 |
| | (0.007) | (0.000) | (0.006) | (0.006) | (0.000) | (0.006) | (0.001) | (0.006) |
| LargeFirmsper100000 | -0.090*** | -0.095*** | -0.102*** | -0.101*** | 0.098*** | 0.101*** | 0.106*** | 0.102*** |
| | (0.024) | (0.024) | (0.024) | (0.024) | (0.026) | (0.026) | (0.025) | (0.025) |
| Urbanization | 0.001 | 0.001 | 0.001 | 0.001 | 0.001** | 0.001** | 0.001** | 0.001** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| OFDIper10000* OFDIPresence3 | | 1.513 | | | | 1.908* | | |
| | | (1.419) | | | | (0.983) | | |
| OFDIper10000* OFDIPresence5 | | | 2.354 | | | | 3.145*** | |
| | | | (1.755) | | | | (0.966) | |
| OFDIper10000* OFDIPresence7 | | | | 2.423* | | | | 1.547* |
| | | | | (1.426) | | | | (0.915) |
| Observations | 1911 | 1911 | 1911 | 1911 | 1911 | 1911 | 1911 | 1911 |
| $R^2$ | 0.115 | 0.123 | 0.122 | 0.123 | 0.030 | 0.032 | 0.040 | 0.033 |

Notes: Dependent variable: ln.Income. ***, ** and * indicate a significance level of 1%, 5% and 10%, respectively. Robust standard errors are in parentheses. | Data sources: National Bureau of Statistics of China (2019) (CCSY), Financial Times (2017) (fDi)

When considering the key independent variable *OFDIper10000*, the effect was negative and highly significant and thus did not seem to support Proposition 1a. This finding was inconsistent with previous cross-sectional studies that found positive reverse effects of China's OFDIs (Yang & Bathelt, 2023). As emphasized in Section 2, this can be explained by inland regions catching-up and benefitting strongly from the fast-growing Chinese economy in the 2000s through high demand for low-cost products and government support programs. This high growth was unrelated to OFDI activity. In coastal city-regions, in contrast, there was a link between OFDI activity and per-capita income. However, this link was still relatively weak in the 2003–2009 period. Firms were still relatively inexperienced in this early period and OFDI flows only beginning.

The specific growth patterns in this first period of OFDI activity are also reflected in the relationships with other independent variables. The coefficient of *HighTechBSLaborShare* was positive but insignificant, while the impact of *AgriMiningLaborShare* was negative and highly significant. *LargeFirmsper100000* also had a negative coefficient with a high significance level, while the associations of per-capita income with *HigherEduShare* and *Urbanization* were insignificant. This suggests that per-capita income growth in this period was particularly high in city-regions with a high share of manufacturing employment particularly in low-and medium-technology operations (instead of high-technology industries or agriculture) and distributed across small- and medium-sized firms (instead of large firms), characterized by simple technologies, all of this being consistent with the needs in simple production and assembly processes. These city-regions' growth paths did not depend on OFDI activity, which any of which did not have the capability to participate in at that point.

To consider this specific situation, we added a minimum-threshold level of investments (i.e. 3, 5 and 7 OFDI projects per city-region in models (2) to (4), respectively) in the form of interaction terms with *OFDIper10000*. This corresponds with Proposition 1b which proposes that OFDIs from Chinese city-regions needed to surpass a minimum-threshold level before reverse income effects could unfold. Through this, essentially only those city-regions counted as internationally connected, which had at least 3, 5 or 7 outward investments. While the control variables in models (2) to (4) remained essentially the same as before, the interaction terms with *OFDIper10000* indicated interesting changes. In models (2) and (3) for a minimum of 3 and 5 investments, respectively, the coefficients were positive instead of negative but insignificant, while model (4) for a minimum of 7 investment projects indicated a positive and moderately significant effect. Overall, in this initial development period OFDI activity had not yet taken off and China had not yet transitioned from a developing to an emergent stage.

