Super Factory Comes to Town: Quantifying the Agglomeration Spillovers from Foxconn Factory in Henan *

Jianpeng Deng
SUFE

Hong Ma
Tsinghua University

Hongbing Wei
CASS

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Abstract

We quantify the agglomeration spillovers of "super factories" on local manufacturing. We study Foxconn's sudden entry into China's Henan and exploit its quasi-experimental timing using a spatial difference-in-differences design. Nearby regions experienced substantially larger productivity gains than more distant areas. To interpret these patterns, we develop and estimate an urban model with spatially decaying externalities, which implies that each Foxconn job created 4.5 additional jobs in the city. Counterfactual analyses reveal strong asymmetries and show that relocating Foxconn to lower-density areas would have generated much larger spillovers. The geographic placement of mega-plants is thus critical for place-based industrial policy.

Keywords: Agglomeration Spillovers; Superstar Firms; Quantitative Urban Model; Place-Based Policy

JEL Codes: R12, F23, R32, R58, O18.

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Contact authors: Jianpeng Deng, Shanghai University of Finance and Economics, e-mail: deng.jianpeng@mail.shufe.edu.cn; Hong Ma (*corresponding author*), Tsinghua University, email: mahong@sem.tsinghua.edu.cn; Hongbing Wei, Institute of World Economics and Politics, Chinese Academy of Social Science, e-mail: weihongbing@cass.org.cn.

1 Introduction

Agglomeration economies play a central role in shaping the uneven spatial distribution of economic activity. A large body of work (e.g., Greenstone, Hornbeck, and Moretti (2010)) shows that cities attracting major industrial investments experience significant productivity gains. Within cities, however, such spillovers are highly localized, decaying rapidly with distance from the source. As a result, when a "superstar" firm establishes a major facility in a city, the scale and distribution of its indirect benefits depend crucially on (i) the strength of agglomeration forces, (ii) the spatial rate of decay, and (iii) the precise placement of the facility within the city.

This paper quantifies the agglomeration spillovers of "super factories" in an industrializing economy. While existing studies have established that attracting large plants can raise regional productivity, much less is known about the spatial decay of these spillovers within cities, particularly in developing countries. This question is of first-order policy relevance: governments devote vast resources to subsidize "million dollar plants," yet the effectiveness of these policies hinges on how far and how strongly agglomeration benefits extend, and whether the firm's specific siting within a region matters.

Identifying agglomeration effects is challenging, because dense clusters may arise from spillovers or from location fundamentals that independently favor production. We address this problem by exploiting the sudden entry of Foxconn, the world's largest electronics assembler, into Zhengzhou, Henan province in China. In June 2010, after an unexpected investment agreement, Foxconn rapidly built three massive factories in Zhengzhou within four months. The plants employed more than 100,000 workers and, by 2011, produced the majority of the world's iPhones.[1] Henan had little prior electronics industry, making this entry a rare and plausibly exogenous shock to local economic density. We leverage this shock to estimate the causal impact and spatial reach of agglomeration spillovers generated by a single superstar firm.

Our analysis proceeds in four steps. First, using a spatial difference-in-differences design at a fine geographic grid, we compare productivity changes before and after Foxconn's arrival across locations differentially exposed by distance. We find large, sharply localized spillovers: locations

[1] As Patrick McGee recounts in his New York Times bestseller *Apple in China: The Capture of the World's Greatest Company*, Foxconn's facilities in Zhengzhou expanded with extraordinary speed—growing to more than 300,000 workers within months and soon producing over half of the world's iPhones, earning the city the nickname "iPhone City."

nearer to Foxconn experienced significantly greater productivity gains than those farther away. Moving 100 km closer to Foxconn is associated with a 0.20 log point increase in labor productivity. These effects are robust to pre-trend checks, placebo locations, and alternative specifications.

Second, guided by the reduced-form evidence, we develop and structurally estimate a quantitative spatial model of the city that features agglomeration externalities. In the model, productivity depends on both intrinsic fundamentals and the density of neighboring employment, subject to land constraints. We formalize two key parameters governing these forces: (i) the elasticity of productivity with respect to nearby employment (which captures the strength of spillovers), and (ii) the spatial decay rate of spillovers (which captures the spatial extent of externalities). Using the Foxconn shock for identification, we estimate an elasticity of about 0.09 — toward the high end of the literature — and a decay rate of 0.11 per kilometer, implying that spillovers fall by roughly two-thirds within 10 km and vanish beyond 40–50 km.[2] These estimates provide new evidence on the magnitude and reach of agglomeration forces in a developing-country city.

Third, we use the calibrated model to quantify Foxconn's overall impact on the local economy. The influx of the Foxconn plants triggers a dramatic expansion of the urban workforce, causing total manufacturing employment in the city to rise by roughly 170–180%, nearly tripling relative to the pre-entry baseline. City-wide productivity increases by more than 10%. Furthermore, each Foxconn job created 4.5 additional jobs elsewhere in the city, with roughly half of these multipliers attributable directly to agglomeration spillovers. Moreover, the benefits of Foxconn's entry are spatially uneven within the city: locations closer to the Foxconn site enjoy larger increases in productivity and employment than those farther away, consistent with the localized nature of spillovers.

Finally, we conduct counterfactual experiments to examine how Foxconn's economic impact would vary if the plants scale up or down, and if they were located in different parts of the city. We show that scaling down Foxconn reduces fewer jobs than scaling up creates, highlighting asymmetries in the productivity–employment relationship. Furthermore, the exact location of the firm can markedly alter the aggregate spillover benefits, an aspect overlooked in most place-based analyses. Relocating Foxconn to lower-density or lower-wage areas would have produced substantially larger spillover benefits, with potential gains of 200,000 additional jobs relative to

[2]By contrast, examining the entry of the million dollar plants (MDP) in the US, Giroud, Lenzu, Maingi, and Mueller (2024) find the local productivity spillover is strong within a 50-mile radius around the MDP plants, weaker within 100 miles, and becomes insignificant beyond.

the observed placement. This implies that place-based subsidies may yield higher returns if directed not only toward attracting large firms but also toward influencing where within a city they locate.

Contribution to the Literature. This paper contributes to three strands of research in urban and spatial economics.

First, we provide new causal evidence on the localized productivity spillovers from large-firm entry. A long tradition of work has examined the spatial concentration of economic activity and the presence of agglomeration externalities (see Ellison and Glaeser 1997, Rosenthal and Strange 2004, Combes and Gobillon 2015). Early studies typically inferred agglomeration from clustering patterns within administrative units such as cities or counties, without directly estimating how externalities attenuate with physical distance. Subsequent research has used micro-geographic data to measure the distance decay of spillovers. Rosenthal and Strange (2003) and Arzaghi and Henderson (2008) show that productivity and knowledge-sharing benefits decline sharply within a few miles or even blocks, while Rosenthal and Strange (2020) review a broad range of evidence pointing to extremely localized effects. More recently, Baum-Snow, Gendron-Carrier, and Pavan (2024) use Canadian administrative data to estimate that productivity spillovers fade quickly across distance bands, while Giroud, Lenzu, Maingi, and Mueller (2024) show that gains from large-plant entry can propagate more widely through multi-plant firm networks, generating "global" spillovers that transcend geography.

However, empirical evidence from developing economies remains scarce. The few existing studies—such as Li, Li, and Liu (2022), who analyze the universe of Chinese manufacturing firms—suggest that productivity externalities in China decay within only a few kilometers, similar in spatial range to those in advanced economies. Yet these estimates are largely descriptive and not tied to exogenous shocks. By exploiting Foxconn's unexpected entry into Zhengzhou, our paper identifies a sharp and plausibly exogenous increase in local economic density and uses this to causally estimate both magnitude and spatial reach of agglomeration spillovers. This approach bridges the gap between descriptive localization studies and structural estimates of distance decay, offering the first quasi-experimental evidence on the geographic scope of productivity externalities in a developing-country city.

Second, we develop and structurally estimate a parsimonious urban model in which productivity is shaped by spatially decaying agglomeration externalities and constrained by land

scarcity. We build on recent work that estimates agglomeration forces within quantitative spatial frameworks (e.g., Ahlfeldt et al. 2015; Heblich et al. 2020; Gaubert 2018; Miyauchi 2024). These models, combining spatial equilibrium logic with microdata, illuminate how productivity, amenities, and land constraints jointly determine urban structure. Our framework shares this spirit but differs in focus and setting. Whereas Ahlfeldt et al. (2015) and Heblich et al. (2020) exploit historical or infrastructural shocks in mature urban economies, we analyze a contemporaneous industrial shock in a rapidly developing city, linking the entry of a single large firm to equilibrium changes in productivity and employment across space. Moreover, by combining reduced-form estimates with structural calibration, we jointly identify the elasticity of productivity with respect to local density and the rate of spatial decay—two parameters rarely estimated together.[3] This dual estimation allows us to quantify how quickly the benefits of density dissipate within a developing-country city, revealing that agglomeration effects are powerful but short-ranged. In addition, we advance the literature by explicitly examining how a firm's precise location within a city shapes the spatial distribution of employment and productivity. That is, how the geography of firm placement interacts with agglomeration forces to determine urban structure.

Third, our findings have direct implications for the design of place-based industrial policies. A large body of work examines whether targeted subsidies to attract firms raise local productivity and welfare, as reviewed in (Neumark and Simpson, 2015).[4] The influential study by Greenstone et al. (2010) evaluates the productivity effects of new "Million Dollar Plants" by comparing counties that won versus those that narrowly lost plant bids, implicitly assuming uniform spillovers within a county.[5] In contrast, we demonstrate that the magnitude of spillovers depends critically on where within a city the firm is located. Our counterfactual simulations reveal that placing Foxconn in lower-density areas would have produced substantially larger aggregate employment

[3] As surveyed by Rosenthal and Strange (2004) and Combes and Gobillon (2015)), most empirical studies estimate either the magnitude of spillovers or the distance decay, but not both jointly. See, for example, Ciccone (2002), Rosenthal and Strange (2003), Duranton and Overman (2005), Rice, Venables, and Patacchini (2006), Arzaghi and Henderson (2008) and Rosenthal and Strange (2008). Rosenthal and Strange (2020) also provides an excellent survey of this literature.

[4] See, for example, Crozet et al. (2004), Bronzini and De Blasio (2006), Devereux et al. (2007), Greenstone et al. (2010), Bernini and Pellegrini (2011) and Criscuolo et al. (2019).

[5] In the same vein, Kline and Moretti (2014) show that the Tennessee Valley Authority program generated persistent gains in manufacturing employment long after federal transfers ended. Slattery (2025) demonstrate that intergovernmental competition for subsidies in the United States largely transfers welfare gains from residents to firms. Similarly, Fajgelbaum and Gaubert (2020) analyze optimal spatial policies in a trade–spatial quantitative model with worker heterogeneity and spillovers, showing that U.S. welfare could rise through a more efficient reallocation of workers.

and productivity gains, while scaling down operations destroys fewer jobs than scaling up creates—highlighting asymmetric effects of expansion versus contraction.

This insight connects to recent work on spatially targeted development programs. In the Chinese context, studies of Special Economic Zones (e.g., Lu et al. 2019; Brooks et al. 2021; Lu et al. 2023) show large local benefits, but often overlook spillovers and general-equilibrium adjustments beyond the zone boundaries. Our analysis moves beyond policy zones to quantify how a single anchor firm reshapes the entire urban structure. More broadly, the results suggest that the returns to place-based policies depend not only on which city secures a large investment, but also on where within the city that investment is situated—a dimension of spatial targeting largely unexplored in prior research.

The remainder of the paper is organized as follows. Section 2 provides background on Foxconn's entry and describes the data. Section 3 presents the empirical results on productivity spillovers and discusses potential mechanisms. Section 4 introduces the quantitative urban model of internal city structure. Section 5 details the model estimation and calibration. Section 6 reports the results of counterfactual simulations, and Section 7 concludes.

2 Background and Data

2.1 Foxconn in Henan

Foxconn Technology Group, formally known as Hon Hai Precision Industry Co., is a Taiwan-headquartered multinational and the world's largest contract manufacturer of consumer electronics. Its product portfolio spans smartphones, televisions, and game consoles, as well as computing devices such as desktops, laptops, and tablets. Foxconn's major clients include Apple, Microsoft, Nintendo, Sony, and Xiaomi. In 2021, its revenue reached $181.9 billion, placing it 22nd on the Fortune Global 500.

While Foxconn owns factories in multiple countries—including Vietnam, India, Hungary, the Czech Republic, Mexico, and Brazil—the majority of its production capacity remains in mainland China. Foxconn is the country's largest private employer and exporter: in 2021, it employed more than one million workers and accounted for roughly 4 percent of China's total exports. Historically, its operations were concentrated in coastal provinces, beginning with its initial investment

in Shenzhen in 1988. By the mid-2000s, however, rising wages in the coastal region prompted Foxconn to consider inland expansion. Provincial governments across central and western China actively competed for Foxconn's investment, offering generous subsidies and infrastructure commitments in return for the promise of massive employment, exports, and potential spillovers.

The case of Zhengzhou in Henan province is especially salient. Despite Henan's negligible prior presence in the electronics industry, the provincial government assembled an unusually comprehensive subsidy package, including tax credits, export rebates, fixed investment subsidies, government-backed loans, and extensive infrastructure support. Foxconn signed the agreement in June 2010, and the speed and scale of implementation were extraordinary: the first plant began operating within one month, and two additional plants were completed in the following four months. By 2011, the Zhengzhou facilities employed over 100,000 workers and were producing more than half of the world's iPhones. At their peak, they expanded to more than 300,000 workers, earning Zhengzhou the moniker "iPhone City."

Several features make Foxconn's Zhengzhou investment ideally suited for studying agglomeration spillovers. First, the abruptness and unprecedented scale of the expansion provide a sharp and plausibly exogenous shock to local economic density. Second, Henan's lack of a preexisting electronics industry implies that the observed productivity changes are unlikely to reflect prior trends or endogenous agglomeration dynamics. Third, the province's intense competition with other localities underscores that the outcome was far from predetermined. Taken together, these features make the Zhengzhou case a rare quasi-natural experiment that allows us to estimate both the magnitude and the geographic reach of spillovers generated by a single superstar firm. In the empirical analysis below, we formally examine and provide supporting evidence for this exogeneity assumption.

2.2 Empirical Strategy

Our identification strategy exploits both the abrupt timing and the localized nature of Foxconn's 2010 entry. The key idea is to compare firm productivity across small geographic cells at varying distances from the new plants, before and after the entry. Because agglomeration forces are inherently spatial and decay with distance, variation in proximity provides a natural source of differential exposure to spillovers while broader temporal shocks are absorbed by fixed effects.

