Mobile Broadband and Firm Efficiency: Evidence from Vietnam

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Abstract

This paper examines the impact of mobile broadband expansion on firm performance in Vietnam, leveraging the staggered rollout of 3G internet between 2009 and 2015 and panel data from the Vietnam Enterprise Census. Using a difference-in-differences approach, I find that access to 3G increases firm employment by 7.6% and reduces inventory holding costs by 10.4%, indicating improved operational efficiency. Despite rising employment, the total wage bill per employee declines by 6.9%, reflecting cost-cutting responses to heightened competition. As mobile broadband reduces information asymmetry and enhances market transparency, firms face downward pressure on prices and margins. Supporting this interpretation, I document a 13.5% decline in average prices and a 2.1% reduction in firm markups. Beyond domestic effects, mobile broadband also facilitates global integration, increasing the likelihood of export participation by 14.6 pp. Overall, the results underscore the role of digital infrastructure in enhancing firm efficiency, competitiveness, and market access.

1 Introduction

Mobile internet is a general-purpose technology that enhances access to information and reduces communication frictions. Its diffusion has supported economic growth across high-, middle-, and low-income countries. Studies show that mobile internet increases employment opportunities (Hjort and Poulsen, 2019) and lowers trade costs (Fernandes et al., 2019; Malgouyres et al., 2021). It also improves within-firm communication and productivity (Jiang, 2023), and strengthens coordination in supply-buyer relationships (Demir et al., 2024). Conversely, less attention has been paid to its pro-competitive effects. A seminal paper by Jensen (2007), using 2G's a predecessor of 3G technology, found to reduce price asymmetries between fish industry in India, where the price converge across the market. As internet access increases price transparency, understanding how firms adjust their pricing and behavior in response is an important avenue for research.[1]

In this paper, we leverage the staggered rollout of mobile broadband across Vietnam at the district level to estimate its effect on firm performance. Notably, 3G was the first generation to provide users with reliable internet access. In developing countries like Vietnam, fixed broadband infrastructure is often scarce and unreliable, particularly in rural areas. As a result, mobile broadband—capable of being deployed more rapidly—offers a more attractive alternative in such contexts (Bahia et al., 2020). This setting suggests a greater potential for mobile technology to improve productivity and efficiency, especially where traditional broadband infrastructure is lacking.

The objective is to examine how the rollout of mobile broadband networks influenced firm efficiency in Vietnam. To obtain causal estimates, we combine unique cell-tower data from OpenCellID (used to construct the treatment variable) with enterprise survey data from 2009 to 2015 (our outcome data). The detailed spatial resolution of the dataset allows us to approximate firm location using the centroid of each district.

The identification strategy relies on a Difference-in-Differences (DiD) design that exploits the staggered rollout of 3G networks across districts to isolate the effect of mobile broadband access on firm performance. We show that the 3G rollout in Vietnam was pri-

[1]This paper focuses on mobile broadband as an expansion of telecommunication infrastructure. Unlike traditional infrastructure such as roads or irrigation systems, telecommunication upgrades facilitate the exchange of ideas through faster communication and network spillovers. The internet accelerates economic activity regardless of geographic distance, much like roads reduce transportation costs. In this way, mobile broadband lowers communication barriers and trade costs (Acosta and Baldomero-Quintana, 2023; Röller and Waverman, 2001).

marily driven by population density, consistent with findings from the broadband rollout in France documented by Malgouyres et al. (2021). This design is well suited to estimating the causal impact of 3G availability by comparing firms located in districts with high mobile internet coverage to those in districts without such access.

Recent studies have shown that two-way fixed effects (TWFE) regressions can produce a negative bias against adopted staggered treatment (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). I estimate the dynamic impacts of the 3G rollout, allowing for heterogeneity of the treatment effect using Sun and Abraham (2021). Recognizing the importance of the parallel trend assumption under the DiD approach, I also assess how sensitive our estimates are to deviations from the parallel trend assumption, using the approach of Rambachan and Roth (2023). Lastly, I also conduct robustness checks using alternative approaches from (Wooldridge, 2021).

Firstly, I examine the impact of 3G internet on firm dynamics in Vietnam. One of the key findings of the paper is that 3G access led to a reduction in inventory holdings by 10.4%, likely reflecting improved coordination with suppliers, more efficient internal communication, and lower operational costs. I also find that 3G internet had a positive effect on employment, increasing it by 7.6 %. Although firm revenue rose modestly during the initial period (0–1 years after connectivity), it declined over time, resulting in no significant improvement in labor productivity. Our results suggest that the introduction of 3G internet in Vietnam reduced communication costs and improved firm efficiency. Firms became larger and streamline their operation and their supply chain.

Second, the importance of 3G lies in its ability to provide readily available connectivity, increase price transparency, and support the development of e-commerce. This enables both firms and consumers to compare prices more efficiently. I examine whether 3G internet affects firm markups in Vietnam, as markups can reveal underlying market competition dynamics. Overall, I find that 3G internet reduces firm markups, suggesting a decline in firm-level profitability and an increase in competition in districts with greater internet connectivity.

Since I measure markups as the ratio of price to the output elasticity of material inputs, following De Loecker and Warzynski (2012), I explore two mechanisms that could explain the observed decline: lower marginal costs and falling average prices. Evidence from earlier results—particularly the reduction in inventory holdings—suggests that firms improved supply chain efficiency and faced lower marginal costs. To examine the demand side, I regress the probability of firms engaging in export activity as a proxy for integration into international markets. The results show that 3G access increases the likelihood of exporting by 14.6 %. While access to larger markets may, in theory, allow firms to charge higher prices, I test the pro-competitive effect of 3G more directly by analyzing firm pricing strategies using product-level data. I find that average prices fall by 13.4 % as internet access expands. The observed decline in average prices suggests that 3G facilitated greater price reduction, primarily driven by intensified competition resulting from increased price transparency. A plausible explanation is that stronger competition forced firms to operate more efficiently and set prices closer to marginal costs.

Third, the effects of 3G access vary across sectors. The wholesale industry, which is on average less complex, appears to benefit disproportionately from the rise of e-commerce activity. I find that the wholesale sector is the main beneficiary of 3G internet in Vietnam, showing a notable increase in employment. However, despite this employment growth, firms in the wholesale sector reduced their overall wage bill, suggesting that the new jobs created were lower-paid. Taken together, the evidence indicates that firms operating in the wholesale sector not only expanded employment but also experienced a decline in markups, consistent with intensified competition and cost-saving.

Related Literature: This paper contributes to three strands of literature. First, there is extensive evidence linking broadband internet to economic development, structural transformation, firm performance, trade, and innovation. For example, Hjort and Poulsen (2019) show that broadband access boosts firm growth in sub-Saharan Africa, while Caldarola et al. (2023) highlight 3G Internet assists structural transformation in labour market toward service sector in Ethiopia. In China, Fernandes et al. (2019) find that broadband internet, pre-Alibaba era, promotes firm-level export activities, and Malgouyres et al. (2021) show that broadband in France increases both exports and import intensity. In terms of innovation, Chakraborty and Zhu (2024) report that broadband access enhances input and output innovation among Chinese firms. Our contribution focuses on mobile broadband, a relatively understudied aspect compared to fixed broadband. While prior research finds that internet access supports firm growth, I show that the effects of mobile internet are industry-specific, with 3G access being particularly relevant for the wholesale sector. Moreover, consistent with DeStefano et al. (2023), I find no evidence of productivity gains among Vietnamese firms.

Secondly, this paper contributes to the literature on impact of digital infrastructure on reductions in information frictions through the lens of streamline supply chain. Earlier studies highlight the role of mobile phones and internet technology in reducing price dispersion and trade barriers, such as Jensen (2007), who show that mobile phones and 2G reduced price dispersion in fishermen and the wholesale market in India. Allen (2014) model search frictions to explain trade barriers and price gaps among Philippine farmers, the model estimate 50% of the regional price dispersion is due to information friction and not trade cost. Lendle et al. (2016), who find that online trade via eBay significantly reduces the effect of geographic distance due to lower information and trust frictions. Jiang (2023) demonstrate that internet connectivity improves internal firm communication across dispersed locations, and Demir et al. (2024) find that fast internet in Turkiye enables firms to expand their supplier networks and shift sourcing decision to highly connected area. Building on this, better communication improve firm outreach to supplier with instant communication and decentralised their inventory in which lower their warehouse cost (Boyer, 2001). In this paper, I use firm inventory as a proxy for supply chain efficiency and find that firms with better 3G coverage hold significantly lower inventory levels, suggesting reduced reliance on buffer stocks due to improved communication. I also examine product scope and product turnover as proxies for search costs but find no conclusive evidence that internet access significantly affects firms' product dynamics along these dimensions.

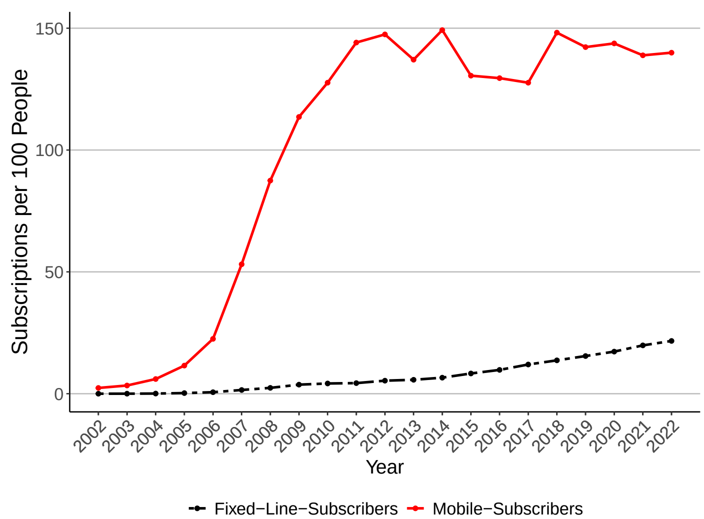
Lastly, I contribute to the literature on internet diffusion and firm competition in Vietnam. Hennig and Vidal-Naquet (2023) show that broadband rollout in France increased firm-level markups and reduced markdowns, reflecting shifts in both product and labor market power. In Vietnam, Li et al. (2022) find that a growing foreign presence intensifies competition and puts downward pressure on domestic firm markups. Baccini et al. (2019) highlight how SOEs weaken the pro-competitive impact of trade liberalization, dampening productivity gains due to political entry barriers and preferential credit access. Building on these insights, this paper investigates how the expansion of 3G mobile internet in Vietnam affected firm-level markups and market concentration. I examine the mechanism through which internet access influences the average prices charged by Vietnamese firms, using detailed firm-product-level data.

The paper is organized as follows: Section 2 provides a brief overview of the institutional background in Vietnam and describes the data source. Section 3 reports on mobile broadband Internet and data description. Section 4 presents the estimation strategy and results, and Section 5 concludes.

2 Institutional Background: 3G Rollout in Vietnam

In Vietnam, private telecommunication providers play a crucial role in deploying and expanding the mobile broadband and 3G mobile network. However, the scale-up of this technology is not determined solely by their commercial interests. The Ministry of Communication imposes coverage requirements and guidelines to ensure that mobile broadband technology reaches both rural and less populated areas equally. This deployment is not just aimed at economic advancement; it is also integral to the socio-economic of various districts. Access to mobile broadband can significantly boost e-commerce, online education, and e-governance.

Figure 1: Mobile and Fixed Broadband Subscriptions in Vietnam



Source: World Bank.

The Ministry of Information and Communication (MIC) approved three strategic plans for the development of Information and Communication Technology (ICT) in the Northern, Southern, and Central economic regions.[2] These plans, established in 2007, outlined ICT development through 2010. Subsequently, in 2009, Viettel Military Industry and Telecoms Group (Viettel) became the first private telecommunication provider to be granted a license for commercial 3G mobile broadband deployment, followed by VinaPhone, MobiFone, and

[2]Decisions No. 13/2007/QD-BBCVT, 14/2007/QD-BBCVT, and 15/2007/QD-BBCVT, all issued on June 15, 2007, outlined ICT development through 2010 with a vision toward 2020 for the Central, Southern, and Northern regions, respectively.

Hanoi Telecom.[3]

Mobile broadband is the primary mode of internet access in many developing countries, with Vietnam as a key example. As shown in Figure 1, Vietnam has 148.17 mobile subscriptions per 100 inhabitants, compared to just 13.69 fixed broadband subscriptions. The rapid uptake of mobile broadband reflects consumer demand for smartphones, driven in part by the introduction of the iPhone (West and Mace, 2010). The launch of 3G services significantly expanded internet access across the country. Vietnam's telecom privatization and limited fixed broadband in the early years make it an ideal case to study the firm-level impact of mobile internet.

3 Data

In this section, I first explain the source of the 3G dataset and provide a methodological explanation of the z-score, which quantifies the level of 3G internet coverage at the district level, following Malgouyres et al. (2021). Next, I conduct a balance test to justify that the 3G internet rollout is exogenous and correlated with the development of socio-economic factors rather than being driven by economic activities. Then, I describe the firm-level data from 2009 to 2015 and provide a data summary. The data and cleaning procedure have been extensively explained in McCaig et al. (2022a). Finally, I explain the data used as control variables.

3.1 Mobile Broadband Internet Data

Defining 3G Coverage Ratio. Third Generation (3G) is a wireless telecommunication technology and the first mobile network technology that can be regarded of as broadband due to its functionality in facilitating high-speed data transfer. In comparison to its predecessor the Second Generation (2G), 2G is limited to calls, messages and minimal access to the Internet (Bessone et al., 2023). Importantly, this paper focuses on the introduction of mobile broadband. I proceed to measure 3G coverage at the district level.

While we do not have information on the fixed broadband rollout in Vietnam. The deployment of cellular tower is the key source variation that we exploited and use it for

[3] https://vccinews.com/news/18261/.html

empirical analysis. We are depending on the information of cellular tower date of deployment and the geo-location of the cellular tower. OpencellID also informs us the type cell technology the cell tower is to ascertain I am working with 3G internet, I filter and keep only firm with a description UMTS in the radio type. The information on Cellular Tower sourced from OpenCellID, a community-driven project compiling GPS coordinates of cell towers along with their location area identifiers. We merged the Cellular Tower with Vietnam Geographical File help us to identify the location of the tower at the ward level.