However, the situation in the 2010s was a different one, with the country still growing strongly and making large progress in developing from a low-cost commodity producer into an advanced manufacturing hub. Models (5) through (8) reveal in the same sequence as before that some associations of independent and control variables changed substantially as economic development progressed. In the base model (5) for the second period, *GRPGrowthRate* still had a positive and significant association with per-capita income, while the impact of *CitySize* remained insignificant. The most important change was signaled in the coefficient for our main investment variable *OFDIper10000*, which turned positive but insignificant – due to the large heterogeneity of Chinese city-regions regarding their growth dynamics. The other independent variables in model (5) are also interesting. *HighTechBSLaborShare*, *AgriMiningLaborShare* and *HigherEduShare* had no significant association with city-region income levels (although the coefficient for the share of highly-educated residents turned positive). In this period of fast development, the role of large firms and urbanization processes now became more important. This is indicated by consistently positive and significant or highly significant coefficients for *Urbanization* and *LargeFirmsper100000*, respectively. Again, this is consistent with our prior observations regarding the regional growth patterns in China and the country's progression to an emerging economy.

We investigated this transformation further in models (6) through (8), where we introduced minimum-threshold levels of OFDI projects and interacted these dummy variables with our main investment variable *OFDIper10000*. As opposed to the 2003–2009 period, all interaction terms for different threshold values were now positive and highly or moderately significant, providing substantial support for Proposition 1b. These results suggested for the 2010–2016 period that per-capita income increases were particularly large in those Chinese city-regions with substantial OFDI activities. This observation aligned with the actual geography of Chinese OFDIs, as illustrated in Figure 1, where regions with a high number of OFDI projects, especially the largest city-regions Beijing, Shanghai and Guangzhou and city-regions in coastal regions, experienced substantive positive impacts on per capita income, while others with no or limited OFDI activity did not. Additionally, our findings suggest that per-capita income increases also benefitted from agglomeration economies (related to a high urbanization degree) and the growing impact of large firms.

Table 4 presents the results of similar panel regressions that include the role of time lags in our model and speak to Proposition 1c, suggesting that reverse effects of OFDIs on home-location income require one or several years to unfold. The table covers the entire period 2003–2016. The coefficients in Table 4 suggest that *GRPGrowthRate* and, for models (1) through (3), *LargeFirmsper100000* had a positive and highly significant impact on per-capita income increases in Chinese city-regions, while other independents aside from the investment variables were insignificant when measured over the full-time period.

**Table 4:** *Effects of OFDIs on regional per-capita income in Chinese city-regions | two-way fixed-effects panel OLS estimates with time lags, 2003–2019*