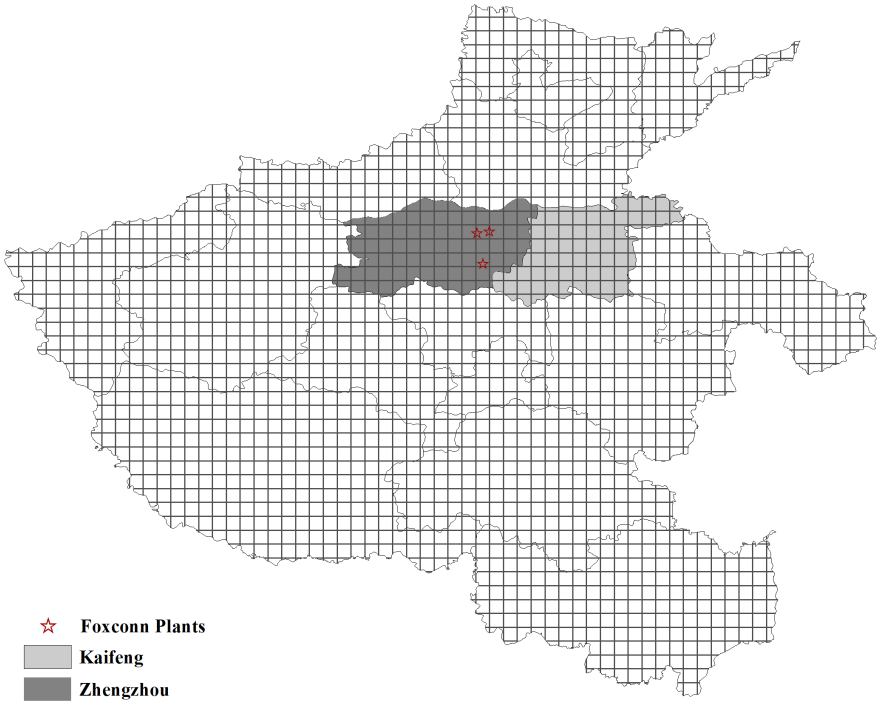


Figure 1: A Square Grid of Henan

To implement this strategy, we partition Henan into a uniform square grid. This approach avoids the modifiable areal unit problem associated with administrative boundaries, which may reflect political or economic considerations. Grids ensure neutral and fine-grained spatial units, allowing exposure to be measured continuously with respect to geographic distance. Each cell is $0.1^\circ \times 0.1^\circ$ (about 11 km $\times$ 11 km), which balances granularity with sufficient observations for panel estimation. Figure 1 shows the map of Henan with square grids.[6]

We then apply a difference-in-differences design, comparing changes in labor productivity between cells closer to Foxconn and those farther away, before and after the entry. Formally, we estimate:

$$\ln(y_{it}) = \beta POST10_t \times f(Dist_i) + \gamma POST10_t \times Z_i + fe_{c(i),t} + fe_i + \epsilon_{it}, \tag{1}$$

where $\ln(y_{it})$ is labor productivity in cell i at time t. $POST10_t$ is an indicator equal to one for years after 2010 and zero otherwise. $f(Dist_i)$ captures exposure to Foxconn, measured initially as the inverse of distance from grid i to the nearest Foxconn plant. Z_i includes pre-entry characteristics

[6]Details of constructing the square grid are described in Appendix A.

such as employment and capital stock in 2003. $fe_{c(i),t}$ are city-year fixed effects, absorbing all time-varying city-level shocks (e.g., political turnover, macroeconomic cycles, exchange rate changes). $c(i)$ denotes the city that cell i belongs to. fe_i are cell fixed effects, capturing all time-invariant cell characteristics.

In this reduced-form setting, β captures the strength of agglomeration forces, i.e. the extent to which productivity increases more in cells closer to Foxconn after 2010. The functional form of $f(Dist_i)$ embeds the spatial reach of these forces. Our baseline uses a simple inverse-distance measure for transparency (i.e., $InvDist_i$). We then refine this using an exponential decay specification, $e^{-\hat{\delta}Dist_i}$, which allows us to quantify the geographic reach of spillovers in a manner consistent with the structural model.

The identification assumption of our DD design is that, conditional on a full list of controls, the interaction term $Post10_t \times InvDist_i$ is uncorrelated with the error term. That is, absent Foxconn's entry, productivity in cells at different distances would have followed parallel trends. We provide evidence for this in Section 3.2 through an event study, controls for expectation effects and city-specific time trends, and placebo tests with simulated plant locations.

2.3 Data

Our empirical analysis combines several data sources. The primary dataset is the Annual Survey of Industrial Firms (ASIF) conducted by China's National Bureau of Statistics. ASIF covers all manufacturing firms above the designated size threshold, defined as five million yuan in annual sales before 2011 and twenty million yuan thereafter. The survey provides rich firm-level information, including names, addresses, employment, wages, output, sales, and exports. Using firm addresses, we employ the GaoDe Map API to obtain latitude–longitude coordinates and assign each firm to a grid cell.

We focus on two cities in Henan province, Zhengzhou and Kaifeng, which are shaded in gray in Figure 1. Together they span 110 grid cells. Combined with the firm-level data, we construct a balanced panel covering 2004–2009 and 2011–2013. The geocoding of firm addresses enables us to measure proximity continuously rather than relying on administrative boundaries. The long pre-treatment window and the construction of a balanced panel allow us to conduct rigorous tests of pre-trends and identification assumptions. Descriptive statistics are reported in Table 1.

Table 1: Descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max	Variable Definition
$loglprod$	990	6.120	0.724	2.371	7.864	logarithm of cell's average labor productivity (firm-employment-share weighted)
$logwage$	912	2.580	0.548	0.644	4.800	logarithm of cell's average wage (firm-employment-share weighted)
$distance$	990	50.131	29.872	2.942	124.039	The distance of a cell to its nearest Foxconn Plant
$EmpSh_{i,2003}$	990	0.176	0.368	0	2.849	cell's employment share to the total employment of Henan (100 percentage)
$FirmSh_{i,2003}$	990	0.197	0.314	0	1.868	cell's firm number share to the total number of firms in Henan (100 percentage)
$CapSh_{i,2003}$	990	0.183	0.450	0	2.786	cell's fixed capital share to the total amount of fixed capital in Henan (100 percentage)
$InputLink_{2003}$	990	0.314	0.425	0	2.267	cell's upstream level to the industry "manufacture of the Communication Equipment" (100 percentage)

Notes: Authors' own calculation.

To illustrate the sharp reallocation triggered by Foxconn's entry, Figure 2 plots the distribution of enterprises weighted by employment as a function of distance to the nearest Foxconn plant, in 2003 (pre-entry, left panel) and 2013 (post-entry, right panel). The x-axis measures distance in kilometers (up to 15 km). The bars show employment-weighted firm counts, and the dashed line depicts the smoothed density. In 2003, enterprise presence rose gradually with distance, peaking around 14–15 km, with no clustering near the future Foxconn sites. By 2013, the pattern had changed markedly: new peaks appear not only at 14–15 km, but also at 2-3 km and 7-8 km, consistent with a layered cluster closer to the Foxconn facilities.

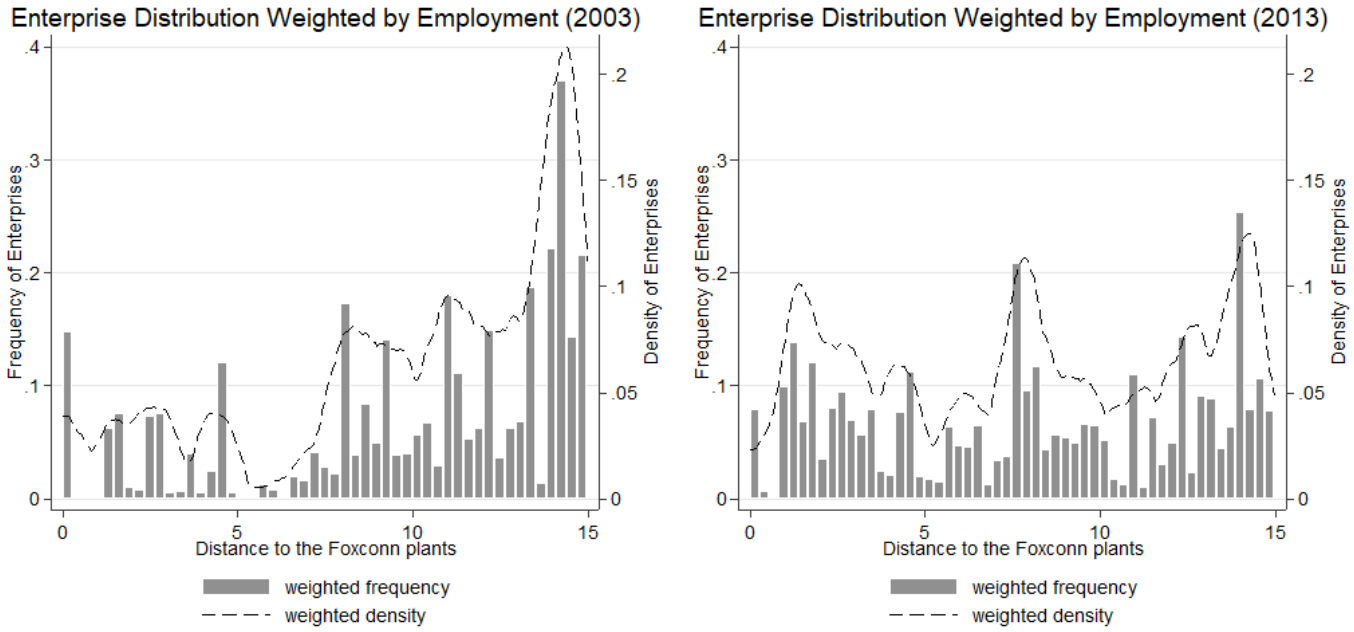


Figure 2: Employment Weighted Firm Distribution

3 Empirical Results

3.1 Productivity Spillovers

Table 2 reports estimates of equation (1) under alternative specifications. Column (1) includes only the difference-in-differences term, $Post10_t \times InvDist_i$, with cell and year fixed effects. Column (2) adds initial cell employment shares, interacted with $Post10_t$, to allow for differential impacts of pre-entry employment composition. Column (3) further includes initial firm and capital shares, also interacted with $Post10_t$. Columns (4)–(6) parallel columns (1)–(3), but replace year fixed effects with city-by-year fixed effects, thereby absorbing all time-varying city-level shocks. Our preferred specification is reported in column (6), which combines the full set of controls with the most stringent fixed effects. Standard errors are calculated using the heteroskedasticity- and autocorrelation-consistent (HAC) estimator of Conley (1999), which allows for both spatial correlation across nearby cells and serial correlation over time.

In all specifications reported in Table 2, the estimated coefficients on the difference-in-differences term (δ) are positive and statistically significant, indicating that labor productivity in cells closer to Foxconn grew faster after its entry into Henan. Across columns (1)–(3), the point estimates are

stable, ranging from 3.75 in column (2) to 4.204 in column (1). In columns (4)–(6), which introduce city-by-year fixed effects, the estimates remain positive and significant but are roughly half as large, suggesting that omitting city-level time-varying shocks may lead to overestimation of spillover effects. Column (6), our preferred specification, yields an estimate of $\delta = 2.189$, significant at the 1 percent level. The effect is also economically meaningful: moving a location from 100 km to 10 km away from Foxconn implies an increase in labor productivity of about 0.197 log points, or roughly 20 percent. Panel B reports the corresponding marginal effects. To aid interpretation, we compare average treatment effects at distances of 20 km, 50 km, and 100 km, relative to 10km.[7]

In the baseline specification, labor productivity is positively and significantly associated with initial cell employment share, while it is negatively and significantly associated with initial cell capital share. Taken together with the main estimates, these results establish a clear pattern: Foxconn's entry generated sizable and geographically concentrated productivity gains in nearby areas, even after accounting for pre-existing differences in local employment and capital intensity.

3.2 Validity of the DD Design

Our identification strategy exploits differential exposure to Foxconn's plants across grid cells at varying distances, conditional on city-year shocks and cell fixed effects. This requires that no unobserved shocks differentially affected cells within the same city as a function of their distance to Foxconn around the time of entry. To assess this assumption, we conduct a series of validity checks, including tests for pre-trends, controls for expectation effects, an event study, and two placebo tests.

Pre-existing Trends. A first concern is that pre-existing productivity trends might correlate with distance to Foxconn's eventual locations. To address this, we regress pre-2010 labor productivity on distance to Foxconn's plants, controlling for initial labor, firm, and capital shares as well as city-year fixed effects.[8] Column (1) of Table 3 reports the results. We find no statistically significant relationship between pre-entry productivity and distance to Foxconn, providing evidence against differential pre-trends.

Dynamic Treatment Effects. The second potential concern is that firms may have adjusted

[7]The sample mean distance is 50.1 km, and the maximum distance is 124.0 km.

[8]Cell fixed effects are excluded because they would absorb the distance variable and the initial controls.

Table 2: Baseline Results

Dep. Var:	log labor productivity of cells (labor-share weighted)					
	(1)	(2)	(3)	(4)	(5)	(6)
$Post10_t \times InvDist_i$	4.204***	3.750***	3.943***	2.179***	2.025***	2.189***
	(1.094)	(1.033)	(1.058)	(0.480)	(0.480)	(0.506)
$Post10_t \times EmpSh_{i,2003}$		0.408***	0.554***		0.272***	0.848***
		(0.086)	(0.178)		(0.060)	(0.185)
$Post10_t \times FirmSh_{i,2003}$			0.198			-0.300**
			(0.165)			(0.145)
$Post10_t \times CapSh_{i,2003}$			-0.291***			-0.340***
			(0.107)			(0.090)
Year FE	YES	YES	YES			
Cell FE	YES	YES	YES	YES	YES	YES
City-Year FE				YES	YES	YES
HAC Spatial Correction	YES	YES	YES	YES	YES	YES
Observations	990	990	990	990	990	990
R-squared	0.673	0.683	0.684	0.740	0.744	0.748
	Panel B: Marginal Effects					
10km to 20km	0.210	0.188	0.197	0.109	0.101	0.109
10km to 50km	0.336	0.300	0.315	0.174	0.162	0.175
10km to 100km	0.378	0.338	0.355	0.196	0.182	0.197

Notes: Panel A reports estimates from our baseline regressions using a strongly balanced panel of cells in Zhengzhou and Kaifeng, defined as cells with non-missing observations in every year from 2004 to 2013. We exclude 2010 because the ASIF data for that year are unreliable. Standard errors are computed using the Conley (1999) heteroskedasticity- and autocorrelation-consistent estimator, which allows for spatial correlation across cells within 50 km and serial correlation across adjacent years. Columns (1)–(3) include cell and year fixed effects, while columns (4)–(6) replace year fixed effects with city-by-year fixed effects, thereby absorbing all city-level time-varying shocks. Panel B reports the corresponding marginal effects. Robust standard errors are reported in parentheses, with ***, **, and * denoting significance at the 1, 5, and 10 percent levels, respectively.