Calculate 3G Coverage Ratio (Z-Score). To measure mobile broadband access (3G) at the district level, we use OpenCellID data and follow the methodology outlined in Malgouyres et al. (2021). The Z-Score, denoted as $\widetilde{Z}_{dt}$, represents the time-weighted percentage of a district's area covered by mobile internet in year t, ranging from 0-1. It is computed using the following formula:

$$\widetilde{Z_{dt}} = \sum_{w \in d} D_{w,t} \frac{A_{w,t}}{\sum_{w' \in o} A_{w',t}} \tag{1}$$

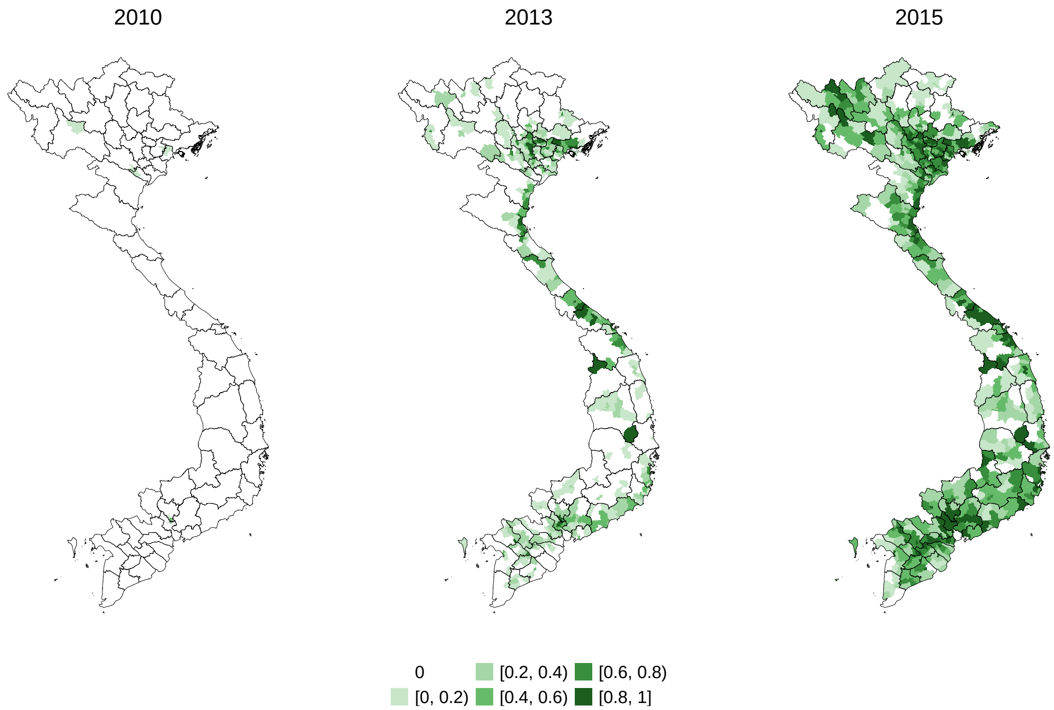
In contrast to Malgouyres et al. (2021), where broadband access is defined by the number of days a fixed broadband connection is available in a city in France, this paper focuses on the 3G internet rollout. Instead of fixed broadband availability, I utilize the location and activation date of each 3G cellular tower within a ward.

Although OpenCellID provides information on the coverage range of each 3G cell tower, its accuracy is a concern. To address this, I adopt an arbitrage approach based on Weitzen et al. (2013), which states that UMTS technology has a coverage range of 1–5 km in urban and suburban areas and 5–10 km in rural areas. For consistency, I take the upper limit of the urban and suburban range (5 km) as the assumed coverage radius for all cellular towers. A ward is thus considered to have 3G access if its centroid falls within 5 km of a cellular tower.

In equation (1), $D_{w,t}$ represents the proportion of days in year t during which w has 3G coverage. A ward is considered connected once the first cellular tower is deployed within its boundaries. The second term in equation (1) represents the proportion of the ward's population relative to the total district population. Here, $w \in d$ denotes the wards within district d. Ultimately, $\widetilde{Z}_{dt}$ quantifies the degree of 3G mobile broadband coverage at the district level.

3G Internet Rollout in Vietnam. Figure 2 illustrates the rollout of 3G internet across Vietnam over time. The figure shows that internet coverage gradually became more con-

Figure 2: 3G Rollout in Vietnam



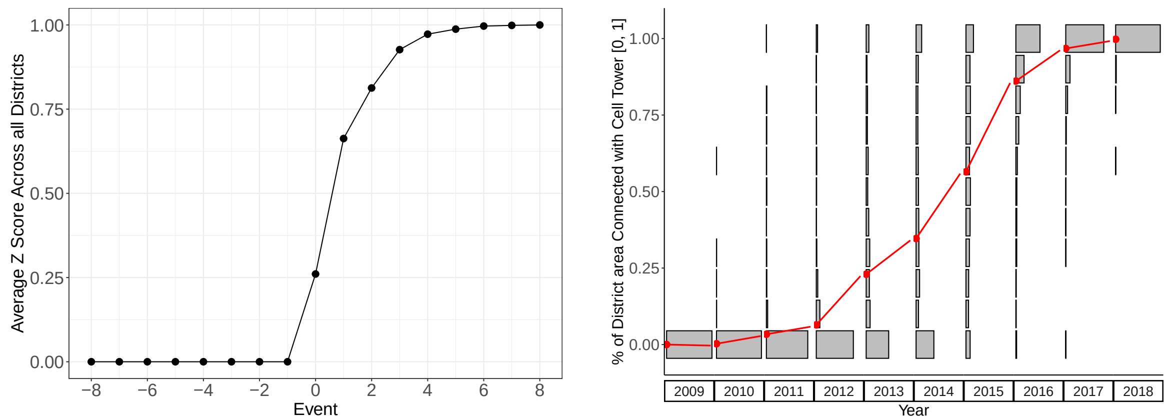
centrated within districts. Initially, in 2010, mobile internet deployment was concentrated in densely populated urban centers such as Ho Chi Minh City. Over time, it expanded into less economically and demographically dense districts. Notably, there was substantial annual variation in the availability of 3G mobile broadband within each district.

Figures 3a and 3b depict the z-score and its treatment effect at the district level in Vietnam. Figure 3a indicates that, on average, 60% of the population in a district had access to 3G internet in the first year a 3G cell tower was within range of the district. This result differs from (Malgouyres et al., 2021); explain the key differences and implications. Figure 3b provides insights into the proportion of districts in Vietnam with 3G internet access. The red line in the figure shows that in 2009, no district in Vietnam received a 3G signal. By 2015, approximately 75% of districts had access, and by 2018, 3G internet had become universally available.

Determining 3G rollout in Vietnam. A key concern in this study is the potential endogeneity of 3G rollout, which may undermine the causal interpretation of the results. As discussed in Section 2, the privatization of the telecommunications sector may have incentivized private firms to deploy 3G technology in economically attractive locations. To assess

Figure 3: 3G Rollout in Vietnam

(a) Average Score Distribution (b) Distribution and z-score



Note: Author's own calculation

this concern, I examine whether the expansion of 3G coverage between 2009 and 2015 was driven by the economic conditions of a district or by its broader socioeconomic characteristics.

$$\widetilde{Z}_{dt} = \beta_1 \text{Density}_{dt} + \beta_2 \text{PCI}_{cpt} + \beta_3 \text{Nightlight}_{dt} + \alpha_d + \theta_t + \varepsilon_{dt} \tag{2}$$

To test this assumption, I estimate the following equation, where $\widetilde{Z}dt$ represents 3G coverage at time t, as defined in Equation 1. The variable $Density_{dt}$ captures the initial population of the district in 2009, divided by the district area, and is interacted with the dummies of the year 2009 to 2015. I also include a list of covariates, including nighttime light per capita as a proxy for GDP per capita, log altitude and ruggedness, provincial competitiveness and development at the provincial level, share of landline users, labor force participation rate, literacy rate, and share of urban population.

Table 1 shows Province-Year-Trend and only variable the Lasso picked up. Table 7 presents the full results of the regression analysis. Table 1 presents the results of a balance test that evaluates the determinants of 3G rollout across Vietnamese districts using a Province-Year Trend specification. Specifically, we estimate how pre-treatment district characteristics predict the timing of 3G expansion, thereby assessing the plausibility of the exogeneity assumption underlying our identification strategy.

Table 1: Balance Test: Province-Year Trend Specification

Covariate	**Province-Year Trend**	
	OLS (1)	**LASSO (2)**
Density × 2009	-0.003	-0.000
	(0.002)	(0.000)
Density × 2010	-0.001	0.002
	(0.002)	(0.002)
Density × 2011	0.027	0.029*
	(0.018)	(0.017)
Density × 2012	0.038*	0.041**
	(0.020)	(0.020)
Density × 2013	0.060***	0.080***
	(0.013)	(0.014)
Density × 2014	0.110***	0.118***
	(0.015)	(0.014)
Density × 2015	0.089***	0.101***
	(0.014)	(0.012)
Share of Labour Force (%)	-0.005	-0.000
	(0.004)	(0.003)
Share of Urban Population (%)	0.002*	0.003***
	(0.001)	(0.001)
Elevation × Year × 2009	0.002*	-0.000
	(0.001)	(0.000)
Elevation × Year × 2010	0.004*	0.001
	(0.002)	(0.001)
Observations	4,781	4,781
R-squared	0.546	0.545
District FE	–	–
Year FE	✓	✓
Province-Year Trend	✓	✓

Note: This table presents balance test results using the Province-Year Trend specification. Standard errors are shown in parentheses and clustered at the province level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Cells marked "–" indicate variables omitted or not selected by LASSO.

Column (1) reports the results from a standard OLS regression that includes full covariates and province-year fixed effects. These covariates include population density (interacted with year dummies), labor force composition, urban population share, and elevation (also interacted with year). Column (2) shows the results from a LASSO regression, which selects the most predictive covariates in a data-driven way, reducing potential overfitting and multicollinearity.[4] I use the LASSO method to select covariates that are most strongly correlated with the 3G rollout (Belloni et al., 2014) in Vietnam and include them as baseline controls in Equation 3.

The LASSO results suggest that only a subset of covariates are strong predictors of 3G rollout timing. Those covariates are primarily those related to population density and the share of urban population are highly significant. LASSO also pickup Elevation as a determinant of the 3G rollout.

Both models yield similar R-squared values (0.545) and account for province-specific shocks by including province-year fixed effects. The significant coefficients on population density and urban share suggest that the 3G rollout was more likely to occur in districts with larger populations and growing urban characteristics. This pattern suggests that rollout decisions were guided more by population demand.

[4] I apply the robust LASSO approach in Stata using the lassopack package developed by Ahrens et al. (2020).

3.2 Enterprise Survey Data

Firm. Our primary dataset is the Vietnam Enterprise Survey (VES), administered annually by the General Statistics Office (GSO) of Vietnam. It provides detailed firm-level information on balance sheets and income statements. This dataset has been widely used in studies on Vietnamese firms (McCaig et al., 2022b).

For this study, where both the treatment and the research question focus on the district level, I first construct firm-level data aggregated at the district level. To account for multi-establishment firms operating within the same district, I group establishments by district and tax identification code, aggregating them into single entities. This process results in a firm-by-district panel dataset. Additionally, I retain only firms with more than 10 employees in any given year. To mitigate the influence of potential outliers, I winsorize all variables at the 1st and 99th percentiles. The Wage Bill variable appears to have some reporting issues in 2014; to address this, I remove the identified outliers (see discussion in Section Appendix A).

Product Level. In addition to balance sheet data, I use detailed firm-level production data at the 8-digit product code level, including quantities produced. Table 2 summarizes the number of products and the number of products. Following Goldberg et al. (2010), I define the number of products at the 4-digit level, with changes measured as the difference in total product count between years t and $t-1$. For average price calculations, I focus on single-product firms and retain only those clearly reporting quantities in standardized units, such as "ton", "item", "meter", "piece", "tablet", "liter", "set", "kilogram", "batch", or "unit". Average price is computed as revenue divided by quantity.

3.3 Control Variables

In this paper, the analysis incorporates firm-by-district fixed effects, year fixed effects, and year-industry fixed effects to control for time-invariant characteristics of firms within each district pair and across year-industry variations. In addition, several key control variables are included to account for differences in provincial characteristics.

Provincial control variables are selected using the LASSO Belloni et al. (2014) approach to retain covariates most relevant for explaining the rollout of 3G. These include Province-Year Trends and District-Population-Year Trends, using 2009 district population data. Nightlight intensity is used as a proxy for district GDP per capita.

To capture provincial characteristics over time, the Provincial Competitiveness Index

(PCI) is used, which measures various aspects of economic governance, infrastructure quality, and socioeconomic conditions at the provincial level. PCI data is sourced from the Provincial Competitiveness Database for the period 2009–2015.

Lastly, I incorporate district terrain ruggedness and Elevation $\times$ Year data. Elevation $\times$ Year data comes from the US Geological Survey (USGS) GTOPO30 dataset (USGS, 2018), while terrain ruggedness information, geo-referenced at a 1 × 1 km grid-square resolution, is sourced from Shaver et al. (2019).