| *Variables* | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* |
|---|---|---|---|---|---|---|
| GRPGrowthRate | 0.005*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| CitySize | 0.007 | 0.005 | 0.005 | 0.001 | -0.000 | 0.002 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $OFDIper10000_{t-1}$ | -2.342 | -5.110*** | -4.245*** | | | |
| | (2.386) | (0.758) | (0.666) | | | |
| $OFDIPresence3_{t-1}$ | -0.068*** | | | | | |
| | (0.014) | | | | | |
| $OFDIPresence5_{t-1}$ | | -0.089*** | | | | |
| | | (0.016) | | | | |
| $OFDIPresence7_{t-1}$ | | | -0.100*** | | | |
| | | | (0.016) | | | |
| $OFDIper10000_{t-3}$ | | | | -1.382 | -4.248*** | -3.333*** |
| | | | | (2.423) | (0.670) | (0.927) |
| $OFDIPresence3_{t-3}$ | | | | -0.049*** | | |
| | | | | (0.012) | | |
| $OFDIPresence5_{t-3}$ | | | | | -0.068*** | |
| | | | | | (0.013) | |
| $OFDIPresence7_{t-3}$ | | | | | | -0.075*** |
| | | | | | | (0.014) |
| HighTechBSLaborShare | 0.003 | 0.003 | 0.003 | 0.001 | 0.001 | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| AgriMiningLaborShare | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) |
| HigherEduShare | -0.010* | -0.008 | -0.007 | -0.002 | -0.000 | 0.000 |
| | (0.006) | (0.006) | (0.005) | (0.005) | (0.005) | (0.005) |
| LargeFirmsper100000 | 0.030 | 0.031 | 0.024 | 0.115*** | 0.113*** | 0.107*** |
| | (0.027) | (0.026) | (0.026) | (0.027) | (0.027) | (0.027) |
| Urbanization | 0.000 | 0.000 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $OFDIper10000_{t-1}$* $OFDIPresence3_{t-1}$ | 1.994 | | | | | |
| | (2.391) | | | | | |
| $OFDIper10000_{t-1}$* $OFDIPresence5_{t-1}$ | | 4.785*** | | | | |
| | | (0.757) | | | | |
| $OFDIper10000_{t-1}$* $OFDIPresence7_{t-1}$ | | | 3.917*** | | | |
| | | | (0.656) | | | |
| $OFDIper10000_{t-3}$* $OFDIPresence3_{t-3}$ | | | | 1.275 | | |
| | | | | (2.435) | | |
| $OFDIper10000_{t-3}$* $OFDIPresence5_{t-3}$ | | | | | 4.157*** | |
| | | | | | (0.664) | |
| $OFDIper10000_{t-3}$* $OFDIPresence7_{t-3}$ | | | | | | 3.231*** |
| | | | | | | (0.911) |
| Observations | 3822 | 3822 | 3822 | 3822 | 3822 | 3822 |
| $R^2$ | 0.087 | 0.108 | 0.107 | 0.072 | 0.091 | 0.088 |

Notes: Dependent variable: ln.Income. ***, ** and * indicate a significance level of 1%, 5% and 10%, respectively. Robust standard errors are in parentheses. The number of OFDIs is measured for the period 2003–2016, all other variables for 2003–2019. | Data sources: National Bureau of Statistics of China (2019) (CCSY), Financial Times (2017) (fDi).

The impact of OFDIs on city-region income levels shows up strongly and consistently in Table 4, where we introduced minimum-threshold levels for investment projects (3, 5 or 7 projects) as before. Models (1) through (3) measured income effects related to OFDI activity that occurred 1 year earlier and models (4) through (6) measured the effects of investments that were made 3 years ago. These time lags correspond with other studies

(Castellani & Pierri, 2013; Crescenzi et al., 2022). The results for the impact of OFDI activity in Table 4 are very consistent and provide strong support for proposition 1c. All interaction terms had positive coefficients that became highly significant when we increased the minimum number of OFDIs to 5 or 7 projects. This provided strong evidence that reverse income effects of investments, made in prior years, were more substantial than those from current-year investments. The findings were similar for time lags of 1 and 3 years, and effects were especially large and highly significant when a minimum-threshold level of 5 or 7 investment projects was applied.

## 5.2 Moderating Role of IFDIs in Generating Absorptive Capacity

The models in Table 5 present the panel regression results related to Proposition 2 about the moderating role of IFDIs in generating regional absorptive capacity. Our presupposition here was that firms in city-regions that benefit significantly from prior IFDIs develop capabilities and a knowledge infrastructure that enables them to exploit the positive effects of OFDIs more effectively than city-regions without prior IFDI activity that have little or no contact with foreign firms.

In Table 5, we excluded the threshold-level dummies used in prior analyses. Instead, we introduced *IFDIper10000* into our models and put *OFDIper10000* and *IFDIper10000* into interaction, using different time lags of 1, 3 and 5 years for IFDIs. This was based on the assumption that firms in city-regions need some time to learn from exposure to IFDIs to develop the capabilities necessary to conduct investment projects in a foreign economy and draw knowledge spillovers and growth impulses from them. Based on the assumption that city-regions require some time to build capabilities and a knowledge infrastructure when exposed to prior IFDI activity in the local environment (Li & Cantwell 2018), we ran consecutive models (1) to (3) with time lags for *IFDIper10000*. The interaction terms were positive and significant or highly significant in all models[9], while other influences on city-region income levels remained similar to prior models. This provided strong support for Proposition 2, suggesting that regional absorptive capacity resulting from prior exposure to IFDIs contributed to a stronger linkage between OFDI activity and per-capita income. When comparing the coefficient magnitudes across models, we found that the moderating effect of IFDIs on the reverse income impact of OFDIs was largest for a time lag of 1 year and decreased over time.[10]

[9]/. The coefficient of the interaction term was also significant and positive for a time lag of 7 years.