Table 3: Validity of the DD Design

	Pre-Trend (1)	Expectation (2)	Year-Trend (3)
$InvDist_i$	-0.600		
	(0.409)		
$EmpSh_{i,2003}$	-1.118***		
	(0.175)		
$FirmSh_{i,2003}$	0.590***		
	(0.192)		
$CapSh_{i,2003}$	0.411***		
	(0.080)		
$Year2004 \times InvDist_i$			-0.155
			(0.653)
$Year2005 \times InvDist_i$			-0.757
			(0.626)
$Year2006 \times InvDist_i$			0.164
			(0.485)
$Year2007 \times InvDist_i$		-0.492	-0.741**
		(0.414)	(0.295)
$Year2008 \times InvDist_i$		-0.261	-0.510**
		(0.443)	(0.250)
$Year2009 \times InvDist_i$		0.249	
		(0.459)	
$Year2011 \times InvDist_i$			2.305***
			(0.292)
$Year2012 \times InvDist_i$			2.120***
			(0.298)
$Year2013 \times InvDist_i$			1.142**
			(0.486)
$Post10_t \times InvDist_i$		2.105***	
		(0.614)	
$Post10_t \times EmpSh_{i,2003}$		0.848***	0.848***
		(0.185)	(0.160)
$Post10_t \times FirmSh_{i,2003}$		-0.300**	-0.300**
		(0.145)	(0.119)
$Post10_t \times FirmSh_{i,2003}$		-0.340***	-0.340***
		(0.090)	(0.075)
Cell FE		YES	YES
City-Year FE	YES	YES	YES
HAC Spatial Correction	YES	YES	YES
Observations	660	990	990
R-squared	0.438	0.748	0.749

Notes: All regressions are estimated on a strongly balanced panel with city-year fixed effects and Conley (1999) HAC standard errors (spatial cutoff = 50 km; temporal lag = 1 in columns (1)–(2), 0 in column (3)). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Column (1) tests for pre-trends in labor productivity growth (2004–2009) by regressing productivity on inverse distance, initial agglomeration variables, and city-year fixed effects. Column (2) examines expectation effects by interacting inverse distance with year dummies over 2004–2013, capturing potential anticipation in the three years before Foxconn's entry. Column (3) reports a standard event-study specification, interacting inverse distance with year dummies (2004–2013) and using 2009 as the reference year.

behavior in anticipation of Foxconn's entry, leading to differential dynamics across cells prior to 2010. To test for such expectation effects, we augment the baseline specification by interacting inverse distance with year dummies for 2007–2009. Column (2) of Table 3 reports the results. The coefficients on these terms are small and statistically insignificant, while the estimate of δ remains positive and significant, indicating no evidence of anticipatory effects.

We further assess dynamics using an event-study specification that replaces the post-entry interaction with a full set of year-by-distance interactions, $Year_t \times InvDist_i$. Column (3) of Table 3 and Figure 3 present the results. In the pre-entry period, the coefficients are either insignificant or negative and small in magnitude. Following Foxconn's entry, the coefficients turn positive, statistically significant, and substantially larger. This pattern indicates the absence of differential pre-trends and provides strong support for the parallel-trends assumption underlying our design.

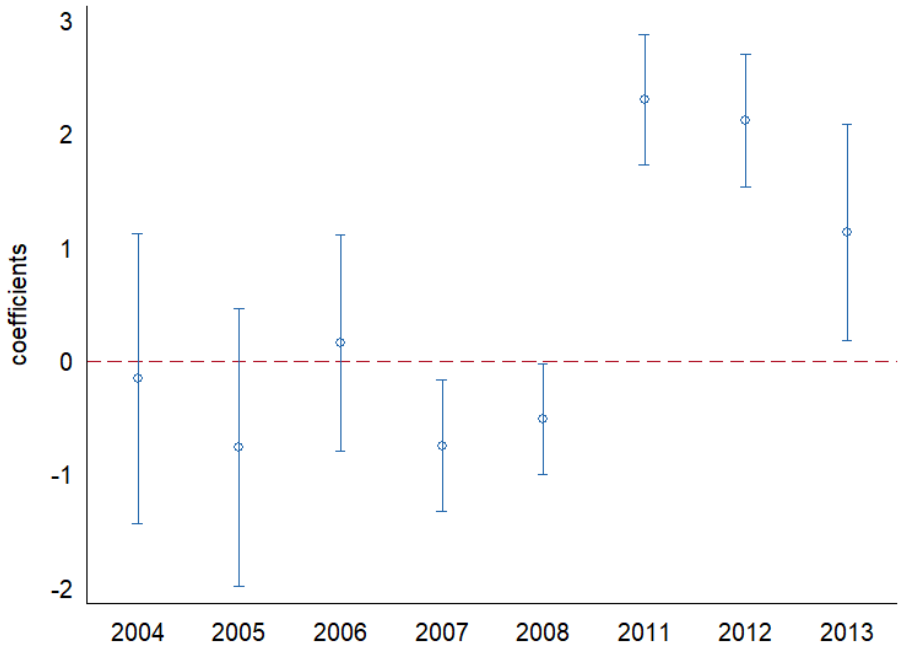


Figure 3: Event Study of Productivity Effects Around Foxconn's Entry (95% Con. Interval)

Notes: The figure plots coefficients from regressions interacting inverse distance with year dummies for 2004–2013, using 2009 as the reference year.

Placebo Tests. We conduct two placebo exercises to further assess the validity of our design. First, we assume Foxconn entered prior to 2010 and re-estimate the baseline specification with placebo entry years $Y \in 2005, 2006, 2007, 2008$, replacing $Post10_t \times InvDist_i$ with $PostY_t \times InvDist_i$ and restricting the sample to 2004–2009. Since Foxconn had not yet entered, the coeffi-

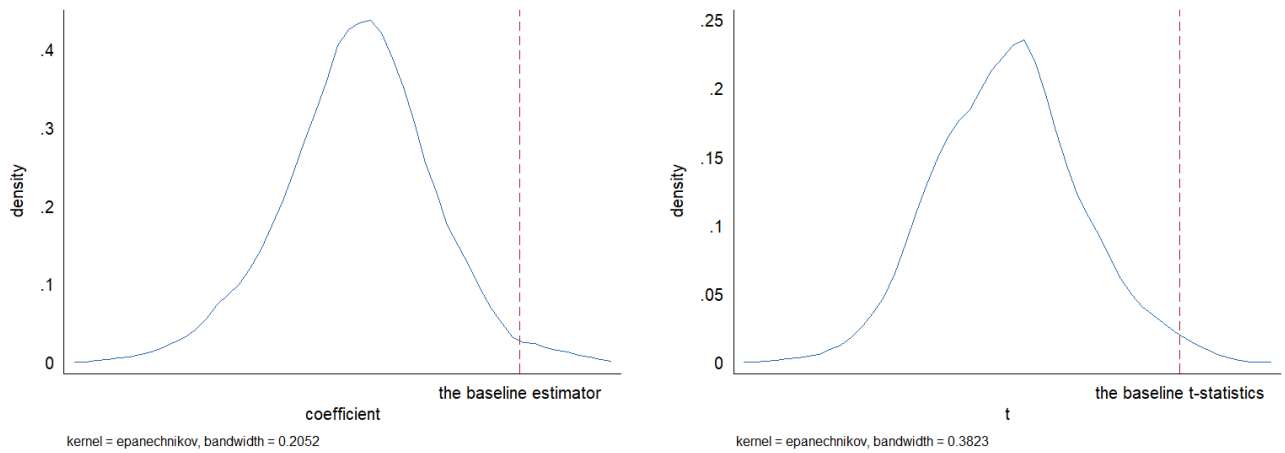
Table 4: Placebo Test by Changing the Entry Year

VARIABLES	Year 2005 (1)	Year 2006 (2)	Year 2007 (3)	Year 2008 (4)
$Post05_t \times InvDist_i$	-0.051			
	(0.608)			
$Post06_t \times InvDist_i$		0.348		
		(0.479)		
$Post07_t \times InvDist_i$			-0.007	
			(0.406)	
$Post08_t \times InvDist_i$				0.250
				(0.377)
Cell FE	YES	YES	YES	YES
City-Year FE	YES	YES	YES	YES
Observations	660	660	660	660
R-squared	0.804	0.805	0.806	0.805

Notes: Each column reports placebo regressions replacing Foxconn's entry year with 2005–2008 in turn, using data from 2004–2009. The dependent variable is labor productivity growth across cells. All regressions include interactions of $PostT$ with initial cell employment, capital, and firm shares (relative to provincial totals), as well as city-by-year fixed effects. Standard errors are computed using the Conley (1999) HAC estimator, with a 50 km spatial cutoff and one-period serial correlation. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

cients on these placebo terms should be insignificant and small in magnitude. Columns (1)-(4) of Table 4 confirm this expectation.

Second, we randomly reassign each cell's distance to Foxconn's plants and re-estimate the baseline specification 1,000 times. Figure 4 plots the resulting distribution of coefficients and t-statistics. The placebo estimates cluster tightly around zero, while the true estimate lies well outside this distribution. Together, these placebo tests provide additional evidence that our findings are not driven by spurious pre-trends or random spatial correlations, but rather by Foxconn's actual entry.



(a) (b)

Figure 4: Placebo Tests

Notes: This figure reports results from the placebo test in which distances to Foxconn's plants are randomly reassigned across cells. Panel (a) shows the distribution of estimated coefficients, and Panel (b) shows the corresponding t-statistics. In both panels, placebo estimates cluster tightly around zero, while the true estimate lies far in the tail, underscoring that the baseline results are not driven by random spatial correlation.

3.3 Robustness

Having established the validity of our identification strategy, we next assess the robustness of the results to several potential threats. First, the estimated effects may reflect longer working hours rather than genuine productivity improvements. Second, inference may be distorted if standard errors do not fully account for spatial and serial correlation. Third, the survey's reporting threshold could affect the composition of firms in the sample, potentially biasing estimates. Fourth, the findings may depend mechanically on the assumed functional form of spatial decay. Finally, we examine whether other confounding factors could be driving the results.

Working Hour. A potential concern is that the observed increase in output per worker may reflect longer working hours rather than genuine productivity improvements from Foxconn's entry. This possibility is partly mitigated by the inclusion of city-by-year fixed effects in our baseline specification, which absorb common shocks to working hours across cities and years. To further assess this concern, we use public provincial data from the China Family Panel Studies (CFPS), a nationally representative biennial survey launched in 2010 that records individual working hours across a wide range of occupations.

Table 5: Robustness of the Significance of the Key Parameter

	HAC				Cluster at the County level
	(1)	(2)	(3)	(4)	(5)
Distance Cutoff (km)	25	75	50	50	
Time Lag	1	1	2	3	
	$\delta = 2.189$				
T-statistics	4.396	4.495	3.893	3.462	1.833

Notes: This table reports robustness of heteroskedasticity-consistent standard errors for the baseline estimate of δ. Columns (1)–(2) vary the spatial cutoff for the Conley (1999) HAC estimator (25 km and 75 km, respectively). Columns (3)–(4) vary the temporal lag (2 and 3 periods). Column (5) reports standard errors clustered at the county level. All regressions include city-by-year fixed effects. t-statistics are reported for each regression.

The CFPS data for Henan show a decline, rather than an increase, in average working hours among manufacturing workers over the post-entry period, from 9.17 hours per day in 2010 to 7.40 hours in 2014. Over the same period, average hourly wages rose sharply from ¥4.10 to ¥16.00. These trends suggest that rising productivity was accompanied by shorter working hours and higher wages, making it unlikely that our results are driven by longer workdays in Foxconn-adjacent areas. We therefore conclude that extended working hours do not confound our estimates of the productivity effects of Foxconn's entry.

Standard Errors. The statistical significance of our baseline estimate of δ is robust to alternative inference methods. Table 5 reports standard errors and t-statistics under different approaches. Columns (1) and (2) vary the spatial cutoff for the Conley (1999) HAC estimator (25 km and 75 km, respectively), leaving standard errors virtually unchanged. Columns (3) and (4) increase the temporal lag (to 2 and 3 periods), which raises the standard errors and correspondingly lowers the t-statistics, as expected when allowing for longer serial correlation. Column (5) clusters at the county level, producing substantially larger standTogether, these results confirm that our baseline findings are robust to alternative inference procedures.ard errors, yet the estimate of δ remains statistically significant.

Survey Threshold. The ASIF survey covers all manufacturing firms above a size threshold that increased from 5 million Yuan before 2011 to 20 million Yuan thereafter. If smaller firms are less productive, the higher cutoff could mechanically raise measured labor productivity after 2011. To address this concern, we re-estimate the baseline specification using two alternative

Table 6: Robustness

	Survey Threshold		Spatial Decay			Other Confounding Factors		
	unbalanced	balanced	$\alpha = 0.5$	$\alpha = 1.5$	$\hat{\delta} = 0.1099$	ZAEZ	Center	ZAEZ&Center
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Post10_t \times InvDist_i$	2.122***	2.121***	1.320***	3.786***	0.711***	3.491***	2.218***	3.639***
	(0.534)	(0.525)	(0.331)	(0.189)	(0.896)	(0.510)	(0.523)	(0.570)
$Post10_t \times InvDist_Center_{i,2003}$							-0.291	-0.803
							(1.860)	(1.978)
Cell FE	YES	YES	YES	YES	YES			
City-Year FE	YES	YES	YES	YES	YES			
Observations	949	801	990	990	990	936	990	936
R-squared	0.725	0.726	0.748	0.747	0.747	0.757	0.748	0.757

Notes: This table reports robustness checks for the baseline specification. Columns (1)–(2) use harmonized survey standards by excluding firms with main business revenue below 20 million RMB in all years; Column (1) uses the unbalanced panel and Column (2) the balanced panel. Columns (3)–(4) vary the spatial decay rate to 0.5 and 1.5, respectively, while Column (5) applies the exponential decay function. Columns (6)–(7) address potential location-specific bias: Column (6) excludes cells in the Zhengzhou Airport Economy Zone, and Column (7) controls for distance to the city center (defined as the cell with the highest employment density in 2003). Column (8) includes both adjustments. All regressions include the same control variables as the baseline (cell employment, fixed capital, and firm shares relative to the provincial total), as well as city-by-year and cell fixed effects. Standard errors are computed using the Conley (1999) HAC estimator with a 50 km spatial cutoff and one-period serial correlation. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

samples: (i) an unbalanced panel and (ii) a balanced panel applying the 20 million yuan cutoff uniformly across all years. Columns (1) and (2) of Table 6 show that both estimates remain statistically significant and quantitatively similar to the baseline, ruling out compositional bias from the survey threshold change.

Varying Spatial Decay Rates. Our baseline specification assumes that spillovers from Foxconn decay with distance according to an inverse-distance function. As a robustness check, we consider alternative functional forms. Specifically, we replace $Post10_t \times InvDist_i$ with $Post10_t \times InvDist_i^{\alpha}$ for $\alpha \in 0.5, 1.5$, and with $Post10_t \times e^{-\delta Dist_i}$ using $\hat{\delta} = 0.1099$, the decay parameter estimated in Section 5. The cases with $\alpha = 0.5$ and $\alpha = 1.5$ correspond to slower and faster spatial decay, respectively, while the exponential form corresponds directly to the structural model. Columns (3) (5) of Table 6 report the results. In all cases, the estimated effects remain positive and statistically significant, confirming that our findings are not sensitive to the assumed functional form of spatial decay. We next examine whether other confounding factors could account for the observed spillover effects.

Other Potential Explanations. One potential concern is that our results reflect preferential policies associated with the Zhengzhou Airport Economic Zone (ZAEZ), which was established by the Henan provincial government with central approval at the same time Foxconn entered. Like other special economic zones in China, the ZAEZ offered preferential tax rates, export subsidies, and improved infrastructure. If these policies disproportionately attracted large and pro-

ductive firms, our estimates could capture the effects of the ZAEZ rather than spillovers from Foxconn. To address this, we re-estimate the baseline specification excluding all cells overlapping with the ZAEZ. Column (6) of Table 6 shows that the coefficient on $Post10_t \times InvDist_i$ remains positive and statistically significant, suggesting that the results are not driven by ZAEZ-specific policies.

A second concern is that the observed productivity gains may be driven by other large manufacturing firms rather than Foxconn itself. To test this, we identify the manufacturing center prior to Foxconn's entry as the cell with the largest manufacturing employment in 2003. We then add an interaction term, $Post10_t \times InvDist_Center_{i,2003}$, to capture potential spillovers from this pre-existing center. Column (7) of Table 6 reports that the coefficient on this term is negative and statistically insignificant, while the coefficient on $Post10_t \times InvDist_i$ remains positive and significant.