Table 2: Descriptive Statistics

	Mean	Median	SD	Min	Max	Obs	Year
I. Outcome Variable, Firm-Dynamic							
Firm Dynamics							
Employment	2.916	2.708	1.305	0.000	7.098	506,563	2009–2015
Revenue	8.952	8.986	2.117	-2.627	13.956	449,386	2009–2015
Inventory	7.705	7.776	1.771	-2.524	12.829	393,523	2009–2015
Wage Bill per Employee	3.532	3.598	0.652	-4.577	5.228	448,498	2009–2015
Labour Productivity	6.001	6.036	1.709	-7.977	9.975	449,374	2009–2015
II. Firm Competition							
Markup	3.354	4.129	3.204	-12.458	17.763	316,225	2009–2015
Total Factor Productivity (TFP)	1.470	1.499	0.292	-6.762	2.439	316,225	2009–2015
Exporting Firm	0.585	1.000	0.493	0.000	1.000	407,415	2009–2015
Average Price	2.762	3.065	2.305	-8.678	13.775	34,746	2009–2015
III Product Dynamics							
Number of Products	0.936	0.881	0.185	0.881	3.093	128,699	2009–2015
Changes in Number of Products	0.078	0.000	0.266	0.000	2.492	98,698	2009–2015
IV. Control Variables, District							
ADSL Adoptor	0.358	0.000	0.479	0	1.000	506,563	2009–2015
Nightlight	12.168	6.374	15.869	0	63.000	4564	2009–2015
Population Density	7.059	7.046	1.604	2.078	12.133	4564	2009–2015
Elevation $\times$ Year	4.029	4.282	2.049	0.039	7.088	4564	2009–2015
PCI Legal	5.060	5.101	1.128	1.996	7.909	4564	2009–2015

Note: Each year, all nominal variables are deflated using the Manufacturing Price Index. Outcome variables such as Employment, Revenue, Inventory, Inventory Ratio, Wage Bill per Employee, Labour Productivity, Markup, TFP and average price are transformed using the natural logarithm. We estimate the Number of Products and Changes in the Number of Products are transformed using the inverse hyperbolic sine (IHS) transformation. This transformation is primarily applied to the Change in the Number of Products to accommodate zeros Exporting Firm and ADSL Adopter are dummy variables. Nightlight and Elevation $\times$ Year represent average values. Population Density is transformed using the inverse hyperbolic sine (IHS) method. PCI Legal is an index ranging from 0 to 10. Note, there is a large number of firms that do not report their inventory and capital in the year 2015. As for Average Price, we only obtain 550 firms out of 34, 746, therefore our analysis is mainly focus on Manufacturing Sector.

4 Empirical Strategy

Given that the 3G rollout in Vietnam was plausibly exogenous—primarily driven by district-level population density—this section investigates its impact on local economies and firm-level outcomes, including total employment, inventory, and inventory ratio. We exploit the staggered deployment of 3G infrastructure across Vietnamese districts between 2009 and 2015.

The main estimating equation is specified as follows:

$$Y_{idjt} = \sum_{d=-6, d\neq -1}^{5} \beta_d \cdot \{3G\_Rollout_{i,d,t}\} + X_{ijt}\delta + \alpha_i + \theta_j + \gamma_{pt} + \varepsilon_{idjt} \tag{3}$$

where Y_{idjt} represents the outcome of firm i, located in district d, province p, and operating in industry j at time t. The variable $3G\_Rollout_{i,d,t}$ is a set of event-time indicators that equal 1 if firm i is located in district d and the year t is d years relative to the district-specific 3G rollout year t_0. The omitted category is $d = -1$, which serves as the reference period.

The treatment variable is defined as:

$$3G\_Rollout_{d,t} = \begin{cases} 1 & \text{if } t \geq t_0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The base year t_0 is defined as the year in which the district experiences the largest year-on-year increase in 3G coverage. Treated districts are those that experience a large 3G adoption in t_0 and remain exposed in all subsequent years $t \geq t_0$. The control group comprises both never-treated districts and not-yet-treated districts within the sample period.[5]. All regressions include firm fixed effects α_i, industry fixed effects θ_j, and province-year fixed effects γ_{pt}, along with time-varying controls X_{ijt}.

The term X_{it} represents a vector of firm- and province-level control variables. These include pre-treatment broadband adoption (ADSL), district Elevation $\times$ Year interacted with time, initial population density in 2009 interacted with time, the quality of provincial legal

[5]This study focuses on the period 2009–2015, which captures the 3G rollout in Vietnam. The analysis ends in 2015 to avoid contamination from the introduction of 4G, which began in December 2015 in Hanoi and Ba Ria–Vung Tau and expanded nationwide in 2016. See: https://international.viettel.vn/news-detail/4g-race-in-vietnam-heating-up

institutions, and nightlight intensity per capita, which proxies local economic activity. We also include province-year trends γ_{pt} to flexibly account for province-specific economic and policy trajectories over time.

Firm fixed effects α_i control for all time-invariant characteristics of firms. Industry-year fixed effects θ_{jt} account for time-varying shocks common to all firms within an industry, such as global demand shifts or industry-specific policies. The inclusion of province-year trends ensures that identification comes from within-province comparisons over time, while flexibly capturing differential growth trajectories across provinces. Together, this specification allows us to estimate the dynamic impact of 3G access on firm outcomes by comparing treated and untreated firms within the same province over time.

Heterogeneous Treatment: Standard two-way fixed effects (TWFE) estimators can produce biased estimates when treatment effects are heterogeneous. This issue is particularly pronounced in staggered treatment settings, where later-treated units may inappropriately serve as controls for earlier-treated ones. These comparisons can introduce negative weights into the estimation, leading to bias in both the direction and magnitude of the estimated treatment effects (Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021).

To address concerns about biased estimates from conventional two-way fixed effects (TWFE) models, I adopt the method proposed by Sun and Abraham (2021) as my baseline. Their event-study framework accounts for arbitrary heterogeneity in treatment effects across cohorts and over time by estimating cohort-specific average treatment effects on the treated (CATTs):

$$\mathrm{CATT}_{e,\ell} = \mathbb{E}\left[Y_{i,e+\ell} - Y^{\infty}_{i,e+\ell} \,\middle|\, E_i = e\right], \tag{5}$$

where $Y^{\infty}_{i,e+\ell}$ denotes the counterfactual outcome had unit i never been treated or not yet treated (last treated cohort). Importantly, the method avoids contamination from already-treated units by using not-yet-treated cohorts as valid controls.

Sun and Abraham (2021) show that TWFE estimates can be misleading due to the use of non-convex or negative weights across cohorts and event times. Instead, their estimator recovers event-time average treatment effects (ATTs) as convex combinations of cohort-specific effects:

$$\widehat{\text{ATT}}_\ell = \sum_e w_{e,\ell} \cdot \widehat{\text{CATT}}_{e,\ell}, \tag{6}$$

with weights $w_{e,\ell}$ reflecting cohort shares at each relative time ℓ. This produces interpretable and robust dynamic effects even under staggered adoption. In our setting, $\widehat{\text{ATT}}_\ell$ captures the average effect of 3G rollout on treated firms ℓ years after 3G connectivity.

Robustness and Alternative Estimators: In addition to Sun and Abraham (2021), I implement alternative DiD estimators as robustness checks. Specifically, I estimate Equation 3 using the approaches proposed by Wooldridge (2021).

Parrallel Trend Assumption: One may be concerned that the 3G rollout is not completely exogenous. I also check how sensitive the results are to possible violations of the parallel trends assumption. Following Rambachan and Roth (2023), I use the `HonestDiD` method to estimate bounds on the treatment effect. These bounds are based on the idea that trends from before the 3G rollout can be used to predict what would have happened without treatment. This method is helpful because it allows us to go beyond assuming perfect parallel trends, and it also shows how the treatment effect could change if those trends had shifted and diverged from linear trend.

5 Result: Effect of Mobile Broadband on Firm Outcomes

Baseline Results. Table 3 presents baseline results for the impact of 3G rollout on firm employment. The dependent variable in all columns is the natural logarithm of firm employment. Column (1) presents a basic specification with firm-by-district and industry-by-year fixed effects. Column (2) adds controls selected based on LASSO, including Elevation × Year , the legal component of the PCI, and a population-year trend. I also include nightlight per capita as a proxy for district-level GDP and a dummy for firms that adopted fixed broadband in 2009. Columns (3) and (4) additionally include a region-year trend and region-by-year fixed effects, respectively. In Columns (5) and (6), I re-estimate the same specification as in Column (2), but include province-year and province-by-year fixed effects, respectively.

Table 3: Employment Regression Results

	Dependent Variable: Employment					
	(1)	(2)	(3)	(4)	(5)	(6)
3G Rollout	0.076***	0.094***	0.075***	0.067***	0.076***	0.058***
	0.018	0.023	0.023	0.022	0.023	0.022
Firm by District FE	✓	✓	✓	✓	✓	✓
Industry × Year FE	✓	✓	✓	✓	✓	✓
Region × Year FE	–	–	–	✓	–	–
Region × Year Trend	–	–	✓	–	–	–
Province × Year FE	–	–	–	–	–	✓
Province × Year Trend	–	–	–	–	✓	–
ASDL Adopter	–	✓	✓	✓	✓	✓
Nightlight per Capita	–	✓	✓	✓	✓	✓
Elevation × Year	–	✓	✓	✓	✓	✓
Province Charac	–	✓	✓	✓	✓	✓
Pop × Year	–	✓	✓	✓	✓	✓
Observations	506,312	506,087	506,087	506,087	506,087	506,087
Adjusted R^2	0.8352	0.8352	0.8353	0.8354	0.8357	0.8361

Notes: The outcome variable is transformed using the natural logarithm. Fixed Broadband indicates firms that adopted ADSL broadband technology as recorded in the VES 2009. Nightlight per capita serves as a proxy for GDP per capita at the district level. PCI refers to the Provincial Competitiveness Index, which reflects provincial-level legal and institutional characteristics. Standard errors are clustered at the district level. The difference-in-differences regression results follow the methodology of Sun and Abraham (2021). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

After applying all specifications described above, the results in Figure 3 show that the 3G rollout has a positive and significant effect on firm employment in Vietnam. Including province-level fixed effects and province-year trends may be too restrictive. Therefore, in analyzing other firm outcomes, we primarily adopt the specification presented in Column (5) of Table 3. Column (5) incorporates province-specific linear time trends to control for unobserved, gradual economic changes at the provincial level, while still permitting the outcome variable to evolve uniquely across provinces over time. Figure 3 presents the event study of employment over time. The results indicate an increasing trend post-treatment. There is no violation of parrallel trend as the pre-trends are not statistically significant. Given that the parallel trends assumption is critical for Difference-in-Differences estimation, we conduct robustness checks and test its validity using the methodology proposed by Rambachan and Roth (2023), as discussed in Section 5.2. Overall, the employment results are robust, with sensitivity tests indicating that the relative magnitude of pre-trend deviations is bounded by $\overline{M} = 0.2$.

Table 4: Impact of 3G Rollout on Firm Dynamics

	Dependent Variables			
	Revenue	Labour Productivity	Wage Bill per Worker	Inventory
	(1)	(2)	(3)	(4)
3G Rollout	-0.058 (0.041)	-0.130*** (0.034)	-0.106*** (0.013)	-0.104** (0.033)
Firm × District FE	✓	✓	✓	✓
Industry × Year FE	✓	✓	✓	✓
Province × Year Trend	✓	✓	✓	✓
ADSL Adopter	✓	✓	✓	✓
Nightlight per Capita	✓	✓	✓	✓
Elevation × Year	✓	✓	✓	✓
Province Characteristics	✓	✓	✓	✓
Population × Year	✓	✓	✓	✓
Observations	446,505	446,488	446,256	388,358
R^2	0.8180	0.7560	0.5870	0.7430

Notes: All outcome variables are in natural logarithms. Standard errors (in parentheses) are clustered at the district level. Specifications follow Equation (3). Estimation uses a Difference-in-Differences approach per Sun and Abraham (2021). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In this paper, I also examine the effect of the 3G rollout on a range of firm-level outcomes, as reported in Table 5. Despite the observed increase in employment among firms located in districts with 3G coverage—consistent with findings in Pham and Caldarola (2024)—I do not find a significant change in firm revenue (Column 1 of Table 3). Moreover, I find a decline in labor productivity (Column 2) among firms in high-3G districts, a result that contrasts with studies such as Hjort and Poulsen (2019) and Fernandes et al. (2019). However, this is in line with DeStefano et al. (2018), who find that broadband access does not necessarily raise productivity but rather facilitates firm expansion, particularly through increased employment and sales. This suggests that, in Vietnam as well, internet technologies are used more for communication than for increasing productivity.

Additionally, I find that the 3G rollout is associated with a decline in the wage bill per employee (Column 3). Using Labour Force Survey data, Pham and Caldarola (2024) similarly report that 3G access is positively associated with increased employment and the prevalence of waged jobs. However, they also find that 3G access increases lower-secondary school completion while discouraging upper-secondary attainment among youth. This trade-off suggests that improved job opportunities following 3G diffusion may have led young people to enter the labor market earlier, potentially lowering the average educational attainment of the workforce. This mechanism may help explain the observed reduction in the wage bill per employee after the 3G rollout.

Taking the view, 3G has the mean of communication. I find a causal effect of 3G rollout on firm inventory behavior. Firms in districts with higher 3G coverage reduced their inventory holdings by approximately 10.4%, conditional on province-year trends. This aligns with Demir et al. (2024), who show that improved internet access enables firms to diversify suppliers and optimize sourcing. My findings suggest that Vietnamese firms with 3G access adopted leaner inventory strategies, reducing reliance on stockpiles. This behavior is consistent with Just-in-Time inventory systems, where digital connectivity supports more responsive logistics (Boyer, 2001; Shirley and Winston, 2004). Complementing this evidence, Li and Li (2013) show that better road infrastructure also reduces delivery times and logistics costs, reinforcing the broader role of infrastructure in enabling inventory efficiency.

5.1 Firm Competition and Product Dynamic

As 3G internet has the mean of improve communication and search cost. This may raise concern about price transparency and firm competition. As access to the 3G Internet reduces search costs and improves communication, it can intensify competition in the product market by allowing firms to benchmark prices more effectively, discover new suppliers and access broader markets. In this section, I explore whether firms facing increased competitive pressure adjusted their behavior in terms of price-setting, and product offerings. Specifically, I examine changes in markups, total factor productivity (TFP), average export prices, and product dynamic at the firm level.