[10]/. This was different from the findings of Merlevede et al.'s (2014) study in a Romanian manufacturing setting, which exhibited that several years had to elapse before IFDIs had their highest positive impact on the host location.

**Table 5:** *Effects of OFDIs on regional per-capita income in Chinese city-regions | two-way fixed-effects panel OLS estimates for interactions with IFDIs, 2003–2016*

| *Variables* | *(1)* | *(2)* | *(3)* |
|---|---|---|---|
| GRPGrowthRate | 0.005*** | 0.005*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) |
| CitySize | 0.008 | -0.007 | -0.010 |
| | (0.000) | (0.000) | (0.000) |
| OFDIper10000 | -0.820* | -0.472 | -0.165 |
| | (0.443) | (0.320) | (0.138) |
| IFDIper10000 $_{t-1}$ | -0.138*** | | |
| | (0.047) | | |
| IFDIper10000 $_{t-3}$ | | -0.140*** | |
| | | (0.034) | |
| IFDIper10000 $_{t-5}$ | | | -0.103*** |
| | | | (0.031) |
| HighTechBSLaborShare | 0.004** | 0.003 | -0.000 |
| | (0.002) | (0.002) | (0.002) |
| AgriMiningLaborShare | -0.000 | 0.000 | -0.000 |
| | (0.001) | (0.000) | (0.000) |
| HigherEduShare | -0.012** | -0.004 | 0.004 |
| | (0.005) | (0.005) | (0.006) |
| LargeFirmsper100000 | 0.016 | 0.071*** | 0.091*** |
| | (0.019) | (0.026) | (0.029) |
| Urbanization | 0.000 | 0.000 | 0.001* |
| | (0.001) | (0.001) | (0.001) |
| OFDIper10000* IFDIper10000$_{t-1}$ | 0.278** | | |
| | (0.134) | | |
| OFDIper10000* IFDIper10000$_{t-3}$ | | 0.204** | |
| | | (0.089) | |
| OFDIper10000* IFDIper10000$_{t-5}$ | | | 0.120*** |
| | | | (0.041) |
| Observations | 3549 | 3003 | 2457 |
| $R^2$ | 0.082 | 0.074 | 0.053 |

Notes: Dependent variable: ln.Income. ***, ** and * indicate a significance level of 1%, 5% and 10%, respectively. Robust standard errors are in parentheses. | Data sources: National Bureau of Statistics of China (2019) (CCSY), Financial Times (2017) (fDi)

## 5.3 Robustness Checks

To test the stability of our findings and provide support for our claim that increasing OFDI activity stimulates regional income growth, we conducted numerous robustness checks for the recent period 2010–2016 in Table 6. For ease of comparison, Models (1) through (4) present the regression results for our base model from Table 3. All robustness checks in the tables used *ln.Income* as the dependent variable. Models (5) through (8) present the results using the generalized method-of-moments (GMM) estimator (Arellano & Bond, 1991), which provides a check for potential endogeneity problems. In the GMM models, we included the lagged level of *ln.Income* as an instrumental variable (with a time lag of 1 year). The models' findings were largely consistent with our base model. In particular, we found that the reverse income effects of OFDIs were positive and, for model (8), significant when minimum-threshold levels of investment projects were applied.