Finally, column (8) of Table 6 includes both adjustments simultaneously—excluding ZAEZ cells and controlling for proximity to the pre-existing manufacturing center. The coefficient of interest remains positive and significant, confirming that the estimated spillover effects are not confounded by either ZAEZ policies or other large firms.

Summary of Robustness Checks: Across a wide range of robustness exercises, the estimated spillover effects remain positive and statistically significant. We show that the results are not driven by longer working hours, alternative inference procedures, or changes in the ASIF survey threshold. The findings are also robust to alternative functional forms of spatial decay, to excluding the Zhengzhou Airport Economic Zone, and to control for pre-existing manufacturing centers. Taken together, this body of evidence strengthens confidence that the estimated productivity gains reflect genuine agglomeration spillovers from Foxconn's entry rather than confounding factors or artifacts of the empirical design.

3.4 Input-output Linkages, Labor Market, and Firm Entry

Having established baseline evidence of productivity gains in areas proximate to Foxconn's plants, we next examine the channels through which these spillovers operate. Classic theories dating back to Marshall (1890) suggest that geographic concentration can boost productivity through input sharing, labor market pooling, and knowledge spillovers. In the context of Foxconn's

Zhengzhou plants, two channels are especially salient. First, as a large-scale export assembler, Foxconn generates strong demand for upstream inputs, creating scope for productivity spillovers to proximate suppliers. Second, Foxconn's massive workforce directly affects local labor markets through higher labor demand, wage adjustments, and changes in the dynamics of firm entry and industry employment.

Following the approach of Greenstone, Hornbeck, and Moretti (2010), we examine whether Foxconn's impact was stronger in locations with industries that were initially positioned to supply Foxconn (input–output linkage channel) and whether nearby areas experienced shifts in wages, firm entry, and industry employment consistent with labor market effects. Together, these results provide reduced-form evidence on the mechanisms through which Foxconn generated first-order spillovers in the surrounding economy.

Input-Output Linkage. Foxconn is primarily an export-oriented assembler, selling finished electronics directly to overseas buyers. This implies that local downstream industries (customers of Foxconn) were minimal, so first-order spillovers would more likely occur upstream, via Foxconn's demand for intermediate inputs. In other words, industries supplying components and materials to Foxconn's plants would be expected to expand their output and productivity in response to Foxconn's entry, consistent with Marshall's input-sharing mechanism. Spillover effects should thus be strongest in areas that had a higher initial presence of Foxconn's upstream linkages (industries closely tied to electronics assembly).

To test this hypothesis, we construct a measure of upstream exposure for each grid cell, $InputLink_{i,2003}$, which captures the extent to which firms in cell i were potential suppliers to Foxconn's industry prior to its entry. Specifically, using the 2007 National Input–Output Table (National Bureau of Statistics of China), we compute the share of Foxconn's three-digit industry's (i.e., manufacture of communication equipment) intermediate expenditures that goes to each industry j, denoted η_j. We then weight these by the employment share of industry j in cell i in the pre-entry year 2003 ($share_{ij,2003}$) and sum over all industries to get:

$$InputLink_{i,2003} = \sum_{j=1}^{J} share_{ij,2003} \times \eta_j, \tag{2}$$

which ranges higher for locations that initially had a greater concentration of Foxconn-supplying industries. Intuitively, a cell with a large footprint of electronics component manufacturers (for

example) would have a high $InputLink_{i,2003}$, indicating that it was well positioned to supply inputs to Foxconn.

We then incorporate this index into a difference-in-differences specification to see if Foxconn's proximity had a larger impact on such areas. In particular, we estimate:

$$\begin{aligned}\ln(y_{it}) =& \beta_1 POST10_t \times InvDist_i + \beta_2 POST10_t \times InvDist_i \times InputLink_{i,2003} + \\ & \beta_3 POST10_t \times InputLink_{i,2003} + \gamma POST10_t \times Z_i + fe_{c(i),t} + fe_i + \epsilon_{it}.\end{aligned} \tag{3}$$

Here $\ln(y_{it})$ is the labor productivity in grid cell i at time t, and $InvDist_i$ is our baseline inverse-distance measure of Foxconn exposure. The term $InputLink_{i,2003}$ is interacted with the post-entry period and proximity to Foxconn to allow the spillover effect to vary with a cell's upstream linkage to Foxconn's industry. The coefficient β_2 on the triple interaction $POST10 \times InvDist \times InputLink$ captures whether productivity gains from Foxconn's entry were stronger in locations that initially had greater upstream connections to Foxconn's industry.

Column (1) of Table 7 reports the results. Consistent with the input–output linkage channel, we find β_2 to be positive and statistically significant. In other words, the productivity spillover effect of Foxconn's entry is significantly larger in grid cells that had a higher pre-existing share of Foxconn-related supplier industries. This supports the hypothesis that Foxconn generated upstream input-demand spillovers: areas with a substantial supplier base experienced a stronger boost, as those firms likely expanded production to meet Foxconn's intermediate input needs.

Firm Entry. As pointed out by Greenstone et al. (2010), if productivity spillovers are larger than the increase in the cost of local inputs, increasing profitability induces entry of new firms. So we examine the effects of Foxconn's entry on firm dynamics and labor costs as indirect evidence of spillovers. While entry is not itself a primitive spillover channel, it reflects how first-order productivity gains translate into firm dynamics. Similarly, wages should rise in areas closer to Foxconn if labor demand increases due to agglomeration spillovers.

To test the prediction for firm entry, we collapse the panel into two periods: before Foxconn's entry (2006–2009) and after Foxconn's entry (2011–2013). We then computed the cell-level entry rates for each period. Specifically, the post-entry rate for grid cell i is defined as

$$E_{i,after} = \frac{\text{NewFirms}_{i,2011-2013}}{\text{BaselineFirms}_{i,2009}},$$

where the numerator is the number of new firms entering cell i between 2011 and 2013, and the denominator is the number of firms in 2009.

Similarly, a parallel measure for firm entry rate is constructed for the pre-entry period (2006–2009):

$$E_{i,before} = \frac{\text{NewFirms}_{i,2006-2009}}{\text{BaselineFirms}_{i,2006}}.$$

We then estimate the following specification:

$$E_{i,t} = \beta POST10_t \times InvDist_i + \gamma POST10_t \times Z_i + fe_{c(i),t} + fe_i + \epsilon_{it}, \text{where } t = \{before, after\}. \quad (4)$$

Column (2) of Table 7 reports the results. Consistent with the prediction, the coefficient on $POST10_t \times InvDist_i$ is positive and statistically significant, indicating higher entry rates in locations closer to Foxconn.

Local Wages. Agglomeration theories predict that positive productivity shocks can lead to increased factor demand, which in turn may bid up wages. In our context, Foxconn's arrival represents a large demand shock for labor, both through its own hiring and through spillover-fueled expansion of other firms. To test the wage prediction, we replace the dependent variable in the baseline specification with the log of the average wage in grid cell i, weighted by firm employment in year t. Column (3) of Table 7 presents the results. The estimated coefficient on the interaction term is again positive and statistically significant, implying that wages rose more sharply in cells proximate to Foxconn's plants than in more distant locations.

Industry Employment. We further analyze how the opening of Foxconn factories affects the employment of Foxconn's two-digit industry. We expect to see that the employment share of Foxconn's two-digit industry increases more in the grid cells closer to Foxconn factories than those further away. To test it, we replace the dependent variable in the baseline specification with the employment share of Foxconn's two-digit industry in grid cell i in year t. Column (4) of Table 7 reports the estimation results, which are consistent with our conjecture.

Table 7: Other Evidence

	IO Linkages (1)	Entry (2)	Wage (3)	Within Industry Employment (4)
$Post10_t \times InvDist_i$	1.034	4.357***	1.839***	0.062**
	(0.645)	(1.234)	(0.496)	(0.031)
$Post10_t \times InputLink_{i,2003}$	-0.065			
	(0.068)			
$Post10_t \times InputLink_{i,2003} \times InvDist_i$	1.995**			
	(0.777)			
Cell FE	YES	YES	YES	YES
City-Year FE	YES	YES	YES	YES
Observations	990	178	912	990
R-squared	0.749	0.598	0.660	0.367

Notes: This table tests alternative outcomes related to spillovers. Column (1) examines labor productivity growth across cells with varying input linkages to electronics. Input linkages are constructed using the 2007 China Input–Output Table: we compute the intermediate input share of each industry to "manufacture of communication equipment," weight these by industry employment shares within a cell in 2003, and aggregate to obtain $InputLink_{i,2003}$. The regression includes the resulting triple interaction term. Column (2) uses the two-period entry rate as the dependent variable, defined as the number of entrants relative to the stock of firms in 2006 (pre-period, 2006–2009) and in 2009 (post-period, 2011–2013). The sample is restricted to firms with revenue above 20 million RMB and cells with balanced production information. Columns (3) and (4) examine wage growth and employment growth in the electronics industry (2-digit CIC) across cells. All regressions include the same controls and fixed effects as the baseline and apply the Conley (1999) HAC correction. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4 Model

Guided by the reduced-form evidence, we develop a parsimonious quantitative urban model that features agglomeration externalities. In particular, in the model, the spatial distribution of economic activity within a city is shaped by two opposing forces: an agglomeration force, operating through production externalities, and a dispersion force, arising from the inelastic supply of land.

The city is embedded in a larger economy and consists of a set of discrete locations indexed by $i = 1, 2, \ldots, N$, with the outside economy denoted by 0. The city is populated by an endogenous measure L of workers, who are perfectly mobile between the city and the outside economy. Each worker receives a reservation utility $\overline{U}$ if employed in the outside economy.

Prior to moving, workers decide whether to enter the city. Upon entry, they draw idiosyncratic

utility shocks for each location and choose the location that maximizes utility. In each location, a unique differentiated good is produced. Goods are traded costlessly both within the city and with the outside economy, ensuring a common goods market. Locations may differ in productivity, amenities, and housing supply.

Workers. A worker o in location i consumes a composite tradable good C_{io} and housing H_{io}. Preferences take the Cobb-Douglas form:

$$U_{io} = z_{io} \left(\frac{C_{io}}{\mu} \right)^{\mu} \left(\frac{H_{io}}{1-\mu} \right)^{1-\mu}, \tag{5}$$

where z_{io} is an idiosyncratic utility shock specific to worker o in location i, and $\mu \in (0,1)$ is the expenditure share on the composite tradable good.

The composite tradable good aggregates varieties produced in all locations (including the outside economy, indexed by 0) through a CES aggregator:

$$Q = \left[\sum_{i=0}^{N} \alpha_i^{\frac{1}{\sigma}} q_i^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{6}$$

where $\sigma > 1$ is the elasticity of substitution, q_i is the quantity of good i, and α_i is a demand shifter. With costless trade, the price index P of the composite goods P is identical across locations. Let r_i denote the rental price of housing in location i.

After moving, workers observe realizations of idiosyncratic shocks z_{io}, drawn independently from a Fréchet distribution

$$F_i(z) = e^{-B_i z^{-\epsilon}}, \tag{7}$$

where $B_i > 0$ scales the average attractiveness of location i, and $\epsilon > 0$ governs the dispersion of shocks. The indirect utility of worker o in location i is then

$$u_{io} = z_{io} \frac{v_i}{P^{\mu} r_i^{1-\mu}}, \tag{8}$$

where v_i denotes worker income in location i.

The probability that a worker chooses location i is:

$$s_i = \frac{B_i(v_i r_i^{\mu-1})^{\epsilon}}{\sum_{k=1} B_k(v_k r_k^{\mu-1})^{\epsilon}}. \tag{9}$$

This follows from the Fréchet structure: since indirect utility is monotonic in z_{io}, the maximum across locations is Fréchet-distributed, yielding closed-form choice probabilities.[9]

Population mobility ensures that expected utility from moving to the city equals the reservation utility in the outside economy:

$$\gamma \left[\sum_{k=1} B_k(v_k r_k^{\mu-1} P^{-\mu})^{\epsilon} \right]^{\frac{1}{\epsilon}} = \overline{U}, \tag{10}$$

where $\gamma = \Gamma(\frac{\epsilon}{\epsilon-1})$, and $\Gamma(\cdot)$ is the Gamma function.

Production. Each location i produces a unique differentiated good under constant returns to scale and perfect competition. The production technology in location i is:

$$y_i = A_i l_i, \tag{11}$$

where y_i denotes output, A_i is the productivity of location i, and l_i is labor input.

Under perfect competition, firms price at marginal cost. Since labor is the sole input, the price of the good produced in location i is

$$p_i = \frac{w_i}{A_i}, \tag{12}$$

where w_i is the local wage rate.

Agglomeration. Productivity in one location depends on its own productivity fundamentals and externalities from nearby economic activity. Specifically, we assume that productivity rises with the density of surrounding workers, but these benefits diminish with geographic distance. For-

[9] Each worker chooses the location delivering the highest utility. With Fréchet shocks, the resulting choice probabilities take the logit form in equation (9).

mally, productivity in location i is given by

$$A_i = \underbrace{\overline{A}_i}_{\text{productivity fundamental}} \times \left(\underbrace{\sum_{k=1}^{N} e^{-\delta d_{ik}} \frac{L_k}{M_k}}_{\text{neighboring worker density}} \right)^{\lambda}, \tag{13}$$

where $\overline{A}i$ denotes the location-specific fundamental productivity, $\frac{L_k}{M_k}$ is the worker density in location k, and d_{ik} is the distance between i and k. The parameter $\delta > 0$ governs the rate of spatial decay, so that more distant locations contribute less to local productivity, while $\lambda > 0$ captures the elasticity of productivity with respect to neighboring density, i.e., the strength of agglomeration spillovers.

Aggregation. Housing market clearing requires that landlord revenue equals the total housing expenditure of workers in each location:

$$r_i H_i = (1 - \mu) v_i L_i \tag{14}$$

where r_i is the rental price of housing, H_i is the aggregate housing demand, and $(1 - \mu)v_i L_i$ is the fraction of worker income spent on housing.

Total income in location i consists of both labor earnings and rents redistributed to workers as lump-sum transfers from landlords:

$$v_i L_i = w_i L_i + r_i H_i, \tag{15}$$

where w_i denotes the local wage. Equation (15) ensures internal consistency: the income workers allocate to consumption of goods and housing equals the sum of their own wages and housing rents returned as transfers.

Product market clearing. Product market clearing requires that total labor income in each location equals the value of goods demanded from that location across the city:

$$w_i L_i = \pi_i \sum_{k=1}^{N} w_k L_k, \tag{16}$$

where $w_i L_i$ is the total production value in location i, and π_i denotes the share of citywide expenditure allocated to goods produced in i. Note that equation (16) already incorporates the role of the larger economy ($i = 0$). The detailed derivation is provided in Appendix B.1.[10]

The citywide trade share π_i is determined by CES preferences as

$$\pi_i = \frac{\alpha_i (\frac{w_i}{A_i})^{1-\sigma}}{\sum_{k=1}^{N} \alpha_k (\frac{w_k}{A_k})^{1-\sigma}}, \tag{17}$$

where α_i captures demand shifters (such as amenity-driven preference weights), $\sigma > 1$ is the elasticity of substitution across varieties, and $\frac{w_i}{A_i}$ reflects the unit cost of production in location i. Equation (16) therefore ensures that each location's wage bill is proportional to its relative competitiveness, as captured by π_i.