Table 5: Impact of 3G Rollout on Firm Dynamics

	Dependent Variables			
	Markup	Total Factor Productivity	Average Price	Export
	(1)	(2)	(3)	(4)
3G Rollout	-0.135***	-0.025***	-0.134*	0.146***
	(0.030)	(0.005)	(0.081)	(0.042)
Firm × District FE	✓	✓	✓	✓
Industry × Year FE	✓	✓	✓	✓
Province × Year Trend	✓	✓	✓	✓
ADSL Adopter	✓	✓	✓	✓
Nightlight per Capita	✓	✓	✓	✓
Elevation × Year	✓	✓	✓	✓
Province Characteristics	✓	✓	✓	✓
Population × Year	✓	✓	✓	✓
Observations	306,646	306,646	32,201	130,333
R^2	0.9590	0.8250	0.8210	0.9300

Notes: All outcome variables are expressed in natural logarithms. Markup is computed following De Loecker and Warzynski (2012), derived as the ratio of the output elasticity of materials to the material cost share of revenue. The large differences between log average price and other variables are explained by the focus on single-product firms. To estimate average price, I merge product-level quantity data with firm-level balance sheet data and calculate the ratio of total revenue to quantity produced in year t. Standard errors (in parentheses) are clustered at the district level. All specifications follow Equation (3) and are estimated using a Difference-in-Differences approach following Sun and Abraham (2021). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Firm Competition. I estimate firm-level markups following the methodology of De Loecker and Warzynski (2012), as detailed in the Appendix. Column (1) of Table 5 shows that the 3G rollout led to a 13.5% decline in markups, consistent with increased product market competition driven by improved access to information and reduced search costs. Despite this, firm-level TFP does not show significant improvement. The reduction in markup is mirroring findings from Abreha et al. (2021) on the Ethiopian 3G expansion, but contrasting with results from developed economies such as Hennig and Vidal-Naquet (2023). This highlights the heterogeneous impact of internet access across development contexts.[6].

To explore the mechanism behind markup reductions, I examine average prices as an outcome. The results indicate that 3G access led to a 16.3% decline in average prices, consistent with the estimated drop in markups. This suggests that digital connectivity enhanced competition by lowering information frictions. This interpretation aligns with Jensen (2007), who show that mobile phones reduced price dispersion in Kerala's fishing industry. Additionally, I find that exports rose by 8.1% following 3G rollout, suggesting that improved communication not only constrained pricing power but also enabled firms to access international markets. These findings are consistent with Lendle et al. (2016), Fernandes et al. (2019) and Malgouyres et al. (2021), who show that digital platforms reduce the trade costs and broadband internet associated with geographic distance. Overall, the evidence highlights the role of internet infrastructure in fostering competition and expanding market access in developing countries.

Product Dynamics. As search costs decline, firms may find it easier to engage in horizontal differentiation by experimenting with new product varieties and adjusting their offerings over time. This raises the question: Does internet access help connected firms increase the number of products they sell over time? Additionally, how often do firms introduce or drop products from their product basket? Table 6 shows that neither the number of products nor the change in product scope is significantly affected by internet access among firms in Vietnam.

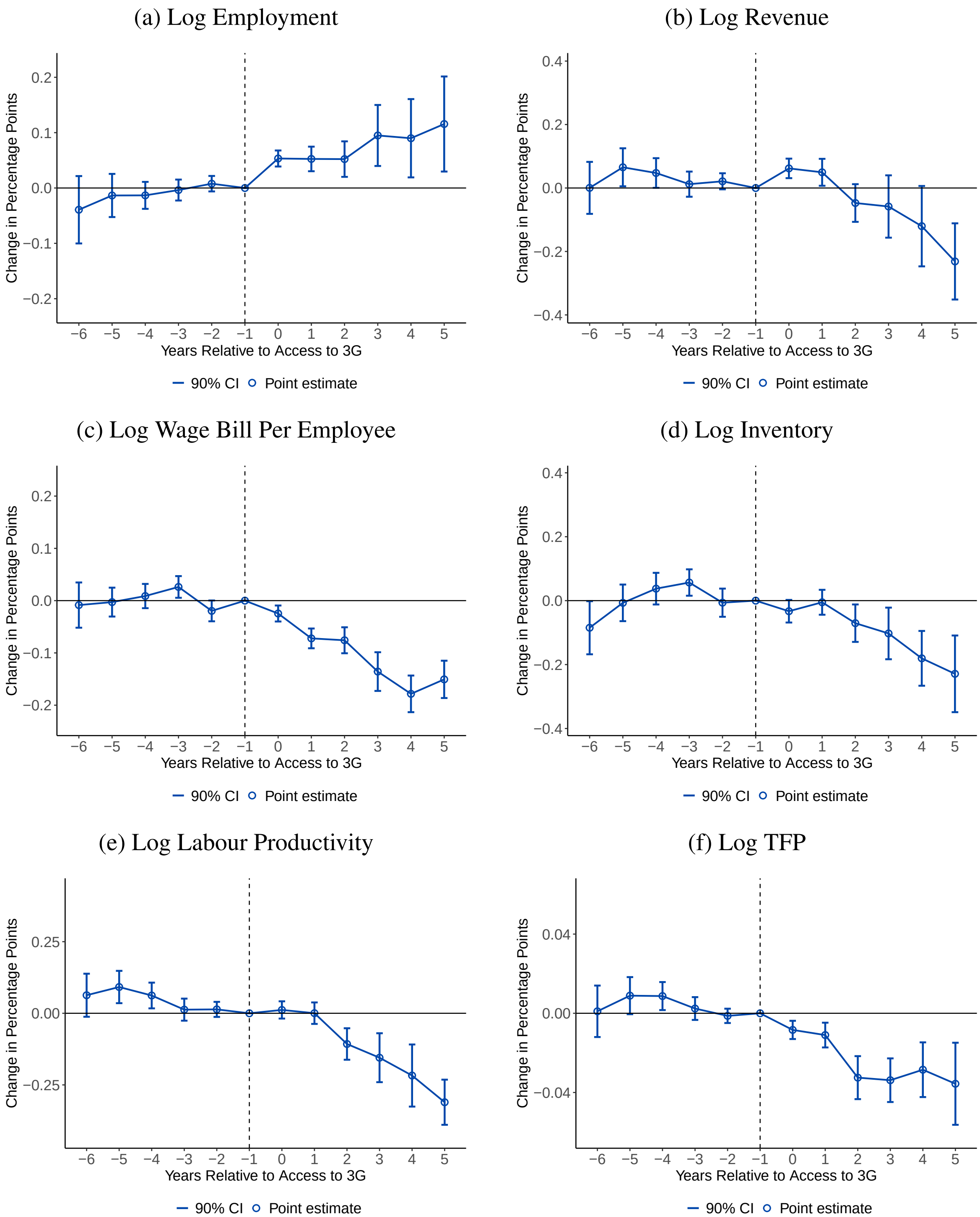
[6] In Vietnam, Baccini et al. (2019) find that trade liberalization reduced markups for private firms (POEs), while SOEs were less affected, likely due to institutional and political protection from competition. Li et al. (2022) similarly show that greater FDI presence lowers markups at the industry level. Eck et al. (2025) evidently showed, on average between 2000 and 2010, manufacturing firms paid workers only 59% of their marginal revenue product of labor (MRPL)

Table 6: Impact of 3G Rollout on Product Dynamics

	Dependent Variables	
	Number of Product	Change in Number of Product
	(1)	(2)
3G Rollout	0.002	-0.008
	(0.006)	(0.008)
Firm × District FE	✓	✓
Industry × Year FE	✓	✓
Province × Year Trend	✓	✓
ADSL Adopter	✓	✓
Nightlight per Capita	✓	✓
Elevation × Year	✓	✓
Province Characteristics	✓	✓
Population × Year	✓	✓
Observations	128,549	78,016
R^2	0.6520	0.4990

Notes: Each product is defined at 4 digits code. Number of Products and Change in Number of Products are transformed using the inverse hyperbolic sine (IHS) transformation. This transformation is primarily applied to Change in Number of Products to accommodate zeros. All specifications follow Equation (3) and are estimated using the Difference-in-Differences method from Sun and Abraham (2021). Standard errors are clustered at the district level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 4: Impact of Firm Dynamics



(a) Log Employment

(b) Log Revenue

(c) Log Wage Bill Per Employee

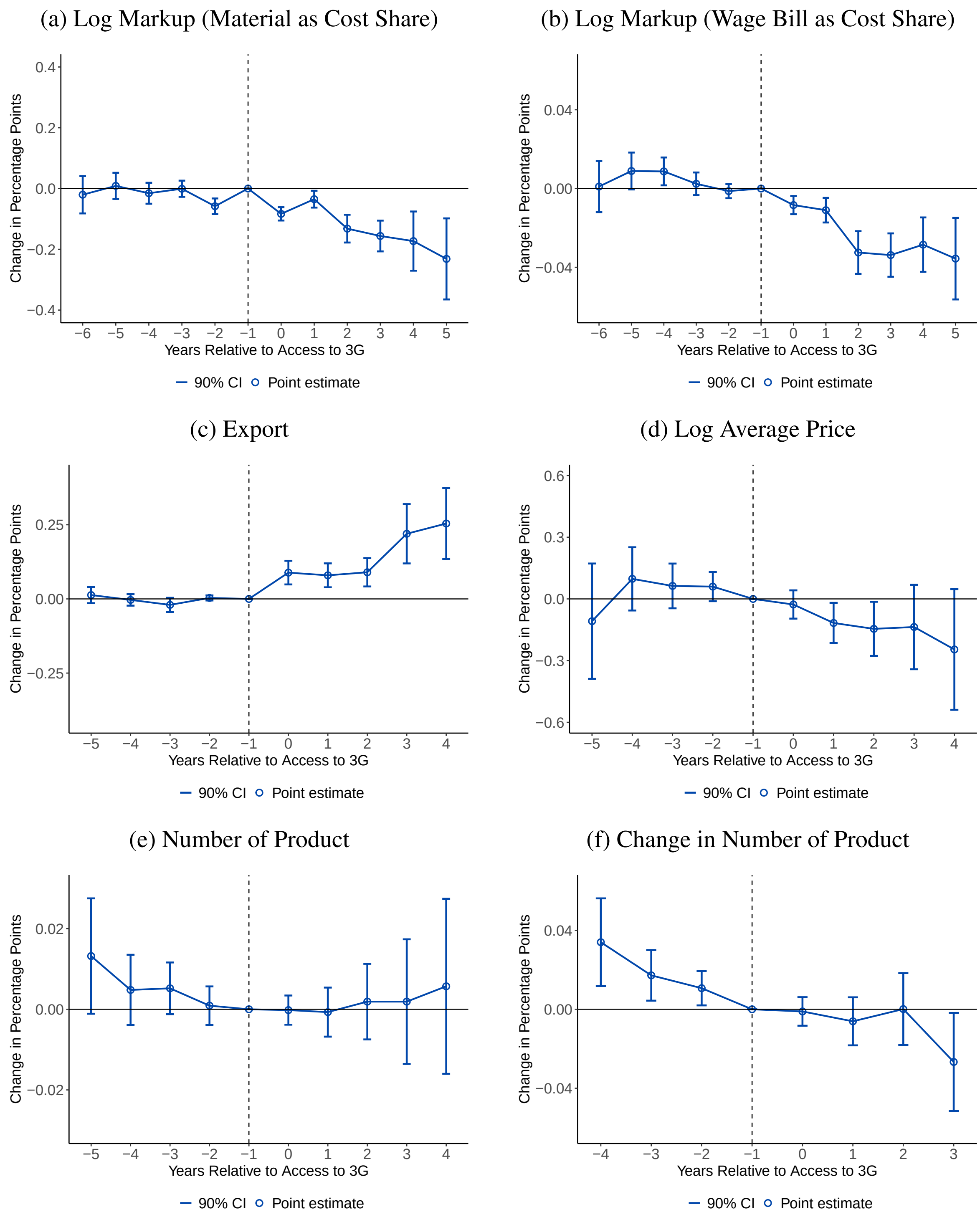
(d) Log Inventory

(e) Log Labour Productivity

(f) Log TFP

Note: This figure presents dynamic difference-in-differences estimates of the impact of 3G roll-out on various firm outcomes. All outcomes are transformed using the natural logarithm. All estimates are based on Equation 3, following the method of Sun and Abraham (2021). Standard errors are clustered at the district level, and the error bars represent 90% confidence intervals.

Figure 5: Impact of Firm Concentration and Product Dynamics



Note: This figure presents dynamic difference-in-differences estimates of the impact of the 3G rollout on various firm outcomes. The first four outcomes are transformed using the natural logarithm. Number of Products and Change in Number of Products are transformed using the inverse hyperbolic sine (IHS) transformation. This transformation is primarily applied to the Change in Number of Products to accommodate zeros. All estimates are based on Equation 3, following the method of Sun and Abraham (2021). Standard errors are clustered at the district level, and the error bars represent 90% confidence intervals.

5.2 Robustness Check

There is concern when evaluating policy shocks using Differences in Differences (DiD). In particularly in the context of infrastructure investment, where the deployment of 3G cellular networks may be predetermined and correlated with macroeconomic shocks. There is concern that the preexisting difference in trend is prevail. To address this concern, I use the sensitivity test proposed by Rambachan and Roth (2023) and package `HonestDiD`. The Rambachan and Roth (2023) test relaxes the parallel trends assumption by allowing limited post-treatment trend differences and uses pre-treatment trends to estimate treatment effects.