**Table 6:** *Effects of OFDIs on regional per-capita income in Chinese city-regions | robustness checks, 2010 - 2016*

| *Variables* | *Base Model* | | | | *Generalized Method of Moments* | | | | *Poisson Quasi-Maximum Fixed-Effects Likelihood Estimator* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| GRPGrowthRate | 0.003** | 0.002** | 0.002** | 0.002** | -0.004** | -0.004** | -0.003** | -0.003** | 0.000* | 0.000* | 0.000* | 0.000* |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| CitySize | -0.004 | -0.004 | -0.004 | -0.004 | 0.066 | 0.071 | 0.061 | 0.047 | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.046) | (0.042) | (0.035) | (0.036) | (0.000) | (0.000) | (0.000) | (0.000) |
| OFDIper10000 | 0.004 | -1.901* | -3.132*** | -1.541** | -0.660 | -5.794* | -4.690 | -4.420** | -0.006 | -0.194** | -0.301*** | -0.154* |
| | (0.071) | (0.983) | (0.965) | (0.921) | (0.555) | (3.907) | (3.220) | (2.028) | (0.008) | (0.092) | (0.092) | (0.087) |
| OFDIPresence3 | | -0.015 | | | | -0.089** | | | | -0.001 | | |
| | | (0.015) | | | | (0.034) | | | | (0.001) | | |
| OFDIPresence5 | | | -0.024 | | | | -0.107* | | | | -0.002 | |
| | | | (0.018) | | | | (0.057) | | | | (0.002) | |
| OFDIPresence7 | | | | -0.012 | | | | -0.084 | | | | -0.002 |
| | | | | (0.021) | | | | (0.054) | | | | (0.002) |
| HighTechBS LaborShare | -0.001 | -0.001 | -0.001 | -0.001 | -0.007 | -0.005 | -0.003 | -0.003 | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.006) | (0.004) | (0.004) | (0.004) | (0.000) | (0.000) | (0.000) | (0.000) |
| AgriMining LaborShare | -0.000 | -0.000 | -0.000 | -0.000 | 0.001 | 0.001 | 0.001 | 0.001 | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| HigherEduShare | 0.003 | 0.004 | 0.004 | 0.004 | 0.014 | 0.013 | 0.007 | 0.011 | -0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.006) | (0.001) | (0.006) | (0.018) | (0.014) | (0.014) | (0.014) | (0.001) | (0.001) | (0.001) | (0.001) |
| LargeFirms per100000 | 0.098*** | 0.101*** | 0.106*** | 0.102*** | -0.041 | 0.048 | 0.121 | 0.101 | 0.010*** | 0.010** | 0.011*** | 0.010*** |
| | (0.026) | (0.026) | (0.025) | (0.025) | (0.156) | (0.102) | (0.101) | (0.105) | (0.002) | (0.000) | (0.002) | (0.002) |
| Urbanization | 0.001** | 0.001** | 0.001** | 0.001** | 0.006** | 0.004* | 0.004* | 0.004* | 0.000* | 0.000* | 0.000* | 0.000* |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) | (0.000) | (0.000) | (0.000) | (0.000) |
| OFDIper10000* OFDIPresence3 | | 1.908* | | | | 5.607 | | | | 0.189** | | |
| | | (0.983) | | | | (3.932) | | | | (0.092) | | |
| OFDIper10000* OFDIPresence5 | | | 3.145*** | | | | 4.559 | | | | 0.297*** | |
| | | | (0.966) | | | | (3.246) | | | | (0.092) | |
| OFDIper10000* OFDIPresence7 | | | | 1.547* | | | | 4.294** | | | | 0.148* |
| | | | | (0.915) | | | | (2.026) | | | | (0.087) |
| Lagged ln.Income (1 year) | 0.090*** | 0.091*** | 0.090*** | 0.090*** | -0.083 | -0.044 | -0.040 | -0.035 | | | | |
| | (0.025) | (0.025) | (0.025) | (0.025) | (0.053) | (0.050) | (0.055) | (0.051) | | | | |
| Observations | 1911 | 1911 | 1911 | 1911 | 1365 | 1365 | 1365 | 1365 | 1911 | 1911 | 1911 | 1911 |
| Sargan p-value | | | | | 0.000 | 0.000 | 0.000 | 0.000 | | | | |
| AR(1) p-value | | | | | 0.019 | 0.007 | 0.008 | 0.000 | | | | |
| AR(2) p-value | | | | | 0.123 | 0.140 | 0.182 | 0.038 | | | | |