We next derive labor supply and demand in each location. Starting from the housing market clearing condition (14), the income identity (15), and the location choice probability (9), labor supply in location i can be written as

$$L_i^{1+(1-\mu)\epsilon} = w_i^{\mu\epsilon} \widetilde{B}_i \frac{\sum_{k=1}^{N} L_k}{\sum_{k=1}^{N} \widetilde{B}_k w_k^{\mu\epsilon} L_k^{-(1-\mu)\epsilon}}, \tag{18}$$

where $\widetilde{B}_i \equiv B_i H_i^{(1-\mu)\epsilon}$ is the adjusted amenity of location i.

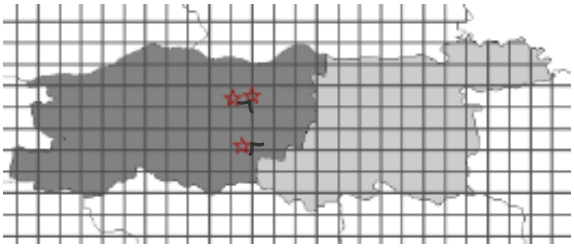
On the demand side, combining the product market clearing condition (16) with the CES expenditure shares (17), labor demand in location i is given by

$$L_i = w_i^{-\sigma} \left(\widetilde{A}_i\right)^{\sigma-1} \frac{\sum_{k=1}^{N} w_k L_k}{\sum_{k=1}^{N} w_k^{1-\sigma} \left(\widetilde{A}_k\right)^{\sigma-1}}, \tag{19}$$

where $\widetilde{A}_i \equiv A_i \alpha_i^{\frac{1}{\sigma-1}}$ is the adjusted productivity of location i. The detailed algebraic derivation for (18) and (19) is provided in Appendix B.2.

Equilibrium. Given model parameters $\{\mu, \sigma, \epsilon, \delta, \lambda\}$, the reservation utility level in the larger economy $\overline{U}$, and the set of exogenous location characteristics $\{\alpha_i, \overline{A}_i, B_i, H_i, M_i\}$, an equilibrium

[10] Formally, total labor income in location i equals the expenditure on good i from all locations, including the larger economy: $w_i L_i = \gamma_i \sum_{k=1}^{N} w_k L_k + \gamma_i w_0 L_0$. Here γ_i is the share of expenditure spent on goods from location i, given by $\gamma_i = \frac{\alpha_i (\frac{w_i}{A_i})^{1-\sigma}}{\sum_{k=0}^{N} \alpha_k (\frac{w_k}{A_k})^{1-\sigma}}$. As shown in Appendix B.1, substituting for $w_0 L_0$ leads directly to equation (16).



location 1 location 2

Figure 5: Foxconn Locations in Henan

is a vector $\{w_i, L_i, A_i\}_{i=1}^N$ that simultaneously satisfies the labor mobility condition (10), the agglomeration equation (13), labor supply (18), and labor demand (19).

5 Structural Estimation

In this section, we use the exogenous variation induced by the unexpected entry of Foxconn to estimate the parameters for agglomeration forces $\{\lambda, \delta\}$. First, we calibrate the adjusted productivity and amenities $\{\widetilde{A}_i, \widetilde{B}_i\}$, as well as model parameters other than those for agglomeration forces. Second, we compute the structural residuals: the differences between the adjusted productivity implied by the model as a result of Foxconn's entry and those calibrated from data after Foxconn's entry. Third, we develop moment conditions in terms of structural residuals, and discuss the General Method of Moments(GMM) estimation.

5.1 Entry of Foxconn in Henan

In the empirical analysis, we calibrate the "city" in the model to the combined area of Zhengzhou and Kaifeng, partitioned into the same 110 grid cells used in the reduced-form exercise. Foxconn's entry is introduced as localized shocks to demand and amenities in the two cells hosting its factories, labeled as locations 1 and 2 in Figure 5.1. Specifically, $\hat{\alpha}_1$ and $\hat{\alpha}_2$ capture increases in the demand shifters, reflecting the surge in global demand funneled through Foxconn's contracts for Apple and other multinationals. Likewise, $\hat{\widetilde{B}}_1$ and $\hat{\widetilde{B}}_2$ capture increases in adjusted amenities, reflecting the infrastructure investments and policy support provided by the Henan provincial government (e.g., subsidies, industrial parks, and logistics upgrades).

Foxconn's entry directly raises the utility of working in the two Foxconn locations, which in turn increases the expected utility of working in the Zhengzhou–Kaifeng area as a whole. As a result, workers migrate into the city. The immediate impact is a sharp rise in employment in the two Foxconn locations. Beyond these direct effects, production externalities generate ripple effects across space: productivity and employment in other locations also expand, with the magnitude of these spillovers attenuating with distance from the Foxconn plants. Locations closer to Foxconn experience more substantial gains, while more distant locations see smaller effects.

These two forms of shocks—demand pull and improved amenities—are consistent with the reduced-form evidence of Marshallian externalities presented earlier. The procedure for determining the magnitudes of $\hat{\alpha}_1, \hat{\alpha}_2, \hat{\widetilde{B}}_1, \hat{\widetilde{B}}_2$ is described in the next subsection.

5.2 Recovering Location Characteristics

We use the labor supply condition (18) and the labor demand condition (19) to recover the adjusted productivity $\widetilde{A}_i$ and the adjusted amenity $\widetilde{B}_i$, treating observed wages and employment as inputs. The intuition is straightforward: locations with both high wages and high employment must feature high $\widetilde{A}_i$ (adjusted productivity), while locations with low wages but high employment must feature high $\widetilde{B}_i$ (adjusted amenities).

To solve for adjusted productivity and amenities, we parameterize a subset of model primitives: σ, ϵ, μ. The elasticity of substitution is set to $\sigma = 4$, consistent with Broda and Weinstein (2006). The dispersion of idiosyncratic location shocks is set to $\epsilon = 1.5$, following Tombe and Zhu (2019). The expenditure share of housing is calibrated using the Chinese Statistical Yearbook 2014, which reports household expenditure patterns for 2013. The data imply a housing share of $1 - \mu = 0.23$, leaving $\mu = 0.77$ for tradable goods.[11]

We recover the adjusted productivity and amenities both before and after Foxconn's entry, using observed data on wages and employment in the two periods.[12] Denote $\widetilde{A}_i^{before}$ and $\widetilde{A}_i^{after}$ as the adjusted productivity measures before and after Foxconn's entry, respectively. Similarly, $\widetilde{B}_i^{before}$ and $\widetilde{B}_i^{after}$ denote adjusted amenities.

Finally, we calibrate the increase in amenities at the Foxconn locations by comparing the pre-

[11] The Chinese Statistical Yearbook 2014 records consumption expenditure shares for 2013, the first year in which the National Bureau of Statistics adopted an integrated household survey combining urban and rural households.

[12] Details of the data sources and variable construction are provided in Appendix A.

Table 8: Calibrated Parameters

Parameters Calibrated Independently			
Parameter	Definition	Value	Source
ϵ	shape para. of amenity shocks	1.5	Tombe and Zhu (2019)
σ	elasticity of substitution	4	Broda and Weinstein (2006)
$1-\mu$	expenditure share on housing	0.23	Chinese Statistics Yearbook 2014

Parameters Calibrated in Equilibrium			
Parameter	Definition	Value	Source
$\hat{\widetilde{B}}_1$	change in adjusted amenity of location 1	4.03	calibrated from and data on wage and employment using eq. (18)
$\hat{\widetilde{B}}_2$	change in adjusted amenity of location 2	2.15	

and post-entry measures. Specifically,

$$\hat{\widetilde{B}}_1 = \frac{\widetilde{B}_1^{after}}{\widetilde{B}_1^{before}}, \quad \text{and} \quad \hat{\widetilde{B}}_2 = \frac{\widetilde{B}_2^{after}}{\widetilde{B}_2^{before}}.$$

The parameter values and the recovered adjusted productivity and amenities are summarized in Table 8. These calibrated increases in amenities at the Foxconn locations capture the direct effects of Foxconn's entry, while the broader spillover effects across other locations arise endogenously through the model's general equilibrium structure.

5.3 Structural Residuals

In this section, we describe how we compute the differences between the adjusted productivities implied by the model after Foxconn's entry and the calibrated adjusted productivities from the data, $\widetilde{A}_i^{after}$. These differences serve as the residuals used in our structural estimation.

To obtain the model-implied adjusted productivities, we compute the counterfactual equilibrium in which the demand shifters and adjusted amenities of the Foxconn locations increase following Foxconn's entry. We implement this using the "exact-hat" algebra developed by Dekle et al. (2008). Let z' denote the post-entry value of variable z and $\hat{z} = z'/z$ its relative change. In this framework, changes in equilibrium outcomes—wages, employment, and adjusted productivities $(\hat{w}_i, \hat{L}_i, \hat{\widetilde{A}}_i)$—can be expressed as functions of the exogenous shocks $(\hat{\alpha}_i, \hat{\widetilde{B}}_i)$, observed

pre-entry variables (w_i, L_i), and model parameters $(\epsilon, \sigma, \mu, \lambda, \delta)$. This approach has become standard for quantifying counterfactual changes in spatial equilibrium. The full system of equations in relative changes is presented in Appendix B.3.

Combining the counterfactual changes in adjusted productivity with the calibrated pre-entry values $\widetilde{A}_i^{before}$ yields the model-implied adjusted productivities after Foxconn's entry, denoted $\widetilde{A}_i^{after,model}$. We then construct structural residuals as

$$\ln\left(\frac{\widetilde{A}_i^{after,model}}{\overline{\widetilde{A}}^{after,model}}\right) - \ln\left(\frac{\widetilde{A}_i^{after}}{\overline{\widetilde{A}}^{after}}\right), \tag{20}$$

where $\overline{\widetilde{A}}^{after,model}$ is the geometric mean of the model-implied adjusted productivities,

$$\overline{\widetilde{A}}^{after,model} = \exp\left(\frac{1}{N}\sum_{i=1}^{N} \widetilde{A}_i^{after,model}\right),$$

and $\overline{\widetilde{A}}^{after}$ is the geometric mean of the calibrated adjusted productivities

$$\overline{\widetilde{A}}^{after} = \exp\left(\frac{1}{N}\sum_{i=1}^{N} \widetilde{A}_i^{after}\right).$$

These residuals form the basis for estimating the agglomeration parameters λ and δ, which govern the strength and spatial reach of spillovers.

5.4 GMM Estimation

This subsection outlines the construction of moment conditions, the identification strategy, and the implementation of the generalized method of moments (GMM) to estimate the model parameters.

Moment Conditions. We construct two sets of moment conditions.

(i) Distance-based moments. Motivated by the reduced-form results, our first set of moments requires that the difference between the model-implied adjusted productivity and the data-implied adjusted productivity is uncorrelated with distance from Foxconn's super-factories. For-

mally,

$$\mathbb{E}\left[\left(\ln\left(\frac{\widetilde{A}_i^{after,model}}{\widetilde{\overline{A}}_i^{after,model}}\right)-\ln\left(\frac{\widetilde{A}_i^{after}}{\widetilde{\overline{A}}_i^{after}}\right)\right)\times\mathbb{I}_k\right]=0,\quad k=\{1,2,...,5\},\tag{21}$$

where $\mathbb{I}_k$ for $k=\{1,2,...,5\}$ are indicators for the k-th quintile of distance to Foxconn's superfactories. These moments impose that, within each quintile, the mean residual difference in adjusted productivity is zero.

The key identifying assumption is that systematic changes in the spatial distribution of manufacturing activity in Zhengzhou and Kaifeng after Foxconn's entry are explained by the model, rather than by systematic shifts in unobserved factors. Because Foxconn's investment was largely unexpected, the resulting changes in the spatial concentration of economic activities can plausibly be attributed to agglomeration spillovers rather than confounding shocks.

(ii) Foxconn-location employment moments. Our second set of moments ensures that the model matches the observed increase in employment at Foxconn's two plant locations. Specifically,

$$\mathbb{E}\left[\left(L_i^{after,model}-L_i^{after}\right)\times\vartheta_i^k\right]=0,\quad k=\{1,2\},\tag{22}$$

where $L_i^{after,model}$ is the model-implied employment in location i after Foxconn's entry, L_i^{after} is the observed employment, and ϑ_i^k for $k=\{1,2\}$ are dummy variables indicating whether location i corresponds to Foxconn's k-th location of plants.

Estimation. We jointly use the two sets of moments to estimate the agglomeration parameters and Foxconn's demand shocks:

$$\Theta=(\lambda,\delta,\hat{\alpha}_1^{\frac{1}{\sigma-1}},\hat{\alpha}_2^{\frac{1}{\sigma-1}}).$$

Specifically, the GMM estimator solves

$$\hat{\Theta}=\arg\min\left(\frac{1}{N}\sum_{i=1}^{N}m(X_i,\Theta)'\right)W\left(\frac{1}{N}\sum_{i=1}^{N}m(X_i,\Theta)\right),\tag{23}$$

where $m(X_i,\Theta)$ denotes the vector of moment conditions for location i, and W is the efficient weighting matrix.

Identification. Foxconn's entry raises production externalities in locations proximate to its plants. The parameters $\{\lambda, \delta\}$ govern both the magnitude of these externalities and their rate of decay with distance. Moment condition (21) identifies these parameters by requiring that the mean changes in log adjusted productivity are close to zero within each quintile of distance to Foxconn's plants. Conditional on $\{\lambda, \delta\}$, the demand shifters $\{\hat{\alpha}_1^{\frac{1}{\sigma-1}}, \hat{\alpha}_2^{\frac{1}{\sigma-1}}\}$ are identified from moment condition (22). These parameters ensure that the model reproduces the observed increase in employment at the two Foxconn plant locations after entry.

To visualize identification, we evaluate the fit of the productivity-based moments across the parameter space. Specifically, we compute the sum of squared mean deviations in log adjusted productivity across distance quintiles for 11 candidate values of λ (ranging from 0.05 to 0.15) and 11 candidate values of δ (also ranging from 0.05 to 0.15). Figure C.1 presents contour plots of this objective function. The contours reveal a well-defined global minimum, providing clear identification of $\{\lambda, \delta\}$.

GMM Estimation Results. Table 9 reports the results of the GMM estimation. We find substantial and statistically significant evidence of agglomeration forces. The estimated elasticity of productivity with respect to neighboring employment density is 0.09, a value toward the upper end of the 3–13 percent range documented in the literature.[13]

The estimated rate of decay is 0.11. This magnitude implies that the productivity spillover diminishes rapidly with distance: it falls by roughly 67 percent at a distance of 10 kilometers, and becomes nearly negligible beyond 40 kilometers.

Turning to local demand conditions, we estimate substantial increases in the demand shifters for Foxconn locations. The estimated rise in the demand shifter is 7.78 for location 1 and 3.56 for location 2. These substantial increases are required for the model to match the observed post-entry employment levels in the two Foxconn locations. Moreover, the estimates are consistent with the surge in global demand for iPhones during this period, given that Foxconn's Zhengzhou plants produced over 80% of the world's supply.

GMM Model Fit. To evaluate the fit of the estimated model, we compare how well it replicates the reduced-form evidence on productivity spillovers. Specifically, we use the estimated param-

[13]See Duranton and Puga (2004) for a classic survey of empirical estimates of agglomeration economies, and Combes and Gobillon (2016) for a more recent overview.