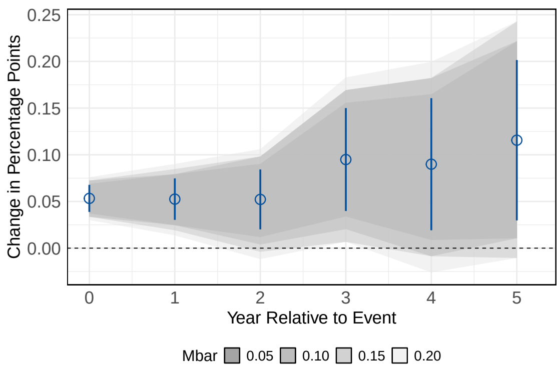
Figure 7 applies the sensitivity analysis of Rambachan and Roth (2023), which relaxes the strict parallel trends assumption by allowing for bounded deviations from linear pre-trends. The blue dots represent baseline event-study estimates, while the shaded regions depict robust confidence sets under varying values of the relative magnitude parameter $\overline{M} \in \{0.05, 0.10, 0.15, 0.20\}$. As $\overline{M}$ increases, the confidence bounds widen, reflecting greater allowance for deviations in the untreated outcomes from the pre-treatment trend. This sensitivity analysis helps evaluate how much deviation from the pre-existing trend would be required to invalidate the estimated treatment effects. In this example Figure 7a, Log Employment ATT effects remain robust when $\overline{M} = 0.05$. Once $\overline{M}$ exceeds 0.10, the test becomes less informative. A value of $\overline{M} = 0.05$ indicates that the results are robust to small violations of the parallel trends assumption

Ultimately, this paper relies on the dynamics of treatment effects using the interaction-weighted approach by Sun and Abraham (2021). This method addresses TWFE biases by assuming that the parallel-trend assumption holds unconditionally. Second, treatment does not affect outcomes before it occurs. Third,, treatment effects may differ across cohorts, but the pattern of effects over time is the same. These features make it appropriate for evaluating the 3G rollout. For robustness, I also apply the alternative estimator proposed by Wooldridge (2021), using the same specification as described in Equation 3. The results from both estimators are consistent.

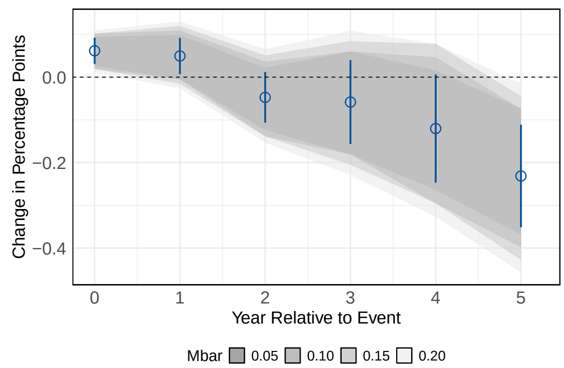
Lastly, as discussed in Section 4, treatment is defined at the district level, based on the year in which each district experiences the largest year-over-year increase in 3G coverage. As a robustness check, I reestimate all outcomes using an alternative treatment definition: districts are treated in time t if their Z-score (3G coverage) exceeds 0.5. The results remain robust, except for Average Price, which shows similar trends but loses statistical significance.

Figure 6: Rambachan and Roth Sensitivity Test: Firm Dynamics

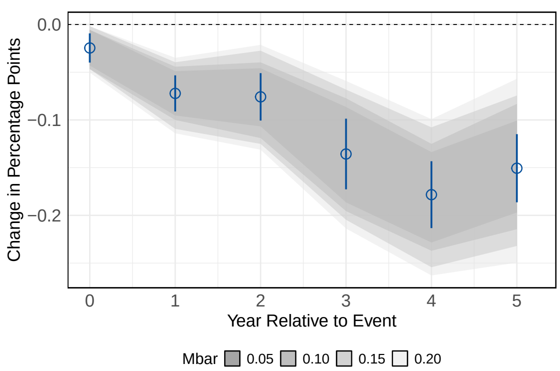
(a) Employment



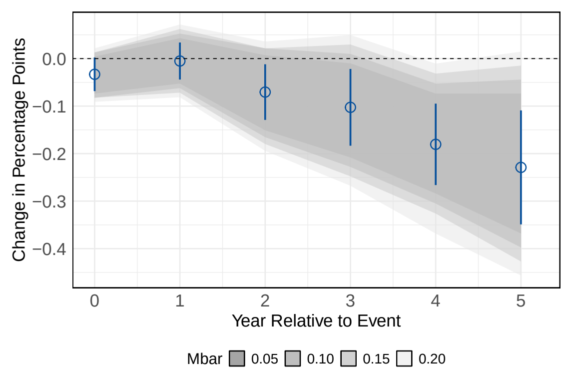
(b) Revenue



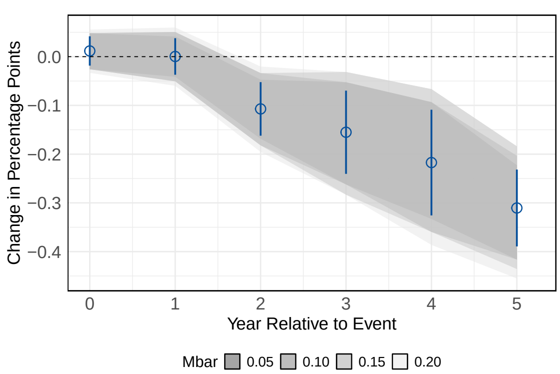
(c) Wage Bill Per Employee



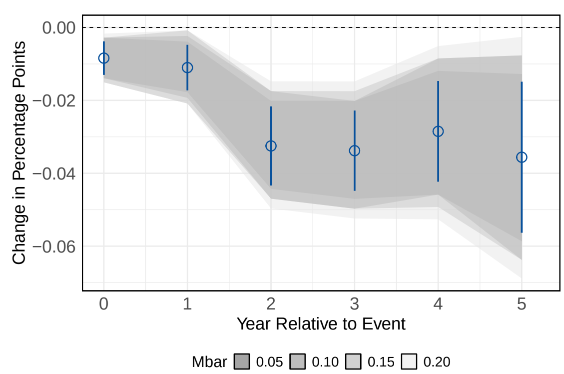
(d) Inventory



(e) Log Labour Productivity

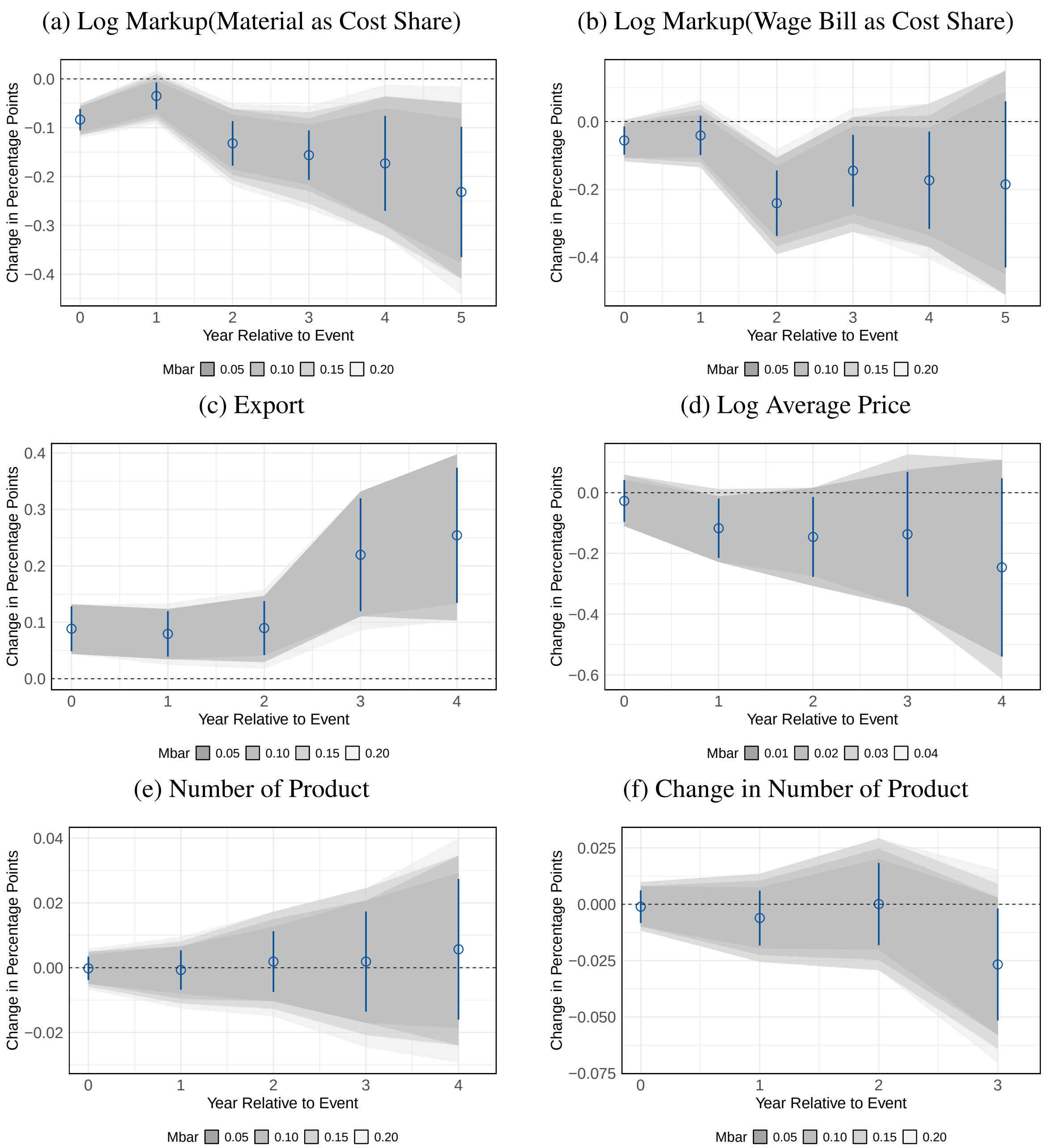


(f) Log TFP



Note: The figure presents a sensitivity analysis of post-treatment event-study estimates for the outcomes using the methodology of Rambachan and Roth (2023). Rather than assuming strict parallel trends, the analysis permits deviations in the counterfactual trend, bounded by a parameter M. The blue dots represent baseline estimates obtained using the method of Sun and Abraham (2021). The shaded regions correspond to confidence sets that allow for both linear and non-linear time trends. When $M = 0$, the confidence set assumes a linear trend. As M increases, the model allows for greater flexibility in time trend deviations, capturing increasing sensitivity to violations of the parallel trends assumption.

Figure 7: Rambachan and Roth Sensitivity Test: Firm Dynamics



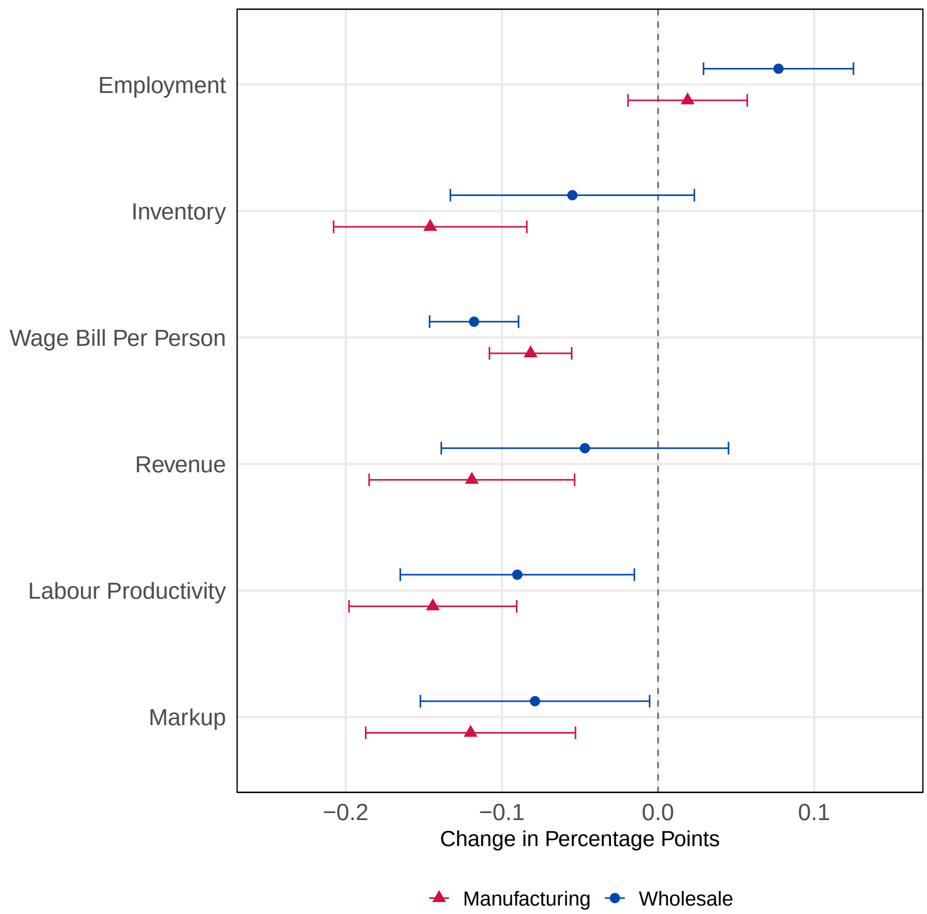
Note: The figure presents a sensitivity analysis of post-treatment event-study estimates for the outcomes using the methodology of Rambachan and Roth (2023). Rather than assuming strict parallel trends, the analysis permits deviations in the counterfactual trend, bounded by a parameter M. The blue dots represent baseline estimates obtained using the method of Sun and Abraham (2021). The shaded regions correspond to confidence sets that allow for both linear and non-linear time trends. When $M = 0$, the confidence set assumes a linear trend. As M increases, the model allows for greater flexibility in time trend deviations, capturing increasing sensitivity to violations of the parallel trends assumption.