Notes: Dependent variable: ln.Income. ***, ** and * indicate a significance level of 1%, 5% and 10%, respectively. Robust standard errors are in parentheses. AR(1) and AR(2) refer to first-order and second-order autoregressive models, respectively. | Data sources: National Bureau of Statistics of China (2019) (CCSY), Financial Times (2017) (fDi)

Models (9) through (12) have a similar set-up, this time using a Poisson fixed-effects quasi-maximum-likelihood (QML) estimator (Wooldridge, 1999), which is often used as an alternative model formulation. Again, we found that when using minimum-threshold dummies, the interaction terms for OFDI activity were positive and significant.

# 6 CONCLUSION

To sum up, our study investigates the reverse impact of OFDIs on home-location income levels in Chinese city-regions during the period 2003–2016 and provides evidence that a positive relationship exists. We applied an empirical approach that considered minimum-threshold levels of investments, lagged effects of our core investment variables and the moderating role of IFDI activity in generating absorptive capacity. We found strong evidence to support our propositions regarding reverse income effects of OFDIs in Chinese city-regions. Our results demonstrate that OFDIs, on average, do not hurt home-region development but can positively impact per-capita home-location income, not only in developed economies but also in emerging contexts. However, these findings may not apply to the very early developmental stages of an economy. We draw this conclusion from the regional growth paths of Chinese regions after the opening of the economy and from the finding that there needed to be a minimum number of investments and a sufficient level of skills and capabilities within a city-region to benefit from OFDI activity, which suggests that city-regions needed to pass a certain threshold of investment activity for positive reverse effects of OFDIs on per-capita income to be realized. We also found that the effects of OFDIs on home-region income levels can last over several years and may not occur immediately. Finally, we showed that prior exposure to IFDI activity in the same city-region enhances the reverse income effects of OFDIs.

Like all studies, our investigation also has some limitations that need to be acknowledged. To begin, we did not take into consideration the sectoral focus of OFDIs, their target countries/regions or motives (i.e. whether they were efficiency-, market- or knowledge-seeking in character). As such, we could not isolate the impact of knowledge triggers on home-location development (Yang & Bathelt, 2022). Furthermore, since our investment database only considered greenfield investments, brownfield investments in the form of mergers, acquisitions or joint ventures were excluded. Although the structure of investments in this database is consistent with World Bank and United Nations data (Crescenzi et al., 2015), brownfield investments should be included in future studies. This is because such investments generate direct access to resources and knowledge in the host economy (Bathelt & Li, 2020), which may positively affect home-region development. Moreover, we cannot rule out the potential impacts of omitted variables.

Our findings suggest that OFDIs may generate home-region benefits over and above providing market opportunities abroad or securing access to knowledge inputs for investing firms. Although current government policies tend to eschew OFDIs and mainly focus on IFDIs (Baiashvili & Gattini, 2019), our findings cast doubt on this strategy and suggest that using OFDIs and increasing international connectivity can also help to stimulate regional economic development. Accordingly, when designing local policies to encourage OFDIs and helping domestic firms connect with foreign partners, policymakers should think carefully about the reverse impacts of OFDIs. This recommendation, however, must be tempered, acknowledging that pre-existing levels of international experience and capabilities in home city-regions are essential for harnessing the potential benefits of OFDIs. Identifying which regions stand to benefit the most from OFDIs, which ones may be left out, and what the implications could be for regional inequality should also be considered in future policy agendas. We believe that it may also be relevant for other transitional and/or emerging countries that may plan to follow the unique Chinese pathway to encourage the internationalization of local firms in supporting home-region development.

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