Table 9: GMM Estimation Results

Parameter	Definition	Value
λ	agglomeration elasticity	0.0930^{***}
		(0.0011)
δ	agglomeration decay	0.1099^{****}
		(0.0002)
$\hat{\alpha}_1^{\frac{1}{\sigma-1}}$	change in demand shifter of location 1	7.7807^{***}
		(2.4031×10^{-5})
$\hat{\alpha}_2^{\frac{1}{\sigma-1}}$	change in demand shifter of location 2	3.5579^{***}
		(1.8657×10^{-5})

Notes: Numbers in parenthesis are standard errors. * significant at 10%, ** significant at 5%, *** significant at 1%.

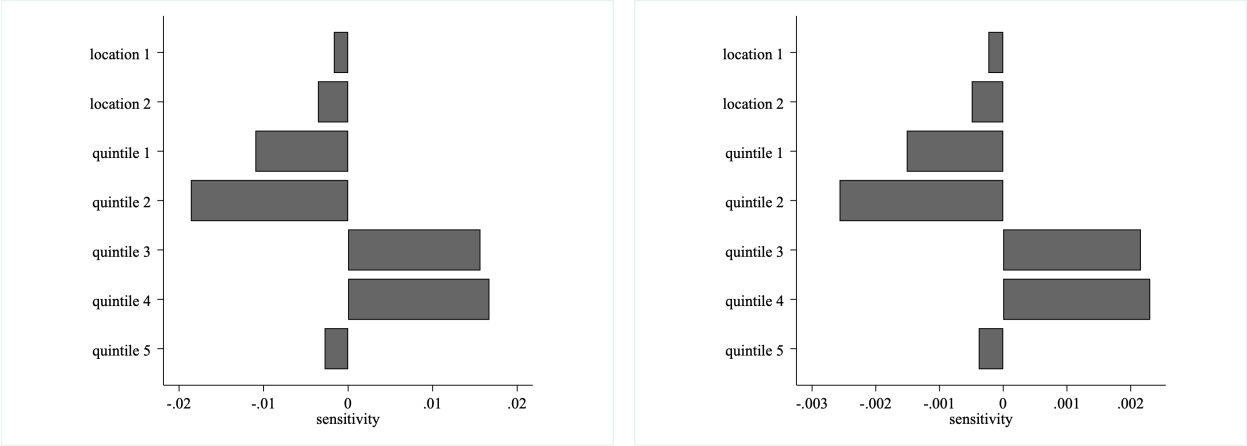
Table 10: Model Fit

	Data	Model
	(1)	(2)
$POST \times InvDist$	2.189^{***}	1.531^{***}
	(0.506)	(0.244)

Notes: This table compares the estimated spillover effect of Foxconn's entry using actual data (Column 1) and counterfactual adjusted productivity generated by the structural model (Column 2). The reported coefficient corresponds to the interaction term in the baseline difference-in-differences specification. Numbers in parentheses are standard errors. * significant at 10%, ** significant at 5%, *** significant at 1%.

eters to solve for the counterfactual adjusted productivity in each location after Foxconn's entry. Treating these model-implied values as data, we re-estimate our reduced-form DD specification. Column (2) of Table 10 reports the results using model-implied productivity, while Column (1) reproduces the corresponding estimate from the actual data, as reported in column (6) of Table 2. The estimated coefficient on proximity to Foxconn in Column (2) is 1.53, which is close in magnitude to the estimate of 2.19 obtained with the real data in Column (1). This similarity suggests that the model captures the key spatial productivity patterns observed in the data. Importantly, this provides an external validity check, as our GMM estimation did not directly target the reduced-form DD coefficient.

Sensitivity. We assess the sensitivity of our GMM estimates to individual moment conditions using the measure proposed by Andrews, Gentzkow, and Shapiro (2017). This metric quantifies



(a) Sensitivity of the Parameter Estimate λ (b) Sensitivity of the Parameter Estimate δ

Figure 6: Sensitivity of the Parameter Estimates

Notes: Panel (a) reports the sensitivity of the parameter λ with respect to the vector of estimation moments. Panel (b) reports the corresponding sensitivities for the parameter δ. Values are normalized by the standard deviation of each moment and can therefore be interpreted as the effect of a one–standard deviation change in the moment on the parameter estimate.

the extent to which parameter estimates are influenced by perturbations in specific moments, which may arise either from model misspecification or from measurement error in the empirical counterparts of the moments. Formally, sensitivity is defined as

$$\Lambda = (G'WG)^{-1}G'W,$$

where G is the Jacobian matrix of the moment conditions with respect to the parameters, evaluated at their true values, and W is the optimal weighting matrix.

Figure 6 illustrates the sensitivity of the agglomeration parameters λ, δ. Panel (a) displays the normalized sensitivities of λ with respect to each moment, while Panel (b) does the same for δ. Normalization by the standard deviation of each moment allows the values to be interpreted as the effect of a one–standard deviation perturbation in the moment on the parameter estimate. The results confirm our intuition about identification: moments associated with the distance quintiles play the central role, while other moments have only limited influence.

6 Counterfactual Experiments

With the estimated structural model, we now turn to counterfactual analysis. We pursue two sets of exercises. The first quantifies the effects of Foxconn's entry on the size and spatial structure of the Zhengzhou–Kaifeng economy, as well as the consequences of a hypothetical scale-down in Foxconn's production—a scenario motivated by Apple's recent diversification of iPhone assembly outside China. The second exercise explores how the magnitude and distribution of spillovers depend on the precise siting of Foxconn's plants within the city. Together, these experiments highlight both the realized impact of Foxconn's entry and the sensitivity of urban development outcomes to firm-scale and locational choices.

6.1 Impacts of Foxconn's Entry and Scale-Down

To quantify Foxconn's impact on the local economy, we compare the observed equilibrium before Foxconn's arrival to a counterfactual equilibrium where Foxconn begins operations in Henan. In our model, Foxconn's entry is represented by an upward shift in demand and improved amenities at Foxconn's host locations, with the magnitudes of these changes calibrated from the data in the previous section. This approach allows us to isolate how much Foxconn's presence alone would change key economic outcomes relative to the baseline.

The results of this simulation are presented in Column (1) of Table 11. Foxconn's establishment in the city triggers a dramatic influx of labor—total employment rises by about 179.32% relative to the no-Foxconn baseline. Thanks to agglomeration economies, this surge in workers translates into a 10.68% increase in aggregate productivity, which is measured as the employment-weighted average productivity across all locations. Taken together, these changes imply an overall agglomeration elasticity of 0.0988.[14]

The spillovers to non-Foxconn locations are sizable. As shown in Row (c) of Table 11, for each job created in Foxconn plants, an additional 4.53 jobs emerge elsewhere in the city. Our model attributes these indirect gains to two mechanisms. First, Foxconn's entry raises the expected utility of working in the city, drawing new workers who subsequently allocate across locations (grid cells) after realizing their idiosyncratic preferences. Some of these migrants settle in non-Foxconn

[14]The agglomeration elasticity λ is calculated as $\lambda = log(A^{'}/A)/log(L^{'}/L)$, where A' and L' are aggregate productivity and total employment after Foxconn's entry, and A, L are their baseline values. Substituting the 10.68% productivity increase and 179.32% employment increase yields $\lambda \approx 0.0988$.

Table 11: Impacts of Foxconn's Entry on the Size and Structure of the City

	Overall	Distance to Foxconn Factories					
		Quintile 1	Quintile 1 excl. Foxconn locations	Quintile 2	Quintile 3	Quintile 4	Quintile 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(a) Employment (percentage change)	179.32	229.78	151.39	150.61	149.85	149.79	149.76
(b) Productivity (percentage change)	10.68	12.66	10.15	9.59	8.97	8.91	8.89
(c) $\frac{\Delta \text{ employment except Foxconn locations}}{\Delta \text{ employment in Foxconn locations}}$	4.53	1.60	1.60	1.04	1.08	0.51	0.29
(d) Employment share before entry (%)	100	36.67	34.24	22.50	23.37	11.16	6.30
(e) Employment share after entry (%)	100	43.29	30.82	20.19	20.90	9.98	5.63

Notes: This table reports percentage changes in employment and productivity from the observed equilibrium before Foxconn's entry to the counterfactual equilibrium after Foxconn begins operations. Column (1) shows the impacts for the entire city. Columns (2) and (4)–(7) disaggregate the impacts by distance quintiles from Foxconn's plants, while Column (3) reports outcomes for non-Foxconn locations within the first quintile.

locations, thereby increasing local employment. Second, agglomeration forces amplify this process: the inflow of workers boosts city-wide productivity through higher worker density, which in turn attracts even more workers. To separate the two mechanisms, we compute the impacts of Foxconn's entry in a counterfactual without agglomeration spillovers ($\lambda = 0$). The results, reported in Appendix Table D.1, imply that 2.23 out of the 4.53 additional jobs are generated through agglomeration forces, and the remaining 2.3 jobs result from the first mechanism.

Columns (2) and (4)–(7) of Table 11 report how Foxconn's entry affected areas within each distance quintile, while Column (3) isolates the effect on non-Foxconn locations in the first quintile. Several observations are worth noting. First, locations within the closest distance quintile experience the most significant employment growth, at 229.78%, as well as the highest increase of productivity, at 12.66%. Consequently, there's a higher concentration of workers in this area, with their employment share rising from 36.67% before Foxconn's arrival to 43.29% afterward. Second, employment growth in non-Foxconn locations is broadly similar across distance quintiles, but areas nearer to Foxconn plants see slightly larger increases than those farther away. This pattern reflects the balance between agglomeration benefits and the dispersion force of increasing rents. For instance, non-Foxconn areas within the closest quintile see a 151.39% rise in employment, while those in the farthest quintile experience a 149.76% increase (see Column (3) versus Column (7)). Third, non-Foxconn locations closer to Foxconn plants enjoy higher productivity growth than those farther away. Given that non-Foxconn areas show comparable employment growth, the remaining differences in productivity across distance quintiles largely trace back to proximity to Foxconn plants. However, the advantage almost disappears beyond the second distance

quintile (more than 40 kilometers from Foxconn plants), aligning with our estimate of the spatial decay rate that the production externality almost vanishes at distances greater than 40 kilometers.

Interestingly, even the farthest quintile of locations experiences an 8.99 percent productivity increase. This suggests that the reduced-form difference-in-differences estimates understate Foxconn's aggregate effects. By construction, the reduced-form approach identifies productivity spillovers relative to more distant areas and therefore cannot fully capture the citywide general equilibrium impacts operating through migration and density. Therefore, our structural framework complements the reduced-form analysis by quantifying both the localized spillovers and the broader economy-wide effects of Foxconn's entry.

Next, we examine how the impacts of Foxconn's entry vary with the scale of its operations. Specifically, we consider four counterfactual scenarios in which the size of Foxconn's plants ranges from 20 to 80 percent of their observed post-entry scale, comparing with our baseline 100%. The results are reported in Table 12 and the baseline scenario is shown in Column (1). Larger plants generate greater inflows of workers and stronger productivity growth. For instance, as shown in Rows (a) and (b), at 80 percent of the observed size, employment rises by 143.13 percent and productivity by 9.15 percent, whereas at 20 percent of the observed size, employment increases by only 25.6 percent and productivity by 2.21 percent. The marginal effects decline with scale: expanding plant size from 20% to 40% adds about 40.84% employment growth and 2.88% increase in productivity, while the jump from 60% to 80% adds only 37.57% and 1.82%.

Row (c) of Table 12 reports the overall agglomeration elasticity, measuring the percentage change in productivity associated with a percentage change in employment. This elasticity rises as the size of Foxconn locations expands, but the marginal increase becomes smaller at larger scales. The upward trend reflects two forces: first, locations closer to Foxconn plants experience stronger productivity gains than those farther away; second, as Foxconn plants grow, a larger share of total employment is concentrated in these nearby locations. The tapering of marginal effects stems from the fact that productivity gains themselves increase at a decreasing rate as plant size continues to expand.

The additional employment generated per new hire in Foxconn locations increases first and then diminishes as the size of these locations increases, as illustrated in Row (d) of Table 12. For instance, when Foxconn locations were at 20% of their observed size, each new hire in Foxconn locations resulted in an additional 4.55 jobs elsewhere; when Foxconn locations increase to 40%

Table 12: Impacts of Foxconn's Entry by Size

	Employment in Foxconn locations after entry				
	100% (1)	80% (2)	60% (3)	40% (4)	20% (5)
(a) Employment (percentage change)	179.32	143.13	105.56	66.44	25.6
(b) Productivity (percentage change)	10.68	9.15	7.33	5.09	2.21
(c) $\frac{\Delta \text{ log productivity}}{\Delta \text{ log employment}}$ (percent)	9.88	9.85	9.81	9.74	9.57
(d) $\frac{\Delta \text{ employment except Foxconn locations}}{\Delta \text{ employment in Foxconn locations}}$	4.53	4.61	4.70	4.74	4.55

Notes: This table reports percentage changes in employment and productivity from the observed economy before Foxconn's entry to counterfactual economies where Foxconn begins operations at different plant sizes. Column (1) is the baseline results with 100% Foxconn's entry, the same as in Table 11. Column (2) assumes Foxconn employs 80% of its observed workforce post-entry, while Columns (3)–(5) assume 60%, 40%, and 20%, respectively. Row (c) reports the implied overall agglomeration elasticity. Row (d) shows the number of additional jobs created in non-Foxconn locations per job created in Foxconn locations.

of their observed size, the number of additional jobs per one job created in Foxconn locations increases to 4.74. However, when the size of Foxconn locations expanded to 80% of their observed size, this number decreases to 4.61. The initial increase reflects stronger agglomeration effects as larger plants pull more workers into nearby areas, while the later decline occurs because productivity gains from agglomeration grow more slowly once the workforce becomes large, as shown in Row (b) of Table 12.

Motivated by Apple's ongoing shift of iPhone production out of China,[15] we use the estimated model to quantify the impact of Foxconn scaling down production in Henan. Specifically, we move from the observed post-entry equilibrium to counterfactual equilibria in which Foxconn operates at smaller scales. In the model, this corresponds to a reduction in the demand shifters at Foxconn's locations. We evaluate four scenarios where Foxconn's operational scale declines to 80, 60, 40, and 20 percent of its observed post-entry level.

The results, reported in Table 13, show that Foxconn's contraction would generate sizable negative shocks to the local economy. Each column of Table 13 corresponds to one scenario of reduced production, analogous to Table 12. Employment falls sharply as Foxconn scales down, with total city employment declining by 13.39 percent when Foxconn operates at 80 percent of

[15] Amid escalating U.S.–China trade tensions, many multinationals have adopted a "China+1" strategy—relocating part of their production capacity out of mainland China. For instance, *Reuters* reports that Apple aims to manufacture most U.S.-destined iPhones in India by the end of 2026, as part of its strategy to mitigate tariff exposure and supply-chain risks. See, for example, *Reuters*, "Apple moving to make most iPhones for US in India rather than China, source says", available at https://www.reuters.com/world/china/apple-aims-source-all-us-iphones-india-pivot-away-china-ft-reports-2025-04-25.