5.3 Heterogeneity

While the causal effect of the 3G rollout is evident across Vietnam, an unexplored question remains: does the 3G rollout affect different types of industries differently? The heterogeneity between the manufacturing and wholesale sectors raises an interesting point. Perhaps it may provide a conduits explaining the effect of 3G internet in Vietnam. Manufacturing is generally more technologically and capital intensive, while wholesale sectors tend to be less capital intensive and operate closer to end buyers. Advancements in information technology, particularly the mobile Internet, help reduce communication costs and improve coordination between firms and their suppliers. This enables firms to manage their supply chains, streamline production processes, and enhance logistics operations more efficiently Aker and Mbiti (2010); Demir et al. (2024). Understanding how the effects of 3G rollout differ by sector allows for broader implications regarding the impact of mobile internet technology.

To explore sectoral heterogeneity, I sub-sample the data by industry using the ISIC 1-digit classification, distinguishing between Manufacturing (ISIC 10–33) and Wholesale/Retail Trade (ISIC 45–47). As shown in Figure 8, the effects of the 3G rollout are more pronounced in the Wholesale/Retail sector, particularly in terms of employment growth. Treated wholesale firms exhibit an 8.8% increase in employment, consistent with Caldarola (2022), who document a 6% rise in service sector employment following 3G expansion in Rwanda. The employment expansion mainly attributes in high-value sectors such as health care and finance. In addition, Pham and Caldarola (2024), who report employment gains in both manufacturing and service sectors in Vietnam, I do not find significant employment effects in the manufacturing sector. However, Figure 8 suggests that manufacturing firms with 3G access experienced a reduction in inventory holdings, potentially reflecting improvements in supply chain efficiency. Finally, in terms of market competition, both manufacturing and wholesale/retail sectors show a decline in markups, indicating increased competitive pressure following the rollout.

Figure 8: Average Treatment Effects by Sector



Note: This figure presents the estimated average treatment effects of the 3G rollout on all outcomes discussed in Section 3, separately by sector. All the outcomes variables are in natural logathrim. Figure only show markup derived from ratio of output elasticity of materials to materials cost share The model is estimated for Manufacturing and Wholesale firms using the specification in Equation 3, following the method of Sun and Abraham (2021). Standard errors are clustered at the district level, and error bars represent 90% confidence intervals.

6 Discussion and Conclusion

This paper examines the impact of mobile broadband (3G) rollout on firm performance in Vietnam. The findings show that access to 3G internet leads to increased employment, particularly in the wholesale and retail sectors. Firms in these sectors also exhibit improved inventory management, suggesting enhanced supply chain coordination enabled by better communication.

The 3G rollout is associated with a decline in both the wage bill per employee and firm-level markups, likely reflecting increased market competition and greater price transparency. However, unlike findings from studies on fixed broadband, we do not observe significant improvements in firm-level productivity. This highlights the differing effects of mobile versus fixed internet infrastructure in developing economies.

Overall, mobile broadband appears to support firm expansion and operational efficiency, even in the absence of measurable productivity gains. By lowering information frictions and enabling firms to reach broader markets, mobile internet serves as a complementary tool to fixed broadband. These results suggest that expanding access to mobile broadband should be a key policy priority in developing countries seeking to foster private sector growth and market integration.

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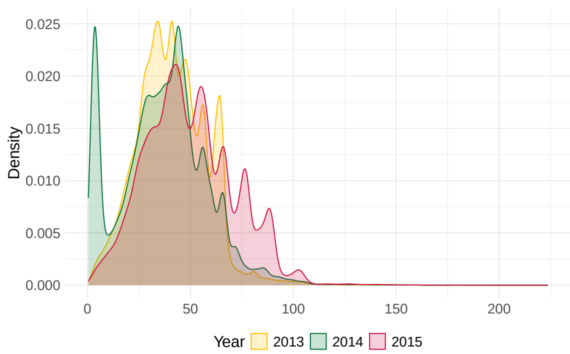
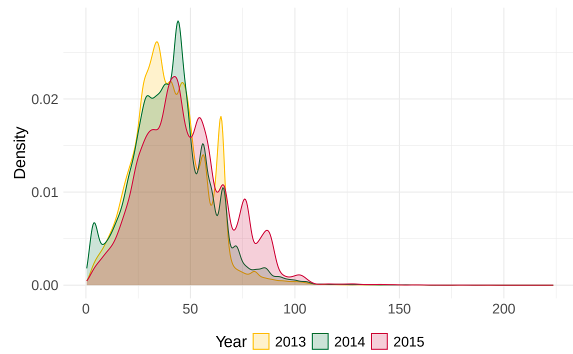
Appendix A Main Outcome Density Plot

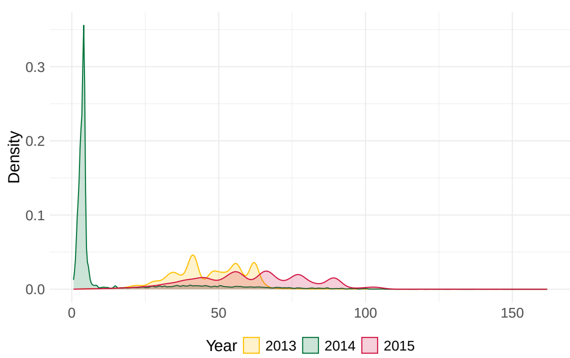
Figure A.1: Wage Bill Per Employee Density Plot



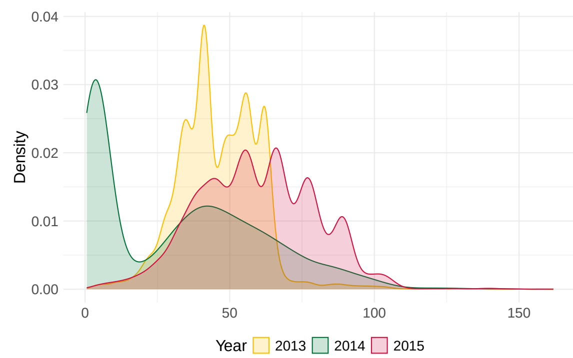
(a) Full Sample



(b) Full Sample (Filter Outliers)



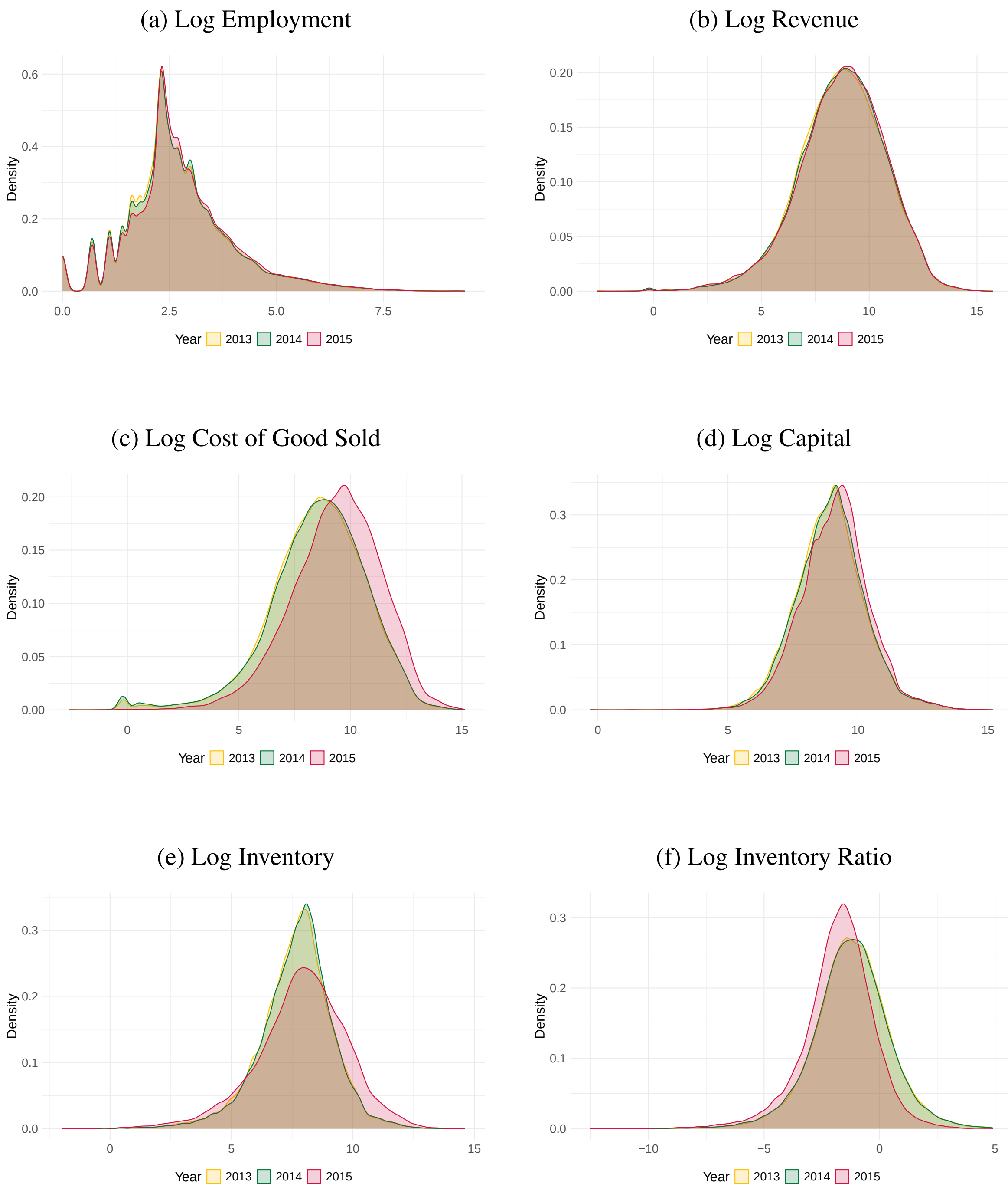
(c) Hanoi



(d) Hanoi (Filter Outliers)

Figure A.1a and Figure A.1c show the original wage bill per employee density plot in Vietnam for 2013, 2014, and 2015. Both figures indicate a severely right-skewed density plot for 2014. To address this issue, I focus on firms in 2013, 2014, and 2015 and compare wages in 2014 with the lagged values from 2013 and the lead values from 2015. Specifically, I calculate the wage growth rate and categorize firms with a wage growth rate exceeding 100% as outliers. In total, I identify 13,454 unique outlier firms in Hanoi, with 79% of them operating in the wholesale industry. After removing the outlier firms, Figures A.1b and A.1d show that the wage bill per employee in 2014 follows a distribution of 2013 and 2015. However, I do not detect any flaw with other variables after cleaning the data and winorised them top and bottom 1%, figures are showed below.

Figure A.2: Density Plot for Other Variable



Appendix B Estimation of Firm-Level Markups

To estimate firm-level markups, I follow the approach proposed by De Loecker and Warzynski (2012), which derives markups from firms' cost-minimizing behavior. Specifically, a firm chooses the level of a flexible input such that its marginal revenue product equals its input price. Under this condition, the markup is defined as the ratio of the output elasticity with respect to a flexible input to the input's share in firm revenue:

$$\mu_{it} = \theta_{it}^{v} \cdot \left(\frac{P_{it}^{v} V_{it}}{P_{it} Q_{it}} \right)^{-1}, \tag{B1}$$

where μ_{it} is the markup for firm i in year t, θ_{it}^{v} denotes the output elasticity with respect to input v (e.g., labor or materials), $P_{it}^{v} V_{it}$ is the expenditure on that input, and $P_{it} Q_{it}$ is firm revenue. This expression assumes that the firm minimizes cost and optimally chooses input v.

Choice of Flexible Input and Revenue Share

Following De Loecker and Warzynski (2012) and Li et al. (2022), I use materials (M_{it}) as the flexible input. Materials are typically less subject to adjustment frictions than labor and are considered to be more freely variable in the short run. Under this choice, the markup becomes:

$$\mu_{it} = \theta_{it}^{m} \cdot (\alpha_{it}^{m})^{-1}, \tag{7}$$

where θ_{it}^{m} is the output elasticity with respect to material input, and $\alpha_{it}^{m} = \frac{P_{it}^{m} M_{it}}{P_{it} Q_{it}}$ is the share of material costs in total revenue.

Production Function and Output Elasticity Estimation

To estimate θ_{it}^{m}, I specify a value-added translog production function:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 \tag{8}$$

$$+ \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{mk} m_{it} k_{it} + \omega_{it} + \varepsilon_{it}, \tag{9}$$

where lowercase letters denote logs of output (y_{it}), labor (l_{it}), capital (k_{it}), and materials (m_{it}). ω_{it} captures unobserved productivity, and ε_{it} is an i.i.d. shock. To address the simultaneity bias between inputs and unobserved productivity, I employ the control function approach of Ackerberg et al. (2015), which uses materials as a proxy for productivity shocks.

This method assumes: - Materials are chosen based on current productivity and capital. - Productivity follows a first-order Markov process. - A nonparametric function relates productivity to observable inputs.

I implement this estimation using the `prodest` package in `Stata` (Rovigatti and Mollisi, 2016), applying both Levinsohn and Petrin (2003) and Ackerberg et al. (2015) estimators to ensure robustness.

Firm-Level Output Elasticity

From the estimated translog coefficients, I recover the firm-specific output elasticity with respect to materials as:

$$\hat{\theta}_{it}^m = \hat{\beta}_m + 2\hat{\beta}_{mm} m_{it} + \hat{\beta}_{lm} l_{it} + \hat{\beta}_{mk} k_{it}. \tag{10}$$

This allows for heterogeneity in elasticities across firms and time. Combining the elasticity with the observed material revenue share, I compute the firm-level markup as:

$$\hat{\mu}_{it} = \hat{\theta}_{it}^m \cdot \left(\frac{P_{it}^m M_{it}}{P_{it} Q_{it}} \right)^{-1}. \tag{11}$$

Appendix C 3GRollout Balance-Test

Table 7 presents the full results of the regression analysis. The odd-numbered columns show OLS regressions with all covariates included. Column (1) follows the specification in Equation 2, Column (3) adds region-year trends, Column (5) includes region-year fixed effects, and Column (7) uses province-year fixed effects. The even-numbered columns report results from regressions using covariates selected by LASSO.[7] I use the LASSO method to select covariates that are most strongly correlated with the 3G rollout (Belloni et al., 2014) in Vietnam and include them as baseline controls in Equation 3.