Table 13: Impacts of Foxconn Scaling Down Production

	Employment in Foxconn locations after entry			
	80% (1)	60% (2)	40% (3)	20% (4)
(a) Employment (percentage change)	-13.39	-27.28	-41.82	-57.15
(b) Productivity (percentage change)	-1.35	-2.96	-4.96	-7.57
(c) $\frac{\Delta \text{ log productivity}}{\Delta \text{ log employment}}$(percent)	9.47	9.43	9.39	9.28
(d) $\frac{\Delta \text{ employment except Foxconn locations}}{\Delta \text{ employment in Foxconn locations}}$	3.68	3.77	3.87	4.0

Notes: This table reports percentage changes in employment and productivity when moving from the observed post-entry equilibrium to counterfactual scenarios in which Foxconn reduces iPhone production in Henan. Column (1) corresponds to the case in which Foxconn's employment falls to 80 percent of its observed size after entry. Columns (2)–(4) present the results for reductions to 60, 40, and 20 percent of the observed size, respectively. Row (c) reports the implied overall agglomeration elasticity. Row (d) shows the number of additional jobs lost in non-Foxconn locations per job lost in Foxconn locations.

its observed size, 27.28 percent at 60 percent, 41.82 percent at 40 percent, and 57.15 percent at 20 percent. Productivity losses are more modest but still economically meaningful: aggregate productivity declines by 1.35 percent, 2.96 percent, 4.96 percent, and 7.57 percent across the same scenarios.

Rows (c) and (d) of Table 13 shed further light on these dynamics. The implied overall agglomeration elasticity—measured as the ratio of changes in log productivity to log employment—remains stable at about 9.3–9.5 percent across all scenarios. Thus, the elasticity of productivity with respect to employment density is robust to the scale of Foxconn's contraction. However, the multiplier effect of Foxconn jobs on citywide employment becomes larger in absolute magnitude as the contraction deepens. At 80 percent of observed size, each job lost in Foxconn plants leads to an additional 3.68 job losses elsewhere in the city; at 20 percent, this rises to 4.0. This pattern reflects the increasing marginal productivity decline induced by agglomeration effects as the city shrinks: with a smaller urban base, the loss of one Foxconn job propagates more widely through the local economy.

When comparing Row (d) of Table 12 with the corresponding results in Table 13, an important asymmetry emerges. Each new hire in Foxconn locations generates significantly more additional jobs elsewhere in the city than the number of jobs lost per worker when Foxconn contracts. For example, expansion scenarios yield spillovers of roughly 4.5–4.7 additional jobs per Foxconn

worker (Row (d), Table 12), whereas contraction scenarios imply only 3.7–4.0 job losses elsewhere per Foxconn job cut (Row (d), Table 13). This asymmetry reflects the nonlinear productivity–size relationship inherent in agglomeration economies. Before Foxconn's entry, the city was much smaller, so the marginal productivity gains from expanding employment were high; after entry, when the city is already large, the marginal productivity losses from contraction are less steep. In other words, the local economy derives disproportionate benefits from the expansion phase of a major employer like Foxconn, while the negative effects of contraction, though severe, are somewhat muted by the larger urban base established post-entry.

6.2 Reallocating Foxconn Across Locations

In many countries, local governments provide financial incentives to attract major firms to establish operations within their jurisdictions. The rationale for these incentives rests on the agglomeration spillovers that such firms generate for the surrounding economy. Yet, an open question remains: do the magnitude and nature of spillovers depend on the precise locations where these firms settle, and if so, to what extent? Despite the central importance of this issue for policy design, prior research has offered limited quantitative evidence. This subsection leverages our estimated model to provide such an assessment.

We consider a set of counterfactual scenarios in which Foxconn's entry pattern differs from the observed one. In each scenario, Foxconn establishes one plant in "location 1," as in reality, and places its second plant in one of the 110 potential locations across Zhengzhou–Kaifeng. The size of the workforce in location 1 is fixed at the observed level, while the second plant employs the same number of workers as Foxconn's actual facility in location 2. This design yields 110 alternative entry scenarios. For each scenario, we compute the outcomes by moving from the pre-entry equilibrium to the counterfactual equilibrium implied by the new location configuration.

This exercise reflects the idea that, while large firms make their own location decisions, local governments can often influence the marginal choice among feasible sites through incentives and zoning policies. In Foxconn's case, we assume that location 1 is a fixed choice, while allowing the siting of the second plant in location 2 as a margin where local government policy may have exerted influence.

Figure 7 plots the relationship between gains in productivity and employment across the 110

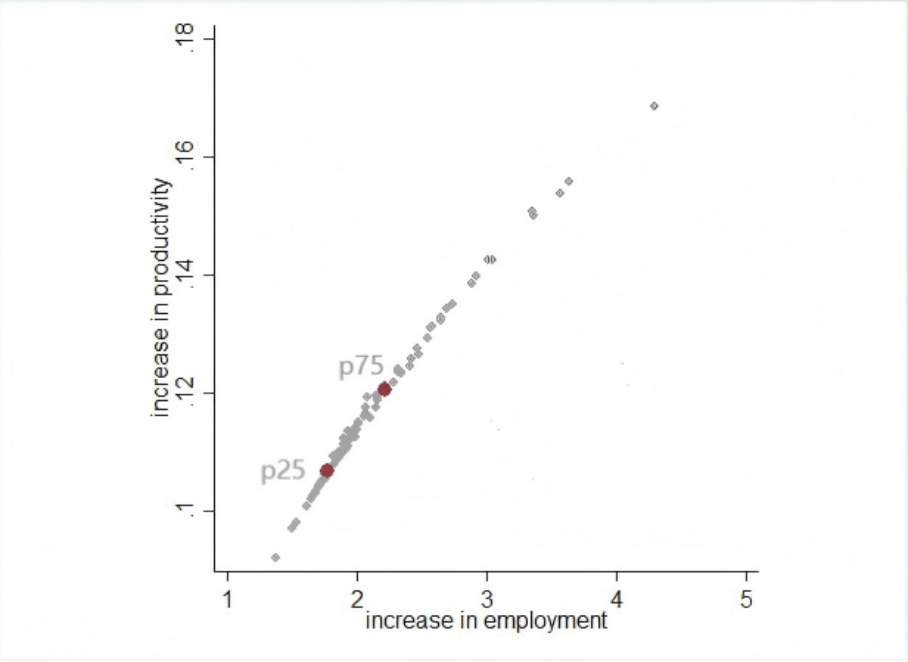


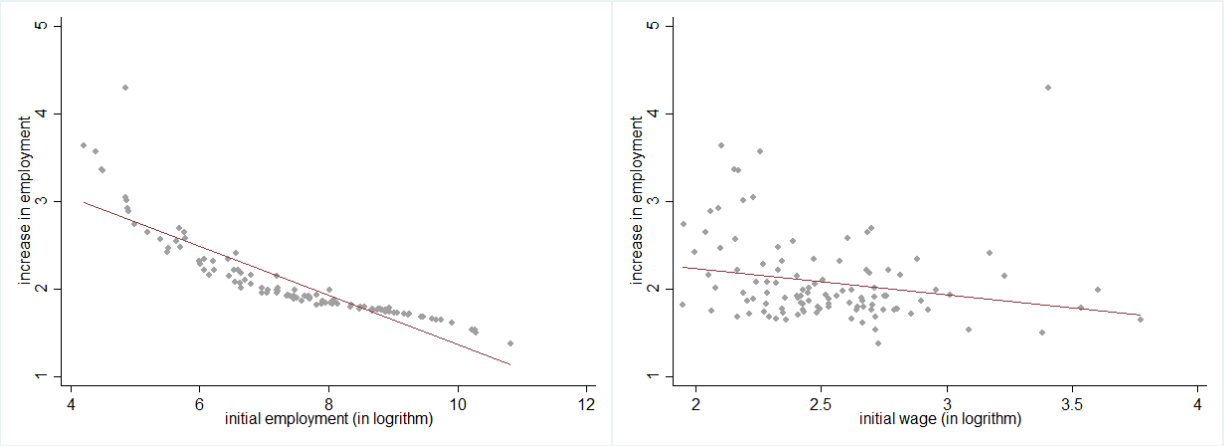
Figure 7: Increases in Employment and Productivity across All Entry Scenarios

Notes: This figure plots the relationship between productivity and employment growth across all 110 counterfactual entry scenarios. Each dot represents one scenario, with the x-axis indicating the percentage change in employment and the y-axis indicating the percentage change in productivity.

counterfactual entry scenarios. The figure reveals a strikingly linear association, implying that overall agglomeration elasticities are tightly aligned across different location choices. At the same time, the magnitude of the gains varies substantially. Employment rises by 177 percent at the 25th percentile of the distribution compared with 221 percent at the 75th percentile, a difference that translates into roughly a quarter million additional jobs. Productivity exhibits a similar pattern, increasing by 10.66 percent at the 25th percentile and 12.06 percent at the 75th percentile.

Employment growth at Foxconn's actual location is roughly at the 25th percentile of all simulated entry scenarios. This finding implies that alternative siting of Foxconn's facilities could have generated substantially larger spillover effects. Of course, real-world constraints—such as infrastructure availability, the presence of a bonded zone, or geographic barriers—may limit the feasibility of moving Foxconn to the model's "optimal" location. A more realistic policy benchmark is to consider relocating the plant to sites in the interquartile range between the 50th and 75th percentiles. In these scenarios, Foxconn's entry would have generated between 60,000 and 200,000 additional jobs relative to its actual location.

What explains why some locations produce larger spillovers? Panel (a) of Figure 8 shows



(a) Initial employment (b) Initial wage

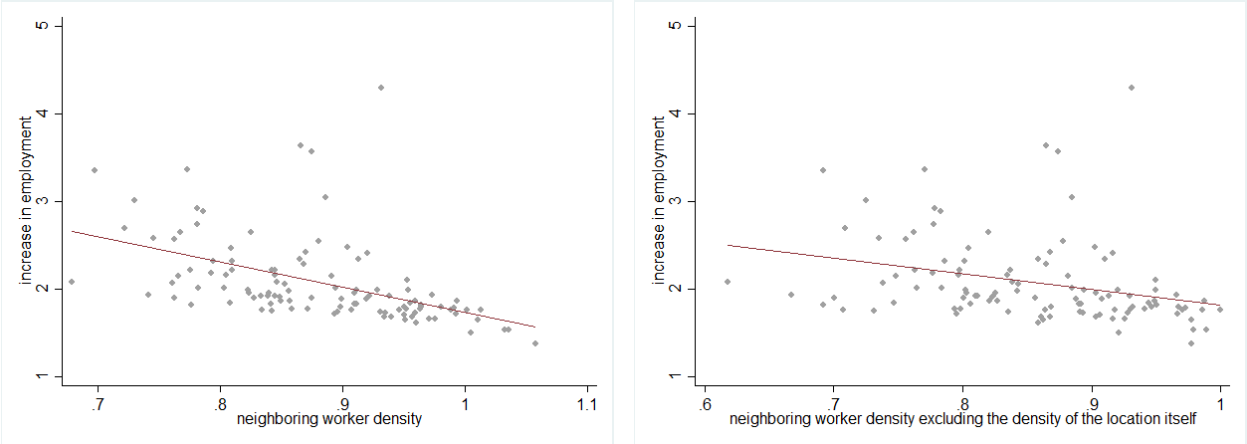
Figure 8: Location Characteristics and Employment Growth across All Entry Scenarios

Notes: This figure shows the relationship between initial local conditions and employment growth across all 110 entry scenarios, with each dot representing one scenario. Panel (a) plots employment growth against initial employment; the slope of the fitted line is -0.28 with a corresponding t-statistic of -12.22. Panel (b) plots employment growth against initial wages; the slope of the fitted line is -0.30 with a corresponding t-statistic of -1.50.

that locations with lower pre-entry employment levels experience greater subsequent aggregate employment growth. Panel (b) displays a similar negative relationship between initial wages and subsequent employment increases. These results suggest that siting in initially less dense and lower-wage areas yields larger spillover effects. The mechanism is straightforward: Foxconn's arrival raises local density, which boosts productivity but also drives up rents, generating a dispersion force that deters additional in-migration. When baseline employment is lower, this dispersion force is weaker, allowing more workers to enter the city and thereby amplifying the agglomeration spillovers.

A similar pattern emerges when examining the density of surrounding locations. Panel (a) of Figure 9 indicates that lower neighboring worker density is associated with stronger employment growth. Panel (b) confirms that this negative correlation persists even when the location's own density is excluded. These findings underscore that Foxconn's productivity shock interacts not only with local fundamentals but also with the density of nearby areas. Locating the plant in less congested neighborhoods reduces the rent-driven dispersion effect, encourages additional in-migration, and magnifies the net spillover benefits.

Taken together, these findings suggest that place-based subsidies or incentives may deliver greater aggregate returns when directed toward lower-density or lower-wage areas, where weaker dispersal forces allow productivity shocks from large firms to generate stronger spillovers, there-



(a) Neighboring worker density

(b) Excluding the location's own density

Notes: This figure shows the relationship between neighboring worker density and employment growth across all 110 entry scenarios, with each dot representing one scenario. Panel (a) plots employment growth against neighboring worker density; the slope of the fitted line is -2.87 with a corresponding t-statistic of -6.50. Panel (b) repeats the analysis excluding the focal location's own worker density from the measure; the slope of the fitted line is -1.78 with a corresponding t-statistic of -3.32.

Figure 9: Neighboring Worker Density and Employment Growth across All Entry Scenarios

fore highlighting the importance of targeting in the design of place-based policies.

6.3 Sensitivity to the Dispersion of Idiosyncratic Location Shocks

Our baseline calibration uses a dispersion of idiosyncratic location shocks of $\epsilon = 1.5$, following Tombe and Zhu (2019). Because their estimate is derived from migration flows across regions in China, and labor tends to be more mobile within a city, the dispersion of idiosyncratic shocks may be smaller. A smaller dispersion is equivalent to a higher value of ϵ, which implies that workers respond less to idiosyncratic shocks, potentially concentrating more workers near Foxconn. To assess the sensitivity of our results, we re-estimate the model using two higher values, $\epsilon = 3$ and $\epsilon = 5$, and then re-evaluate the impacts of Foxconn's entry based on these new estimates.

The estimated parameters, reported in Table 14, remain broadly consistent with the baseline results. Higher values of ϵ yield somewhat larger agglomeration elasticities and faster spatial decay. This pattern reflects the fact that when workers are less responsive to idiosyncratic shocks, they concentrate more tightly around Foxconn. Using these new parameter estimates, we re-evaluate the impacts of Foxconn's entry, as shown in Appendix Tables D.2 and D.3. The implied spillover magnitudes remain stable: in all cases, each new Foxconn job generates about 4.2 additional jobs elsewhere in the city. These results confirm that our main conclusions are robust to

Table 14: GMM Estimation under Alternative Values of Dispersion of Idiosyncratic Shocks

Parameter	Definition	$\epsilon = 3$	$\epsilon = 5$
(1)	(2)	(3)	(4)
λ	agglomeration elasticity	0.1109^{***}	0.1249^{***}
		(2.0318×10^{-4})	(1.7523×10^{-4})
δ	agglomeration decay	0.1343^{***}	0.1681^{***}
		(8.9539×10^{-4})	(6.9778×10^{-4})
$\hat{\alpha}_1^{\frac{1}{\sigma-1}}$	change in demand shifter of location 1	6.7603^{***}	5.2433^{***}
		(2.3745×10^{-5})	(2.2895×10^{-5})
$\hat{\alpha}_2^{\frac{1}{\sigma-1}}$	change in demand shifter of location 2	3.2012^{***}	2.5943^{***}
		(1.8011×10^{-5})	(1.6680×10^{-5})

Notes: This table reports the GMM estimation results under alternative assumptions about the dispersion of idiosyncratic location shocks, $\epsilon = 3$ (Column 3) and $\epsilon = 5$ (Column 4). Reported parameters include the agglomeration elasticity (λ), the spatial decay parameter (δ), and the changes in demand shifters for the two Foxconn locations ($\hat{\alpha}_1^{\frac{1}{\sigma-1}}$ and $\hat{\alpha}_2^{\frac{1}{\sigma-1}}$). Numbers in parentheses are standard errors. * significant at 10%, ** significant at 5%, *** significant at 1%.

reasonable variations in the dispersions of idiosyncratic shocks.

7 Conclusion

This paper investigates how the geographic placement of a single large firm can reshape the size and internal structure of a city through agglomeration spillovers. We exploit Foxconn's sudden entry into Zhengzhou as a natural experiment, combining reduced-form evidence with a structural urban model to shed light on a question of first-order importance for both urban economics and industrial policy.

On the empirical side, we show that Foxconn's entry generated sizable and spatially concentrated productivity gains. Locations closer to Foxconn plants experienced significantly larger increases in labor productivity and wages, as well as stronger firm entry and industry employment growth, compared to more distant areas. On the structural side, we build and estimate a tractable model of city structure with two opposing forces: agglomeration through production externalities and dispersion through inelastic land supply. Estimating the model with the generalized method of moments, we find strong and highly localized agglomeration forces. Our preferred estimates imply that each Foxconn job created an additional 4.5 jobs elsewhere in the city, with productivity spillovers decaying rapidly beyond 40 kilometers.

The structural model allows us to quantify counterfactual scenarios. We show that scaling down Foxconn's production—as Apple diversifies the assembly of iPhones abroad—would trigger significant job losses in Henan. In contrast, simulations in which Foxconn's plants are relocated to alternative sites inside the city reveal substantial variation in the magnitudes of spillover. Locations with lower initial employment, lower wages, and less dense neighboring areas would have generated considerably larger citywide gains.

Taken together, our analysis makes three contributions. First, it provides new reduced-form evidence on the productivity and employment spillovers of a single large firm, leveraging an unusually sharp natural experiment. Second, it develops and estimates a structural urban model that delivers interpretable parameters of agglomeration strength and spatial decay. Third, it delivers quantitative guidance for policy: incentives to attract major firms can yield large benefits, but their effectiveness depends critically on where within a city these firms locate. More generally, our findings suggest that place-based policies should take seriously not only which firms to attract, but also where to place them within local urban systems.

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Online Appendix for: "Super Factory Comes to Town: Quantifying the Agglomeration Spillovers from Foxconn Factory in Henan" (Not for Publication)

A Data Appendix **1**

B Theory **2**

B.1 Derivation of Equation (16) 2

B.2 Derivation of Equation (19) and (18) 2

B.3 "Exact-Hat" Algebra 3

C GMM Estimation **3**

D Additional Counterfactual Results **4**

A Data Appendix

We partition Henan Province into a uniform square grid with cells measuring $0.1^\circ \times 0.1^\circ$ (about 11 km $\times$ 11 km). To construct the grid, we first draw a line of longitude tangent to Henan's western boundary and then add successive longitudes to the east at intervals of 0.1°, continuing until the province is fully covered. Similarly, we draw a line of latitude tangent to Henan's northern boundary and add successive latitudes to the south at 0.1° intervals until the entire area of Henan is included. The intersections of these longitudes and latitudes form the set of grid cells used in our analysis.

Next, we obtain the geographic coordinates of firms using address information from the ASIF. We use the GaoDe Map API service to geocode each firm's address. When address information is missing or incomplete, we instead use the firm's name together with its registered administrative area to retrieve its coordinates. After obtaining all firm locations, we assign each firm to a grid cell based on its geographic coordinates, which allows us to identify the complete set of firms located within each cell.

It is important to note that the GaoDe Map API returns geographic coordinates in the GCJ-02 reference system, an encrypted variant of the global WGS-84 system mandated for digital maps in mainland China. Because a direct conversion from GCJ-02 to WGS-84 is not formally available, we consult field experts and apply widely used inverse transformation algorithms that approximate GCJ-02 coordinates in the WGS-84 system (See, for example, Li et al. (2022)).

Finally, we aggregate the firm-level information to the cell level used in our empirical analysis. For each cell, total employment is obtained by summing over all firms located within the cell. A cell's labor productivity is measured as the employment-weighted average of firm-level labor productivity, and a cell's wage is measured as the employment-weighted average of firm-level wages.

B Theory

B.1 Derivation of Equation (16)

The output of goods produced in location i is equal to the expenditure on good i of all locations including the larger economy:

$$w_i L_i = \gamma_i \sum_{k=1}^{N} w_k L_k + \gamma_i w_0 L_0, \tag{B.1}$$

where γ_i is the share of expenditure that is spent on goods from location i and given by

$$\gamma_i = \frac{\alpha_i (\frac{w_i}{A_i})^{1-\sigma}}{\sum_{k=0}^{N} \alpha_k (\frac{w_k}{A_k})^{1-\sigma}}. \tag{B.2}$$

Using equation (B.1) for $i = 0$ and rearranging it, we have

$$w_0 L_0 = \frac{\gamma_0}{1-\gamma_0} \sum_{k=1}^{N} w_k L_k. \tag{B.3}$$

Substituting $w_0 L_0$ in equation (B.1) by using equation (B.3), we can get equation (16)

$$w_i L_i = \gamma_i \sum_{k=1}^{N} w_k L_k + \gamma_i \frac{\gamma_0}{1-\gamma_0} \sum_{k=1}^{N} w_k L_k = \frac{\gamma_i}{1-\gamma_0} \sum_{k=1}^{N} w_k L_k = \pi_i \sum_{k=1}^{N} w_k L_k. \tag{B.4}$$

B.2 Derivation of Equation (19) and (18)

Equation (19) is derived by combining equation (17) and (16). In particular, substituting π_i in equation (17) by using equation (16), we have

$$\frac{w_i L_i}{\sum_{k=1}^{N} w_k L_k} = \frac{\alpha_i w_i^{1-\sigma} (A_i)^{\sigma-1}}{\sum_{k=1}^{N} \alpha_k w_k^{1-\sigma} (A_k)^{\sigma-1}}.$$

Rearranging the above equation and using $\widetilde{A}_i = A_i \alpha_i^{\frac{1}{\sigma-1}}$, we get equation (19).

We now show how to obtain equation (18). Using equation (14) and (15), we can express v_i and r_i in terms of w_i:

$$v_i = \frac{1}{\mu} w_i, \quad r_i = \frac{1-\mu}{\mu} \frac{H_i}{L_i}.$$

Substituting v_i and r_i into equation (9) yields

$$\frac{L_i}{\sum_{k=1}^{N} L_k} = \frac{B_i H_i^{(1-\mu)\epsilon} w_i^{\mu\epsilon} L_i^{-(1-\mu)\epsilon}}{\sum_{k=1}^{N} B_k H_k^{(1-\mu)\epsilon} w_k^{\mu\epsilon} L_k^{-(1-\mu)\epsilon}}.$$

Rearranging the above equation and using $\widetilde{B}_i = B_i H_i^{(1-\mu)\epsilon}$, we get equation (18).

B.3 "Exact-Hat" Algebra

Given changes in $(\alpha_i, \overline{A}_i, \widetilde{B}_i)$, a competitive equilibrium in changes is a vector of wage changes $(\hat{w}_1, ..., \hat{w}_N)$ and a vector of labor changes $(\hat{L}_1, ..., \hat{L}_N)$ satisfying:
Labor demand:

$$\hat{L}_i = \hat{w}_i^{-\sigma} \left(\hat{A}_i^{\sigma-1} \hat{\alpha}_i \right) \frac{\sum_{k=1}^{N} \pi_k \hat{w}_k \hat{L}_k}{\sum_{k=1}^{N} \pi_k \hat{w}_i^{1-\sigma} \left(\hat{A}_i^{\sigma-1} \hat{\alpha}_i \right)}. \tag{B.5}$$

Labor supply:

$$\hat{L}_i^{1+(1-\mu)\epsilon} = \hat{w}_i{}^{\mu\epsilon} \hat{\widetilde{B}}_i \frac{\sum_k s_k \hat{L}_k}{\sum_k s_k \hat{\widetilde{B}}_k \hat{w}_k{}^{\mu\epsilon} \hat{L}_k^{-(1-\mu)\epsilon}}. \tag{B.6}$$

Population mobility:

$$\sum_k s_k \hat{\widetilde{B}}_k \left(\frac{\hat{w}_k}{\hat{P}} \right)^{\mu\epsilon} \hat{L}_k^{-(1-\mu)\epsilon} = 1. \tag{B.7}$$

Agglomeration spillover:

$$\hat{A}_i = \hat{\overline{A}}_i \frac{\left(\sum_k e^{-\delta d_{ik}} L_k \hat{L}_k \right)^{\lambda}}{\left(\sum_k e^{-\delta d_{ik}} L_k \right)^{\lambda}}. \tag{B.8}$$

C GMM Estimation

To estimate $\Theta = (\lambda, \delta, \hat{\alpha}_1, \hat{\alpha}_2)$ using GMM, we solve the following constrained optimization problem:

$$\begin{aligned} &\min_{(\lambda,\delta,\hat{\alpha}_1,\hat{\alpha}_2)} \left(\frac{1}{N} \sum_{i=1}^{N} m(X_i, \Theta)' \right) W \left(\frac{1}{N} \sum_{i=1}^{N} m(X_i, \Theta) \right), \\ &\text{s.t. Equation (B.5), (B.6), (B.7), and (B.8).} \end{aligned} \tag{B.9}$$

where the moments are presented as in equation (21) and equation (22).

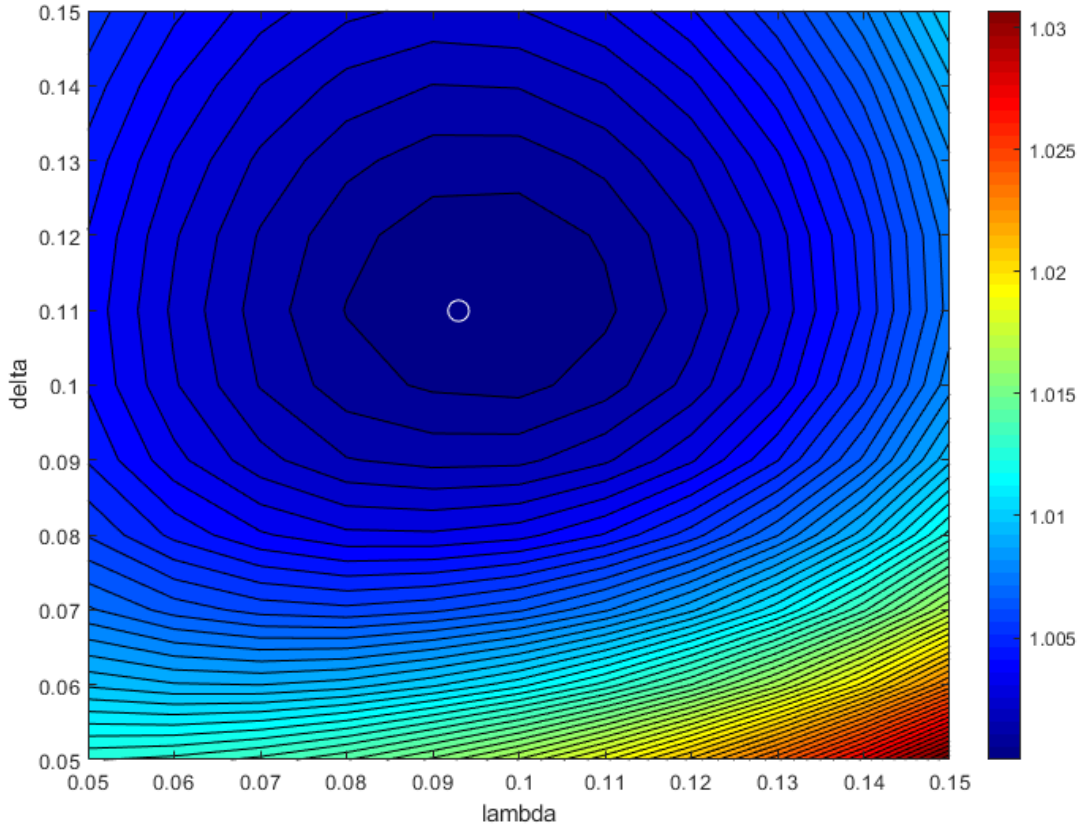


Figure C.1: local optimatization

D Additional Counterfactual Results

Table D.1: Impacts of Foxconn's Entry on the Size and Structure of the City with no Spillovers

	Overall	Distance to Foxconn Factories				
		Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
	(1)	(2)	(3)	(4)	(5)	(6)
(a) Employment (percentage change)	95.62	128.85	76.38	76.38	76.38	76.38
(b) $\frac{\Delta \text{ employment except Foxconn locations}}{\Delta \text{ employment in Foxconn locations in the baseline}}$	2.3	0.81	0.53	0.55	0.26	0.15

Notes: This table reports percentage changes in employment without agglomeration spillovers. In particular, we set $\lambda = 0$.

Table D.2: Impacts of Foxconn's Entry on the Size and Structure of the City with $\epsilon = 3$

	Overall	Distance to Foxconn Factories					
		Quintile 1	Quintile 1 excl. Foxconn locations	Quintile 2	Quintile 3	Quintile 4	Quintile 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(a) Employment (percentage change)	169.18	220.91	141.79	140.35	138.68	138.53	138.47
(b) Productivity (percentage change)	15.35	18.56	14.45	13.55	12.52	12.43	12.39
(c) $\frac{\Delta \text{ employment except Foxconn locations}}{\Delta \text{ employment in Foxconn locations}}$	4.21	2.50	2.50	0.97	1.00	0.48	0.27
(d) Employment share before entry (percent)	100	36.67	34.24	22.50	23.37	11.16	6.30
(e) Employment share after entry (percent)	100	43.72	30.76	20.09	20.72	9.89	5.58

Notes: This table shows the percentage changes in employment and productivity from the observed economy before Foxconn's entry to the counterfactual economy where Foxconn starts its operation. Column (1) shows the impacts on the whole city. Column (2) and Columns (4) -(7) show the impacts on the five areas based on their distance to Foxconn plants. Column (3) describes the outcomes for non-Foxconn locations within the first distance quintile.

Table D.3: Impacts of Foxconn's Entry on the Size and Structure of the City with $\epsilon = 5$

	Overall	Distance to Foxconn Factories					
		Quintile 1	Quintile 1 excl. Foxconn locations	Quintile 2	Quintile 3	Quintile 4	Quintile 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(a) Employment (percentage change)	169.38	221.95	142.9	140.45	138.19	138.03	137.97
(b) Productivity (percentage change)	19.86	24.55	18.32	17.00	15.81	15.72	15.69
(c) $\frac{\Delta \text{ employment except Foxconn locations}}{\Delta \text{ employment in Foxconn locations}}$	4.22	2.51	2.51	0.97	1.00	0.47	0.27
(d) Employment share before entry (percent)	100	36.67	34.24	22.50	23.37	11.16	6.30
(e) Employment share after entry (percent)	100	43.83	30.87	20.09	20.66	9.86	5.57

Notes: This table shows the percentage changes in employment and productivity from the observed economy before Foxconn's entry to the counterfactual economy where Foxconn starts its operation. Column (1) shows the impacts on the whole city. Column (2) and Columns (4) -(7) show the impacts on the five areas based on their distance to Foxconn plants. Column (3) describes the outcomes for non-Foxconn locations within the first distance quintile.