The rollout of 3G cell towers is correlated with district population density and is more heavily directed toward less socio-economically developed areas. This pattern aligns with the central government's objective following the liberalization of the telecommunications industry—to expand access to digital infrastructure in underserved regions. Column (1) shows that 3G rollout is significantly more likely in less densely populated districts and in provinces with weaker Provincial Competitiveness Index (PCI) scores, particularly in sub-indices related to the business environment. Provinces that perform better in PCI sub-indices such as Business Support, Labour Training, and Legal Institutions (i.e., fair and effective legal procedures for dispute resolution) are associated with slower 3G rollout. This counterintuitive result may reflect a targeted investment in lagging regions, where 3G serves as a substitute for other forms of physical infrastructure, helping to bridge digital and economic divides. In Column (3), I introduce Region × Year fixed effects to control for region-specific time trends that could confound the results. The significance of key variables suggests that 3G rollout decisions were shaped by local conditions rather than broad regional trends.

Table 7: Balance Test using Z-Score

	Dependent Variable: 3G Coverage (Z-Score)							
	Baseline		Region-Year Trend		Region × Year FE		Province × Year FE	
Covariates	OLS (1)	LASSO (2)	OLS (3)	LASSO (4)	OLS (5)	LASSO (6)	OLS (7)	LASSO (8)
Density×2009	0.024	-0.000	0.027	0.011	-0.014***	-0.009***	-0.003	-0.000
	(0.021)	(0.025)	(0.025)	(0.026)	(0.003)	(0.002)	(0.002)	(0.000)

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[7] I apply the robust LASSO approach in Stata using the lassopack package developed by Ahrens et al. (2020).

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Covariates	OLS (1)	LASSO (2)	OLS (3)	LASSO (4)	OLS (5)	LASSO (6)	OLS (7)	LASSO (8)
Density×2010	0.028 (0.021)	0.002 (0.025)	0.026 (0.025)	0.010 (0.026)	-0.011*** (0.003)	-0.007*** (0.002)	-0.001 (0.002)	0.002 (0.002)
Density×2011	0.070*** (0.022)	0.053** (0.025)	0.065*** (0.025)	0.049* (0.026)	0.032*** (0.008)	0.032*** (0.008)	0.027 (0.018)	0.029* (0.017)
Density×2012	0.081*** (0.022)	0.068*** (0.025)	0.071*** (0.025)	0.061** (0.026)	0.046*** (0.009)	0.047*** (0.008)	0.038* (0.020)	0.041** (0.020)
Density×2013	0.135*** (0.022)	0.108*** (0.025)	0.123*** (0.026)	0.099*** (0.026)	0.073*** (0.012)	0.085*** (0.011)	0.060*** (0.013)	0.080*** (0.014)
Density×2014	0.167*** (0.022)	0.145*** (0.025)	0.152*** (0.025)	0.132*** (0.026)	0.118*** (0.012)	0.119*** (0.011)	0.110*** (0.015)	0.118*** (0.014)
Density×2015	0.132*** (0.023)	0.129*** (0.026)	0.111*** (0.026)	0.112*** (0.027)	0.084*** (0.013)	0.089*** (0.012)	0.089*** (0.014)	0.101*** (0.012)
Nightlight Per Capita	-9.261 (127.127)		25.941 (125.659)		191.579*** (68.355)		135.101* (78.711)	
PCI Business Entry Cost	-0.007 (0.009)		-0.002 (0.009)		-0.014 (0.009)			
PCI Land Access	0.029*** (0.008)		0.027*** (0.008)		0.005 (0.006)			
PCI Transparency	-0.001 (0.008)		-0.003 (0.008)		0.009 (0.007)			
PCI Admin- sration Cost	-0.004 (0.007)		0.005 (0.007)	-0.000 (0.007)	-0.001 (0.005)			
PCI Informal Charges	-0.008 (0.007)		-0.012* (0.007)		(0.008)			
PCI Local Government	-0.004 (0.005)		-0.009* (0.005)		-0.004 (0.004)			
PCI Business Support	-0.020*** (0.007)		-0.012* (0.007)		0.012** (0.006)			
PCI Labour Training	-0.036*** (0.012)		-0.045*** (0.012)		-0.022 (0.014)			
PCI Legal Institutions	-0.031*** (0.007)	-0.027*** (0.006)	-0.026*** (0.007)	-0.019*** (0.006)	-0.021*** (0.007)	-0.022*** (0.007)		
Share of Literacy (%)					-0.002 (0.001)			

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Covariates	OLS (1)	LASSO (2)	OLS (3)	LASSO (4)	OLS (5)	LASSO (6)	OLS (7)	LASSO (8)
Share of Labour Force (%)					-0.005	-0.000		
					(0.004)	(0.003)		
Share of Urban pop (%)					0.002*	0.003***		
					(0.001)	(0.001)		
Share of Landline (%)					-0.001			
					(0.001)			
Terrain×2009	0.394***		0.328***		-0.006*		-0.001	
	(0.136)		(0.123)		(0.003)		(0.001)	
Terrain×2010	0.397***		0.326***		-0.005		-0.002	
	(0.135)		(0.123)		(0.003)		(0.002)	
Terrain×2011	0.379***		0.303**		-0.017**		-0.004	
	(0.135)		(0.123)		(0.007)		(0.004)	
Terrain×2012	0.377***		0.295**		-0.015		0.004	
	(0.136)		(0.124)		(0.012)		(0.012)	
Terrain×2013	0.388***		0.304**		-0.047**		-0.025	
	(0.134)		(0.123)		(0.020)		(0.019)	
Terrain×2014	0.399***		0.309**		-0.021		-0.002	
	(0.134)		(0.123)		(0.022)		(0.023)	
Terrain×2015	0.362***		0.267**		-0.063***		-0.055**	
	(0.136)		(0.125)		(0.023)		(0.025)	
Elevation × Year ×2009	-0.061	-0.012***	-0.080		0.004	0.002	0.002*	-0.000
	(0.072)	(0.005)	(0.084)		(0.004)	(0.002)	(0.001)	(0.000)
Elevation × Year ×2010	-0.064	-0.014***	-0.081		0.008*	0.003	0.004*	0.001
	(0.072)	(0.005)	(0.084)		(0.005)	(0.002)	(0.002)	(0.001)
Elevation × Year ×2011	-0.039		-0.055		0.036***		0.014	
	(0.073)		(0.083)		(0.011)		(0.009)	
Elevation × Year ×2012	-0.042		-0.057		0.030*		-0.001	
	(0.073)		(0.083)		(0.016)		(0.018)	
Elevation × Year ×2013	-0.026		-0.042		0.022		-0.069*	

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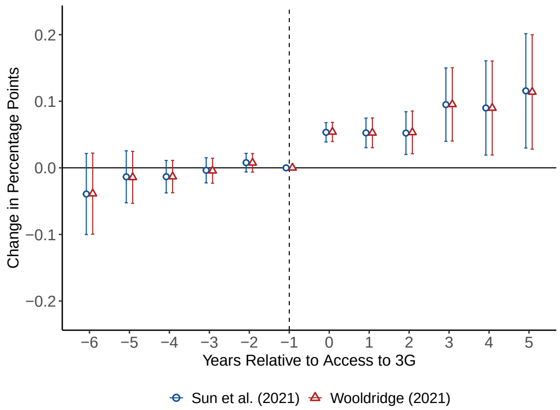
(Continued from previous page)								
Covariates	OLS (1)	LASSO (2)	OLS (3)	LASSO (4)	OLS (5)	LASSO (6)	OLS (7)	LASSO (8)
	(0.070)		(0.079)		(0.025)		(0.039)	
Elevation × Year ×2014	-0.050		-0.064		0.019		-0.047	
	(0.070)		(0.080)		(0.026)		(0.043)	
Elevation × Year ×2015	-0.043		-0.057		0.051*		0.001	
	(0.073)		(0.082)		(0.027)		(0.053)	
Observations	4,781	4,781	4,781	4,781	4,781	4,781	4,781	4,781
R-squared	0.685	0.682	0.687	0.684	0.466	0.461	0.546	0.545
District FE	✓	✓	✓	✓	–	–	–	–
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Region×Year FE	–	–	–	–	✓	✓	–	–
Province×Year FE	–	–	–	–	–	–	✓	✓

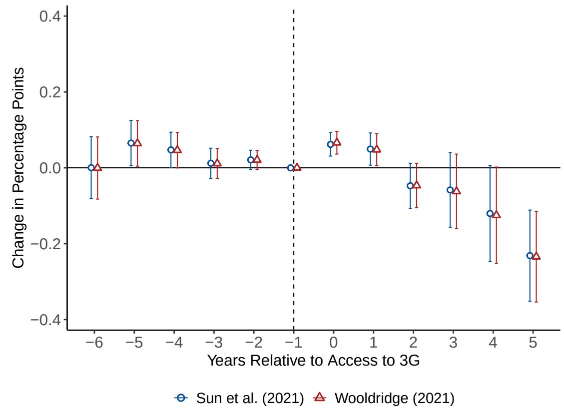
Note: In total, there are 685 districts in Vietnam. For the purposes of this study, I removed two districts from the observations as they are a form of an archipelago. Therefore, the balance test and the rest of the results in the paper focus on 683 districts. Standard errors for columns (1–6) are clustered at the district level, while those for columns (7–8) are clustered at the province level. Statistical significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix D Robustness Check: Event Study

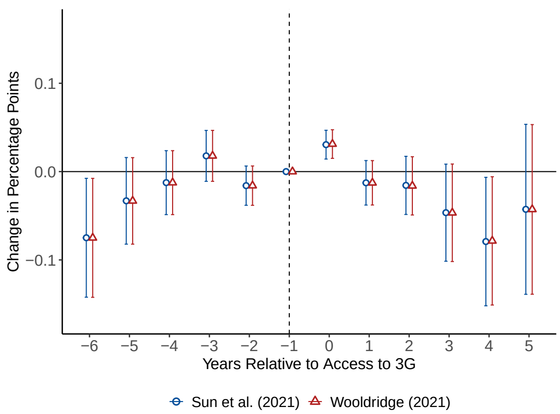
Figure D.1: Impact of Firm Dynamics Treatment: Robustness with Wooldridge (2021)



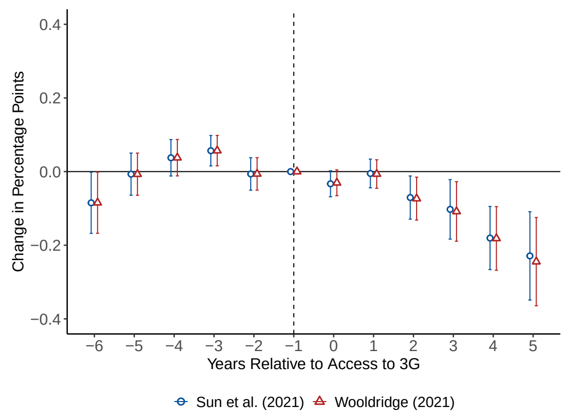
(a) Log Employment



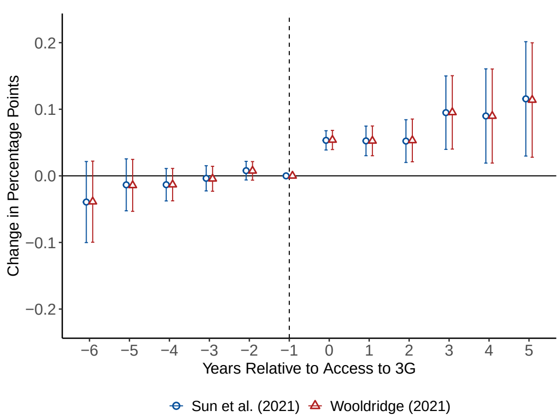
(b) Log Revenue



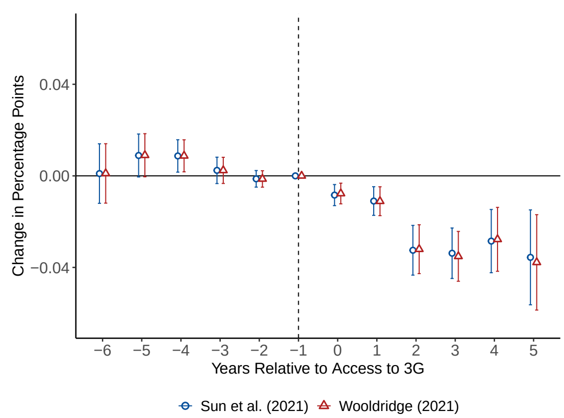
(c) Log Wage Bill Per Employee



(d) Log Inventory



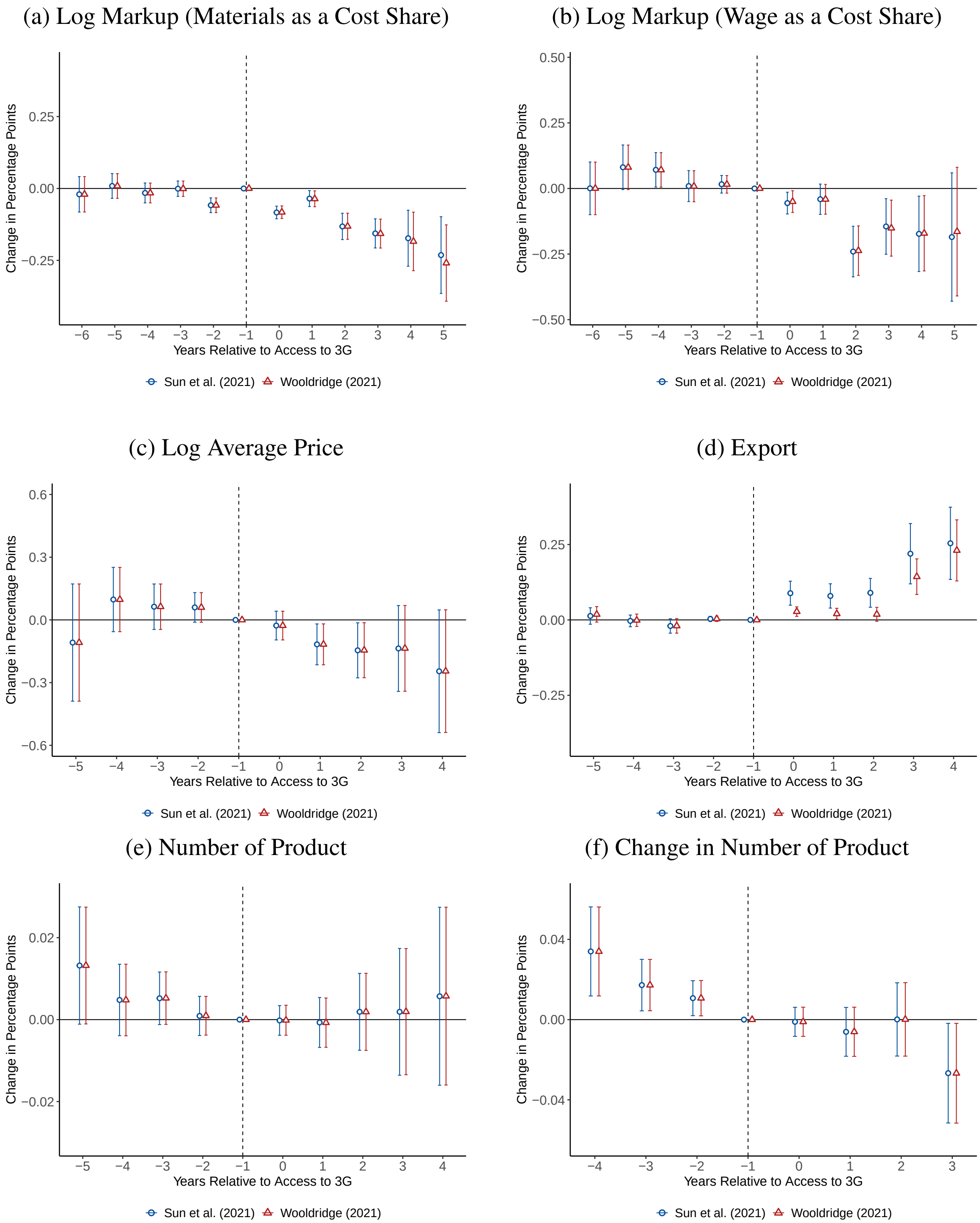
(e) Log Labour Productivity



(f) Log TFP

Note: This figure presents dynamic difference-in-differences estimates of the impact of 3G roll-out on various firm outcomes. All outcome variables are expressed in natural logarithms. Estimates are based on Equation 3, using the estimator proposed by Wooldridge (2021) and implemented as in Sun and Abraham (2021). Standard errors are clustered at the district level. Error bars represent 90% confidence intervals.

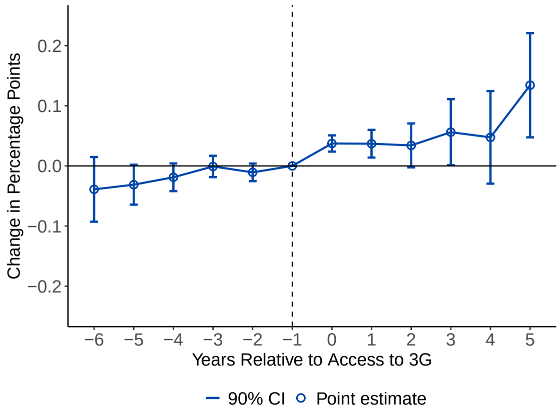
Figure D.2: Impact of Firm Dynamics Treatment: Robust with Wooldridge (2021)



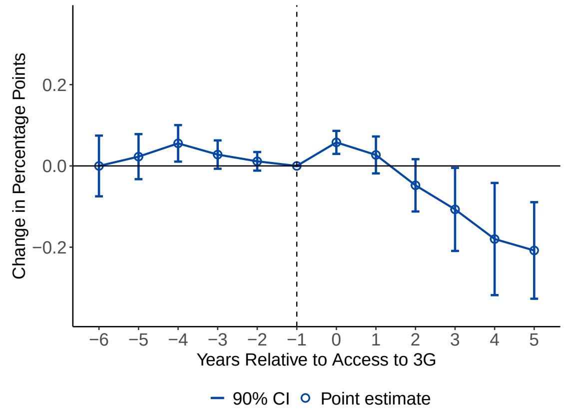
Note: This figure presents dynamic difference-in-differences estimates of the impact of the 3G rollout on various firm outcomes. The first three outcomes are transformed using the natural logarithm. Export is dummy 1 if firm participate in export activity and 0 otherwise. Number of Products and Change in Number of Products are transformed using the inverse hyperbolic sine (IHS) transformation. This transformation is primarily applied to Change in Number of Products to accommodate zeros. All estimates are based on Equation 3, following the method of Sun and Abraham (2021). Standard errors are clustered at the district level, and the error bars represent 90% confidence intervals.

Figure D.3: Impact of Firm Dynamics Treatment: if Z-Score > 0.5

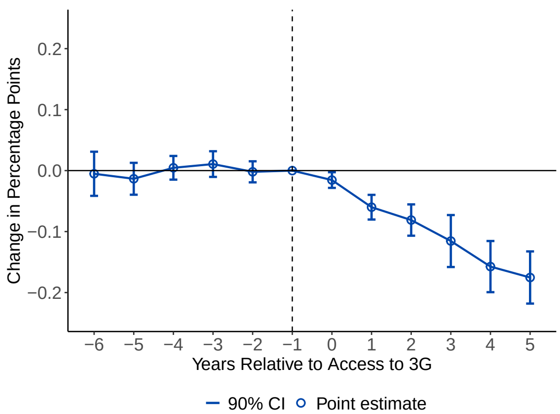
(a) Log Employment



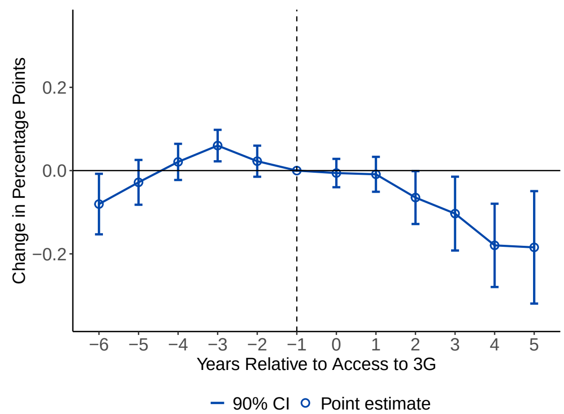
(b) Log Revenue



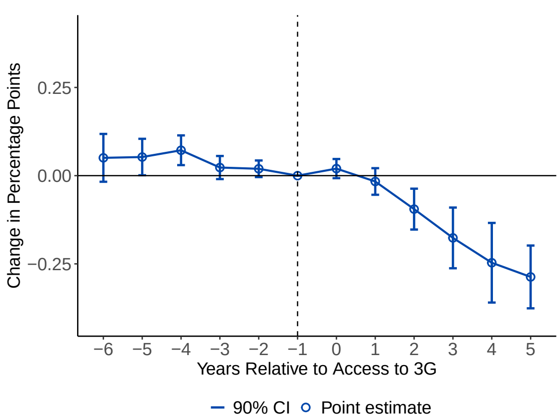
(c) Log Wage Bill Per Employee



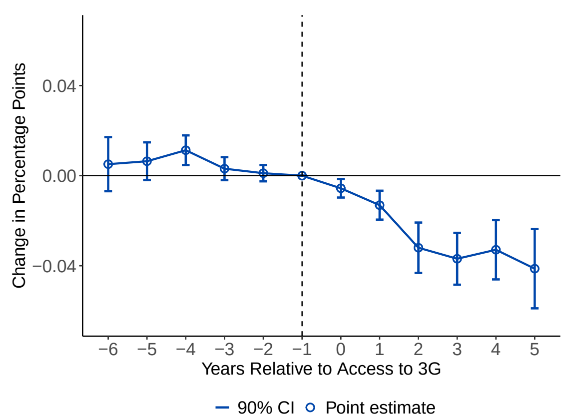
(d) Log Inventory



(e) Log Labour Productivity



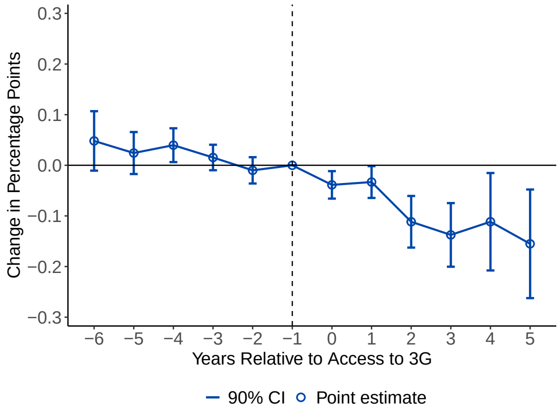
(f) Log TFP



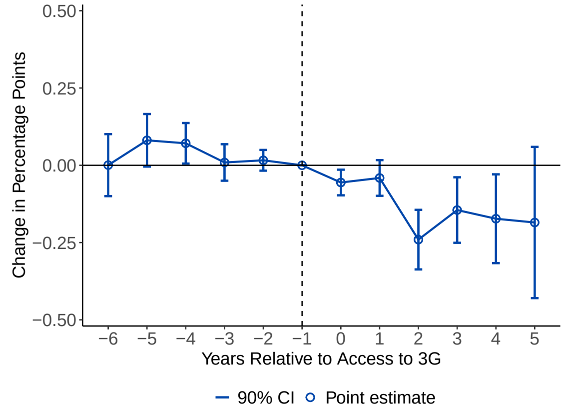
Note: This figure presents dynamic difference-in-differences estimates of the impact of 3G roll-out on various firm outcomes. All outcomes are transformed using the natural logarithm. All estimates are based on Equation 3, following the method of Sun and Abraham (2021). Standard errors are clustered at the district level, and the error bars represent 90% confidence intervals.

Figure D.4: Impact of 3G on Firm Competition: if Z-Score > 0.5

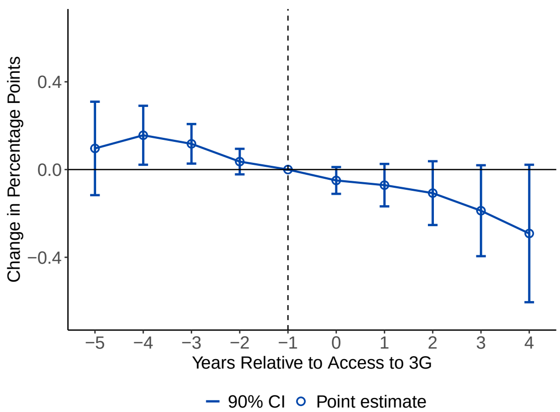
(a) Log Markup (Materials as a Cost Share)



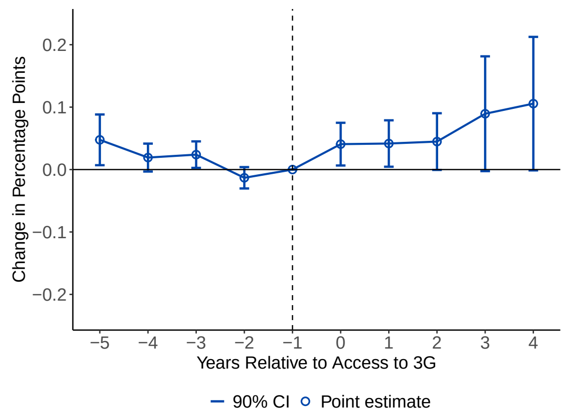
(b) Log Markup (Wage as a Cost Share)



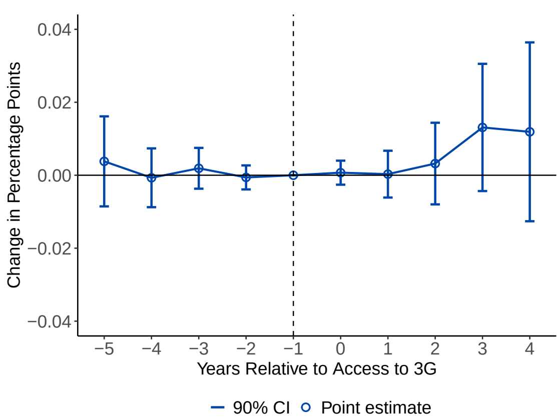
(c) Log Average Price



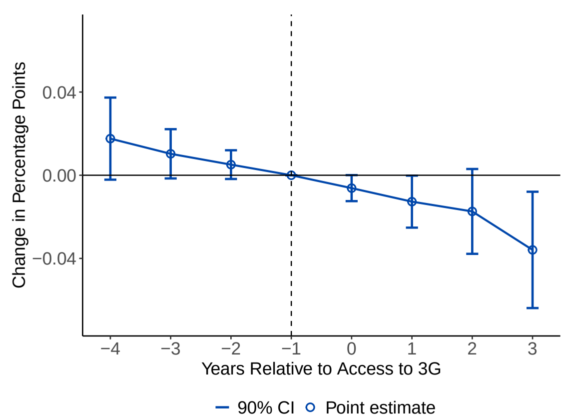
(d) Export



(e) Number of Product



(f) Change in Number of Product



Note: This figure presents dynamic difference-in-differences estimates of the impact of the 3G rollout on various firm outcomes. The first three outcomes are transformed using the natural logarithm. Export is dummy 1 if firm participate in export activity and 0 otherwise. Number of Products and Change in Number of Products are transformed using the inverse hyperbolic sine (IHS) transformation. This transformation is primarily applied to Change in Number of Products to accommodate zeros. All estimates are based on Equation 3, following the method of Sun and Abraham (2021). Standard errors are clustered at the district level, and the error bars represent 90% confidence intervals.