Mobile Internet and Structural Transformation in Vietnam

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Abstract

Structural transformation is central to economic development, yet workers may face barriers to accessing employment opportunities created by expanding modern sectors. Can mobile internet accelerate structural transformation and expand employment opportunities for women in developing economies? We examine this question by exploiting the staggered rollout of 3G mobile internet across over 650 districts in Vietnam between 2010 and 2017. Our estimates, which mirror a triple-differences design, show that 3G access facilitates the reallocation of workers out of agriculture and into manufacturing, with particularly strong effects for young women. We also document increased formal employment and higher earnings among employed women. To shed light on the underlying mechanisms, we construct a novel dataset of over 400,000 job roles advertised on Facebook and employ natural language processing techniques to identify explicit and implicit gender preferences in recruitment. We find that 3G expansion led to a boom in online recruitment activity, including more vacancies targeting female applicants. Together, these findings suggest that mobile internet can alleviate labour market information frictions and support structural transformation, with particularly important implications for women's access to formal employment.

Keywords: mobile internet, digital infrastructure, structural transformation, informality, formalisation, gender.

JEL Codes: O33, O14, J21, J24, F63, L96.

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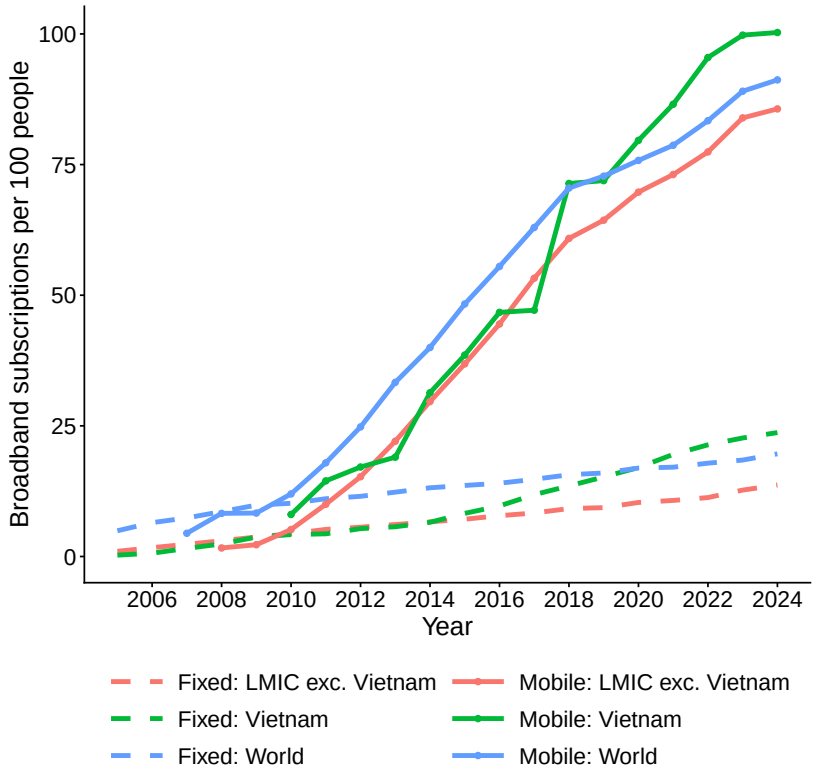
1 Introduction

Technological progress is a central driver of economic growth and development, and the internet is one of the most transformative technologies of recent decades. As innovations continue to facilitate access to affordable, high-speed internet, approximately 200 million new users come online each year (International Telecommunication Union, 2023). A growing body of research shows that internet connectivity enhances firm productivity and expands market access for consumers and businesses (Fan et al., 2018; Goldfarb and Tucker, 2019; Couture et al., 2021; Hjort and Tian, 2025). Additionally, the economic returns to internet access and other information and communication technology (ICT) investments appear to be particularly large in developing countries where information frictions are more pronounced (Jensen, 2007; Alfaro and Chen, 2014; Hjort and Tian, 2025). Much of this expansion in connectivity has been driven by the rapid diffusion of mobile internet, which has substantially expanded connectivity in developing countries where little to no fixed broadband infrastructure is in place. Despite this, causal evidence on its labour market implications remains relatively scarce (Chiplunkar and Goldberg, 2022; Hjort and Tian, 2025).

In this paper, we investigate the impact of third-generation (3G) cellular network technology on the structural transformation of the labour force in a developing context, i.e., the movement of the workforce away from agriculture and into more productive sectors such as manufacturing or services. This is crucial since the reallocation of workers can contribute substantially to economic development and productivity growth (Gollin et al., 2014; McMillan et al., 2014). We choose to focus on 3G networks because, unlike their predecessors, which were designed primarily for voice calls and text messaging, they were the first to provide fast mobile internet. Our analysis focuses on Vietnam due to its exceptionally high level of mobile internet penetration. Since 2014, the country has recorded more than 130 mobile cellular subscriptions per 100 people, of which 90 percent provided access to mobile internet in 2024. In contrast, fixed broadband subscriptions remain comparatively low at only about 24 per 100 people in 2024 (World Bank, 2025). As shown in Figure 1, Vietnam's mobile internet adoption expanded rapidly over the past decade, surpassing the global average and reaching near-universal coverage.

In Vietnam, 3G networks were implemented nationwide between 2010 and 2017, a period that coincided with rapid economic growth and structural transformation. Specifically, the share of workers in agriculture fell from 49 to 40 percent between 2010 and 2017 (World Bank, 2026). At the same time, the share of informal workers fell from 63 to 55 percent (ILO, 2017). Existing studies credit much of the country's economic development to trade openness and export opportunities, which also promoted the formalisation of labour (McCaig and Pavcnik, 2018). The benefits of an export-oriented economy also appear to have accrued more to Vietnamese female workers than to male workers (Huynh and Ku, 2025; Rotunno et al., 2026). This paper investigates another potential driver of Vietnam's rapid

Figure 1: Fixed and mobile broadband adoption



Notes: Fixed and mobile broadband subscriptions per 100 people in Vietnam, in low- and middle-income countries excluding Vietnam, and worldwide. Source: International Telecommunication Union (2025).

transformation, namely, mobile internet. In doing so, we also seek to understand how technology-induced economic development might affect labour market outcomes differently across genders.

We first estimate the effects of mobile internet on labour force participation (LFP) and the sectoral composition of the labour force. We then assess whether 3G expansion contributes to labour formalisation by examining changes in the prevalence of holding a second job, employment in household businesses, employment in registered firms, and coverage by social insurance. Finally, we show how income and expenditure respond in districts experiencing sectoral reallocation and formalisation following access to 3G. To shed light on the underlying channels, we construct a novel dataset containing over 400,000 job roles advertised on social media and explore two mechanisms through which mobile internet may facilitate structural transformation in Vietnam: reduced information frictions in the firm–worker matching process and gender-biased patterns in online job posting.

The staggered rollout of 3G infrastructure in Vietnam provides a unique opportunity to examine the labour market impacts of mobile internet. To measure 3G coverage, we construct population-weighted district-level mobile internet coverage using georeferenced cell tower data from OpenCelliD and population data from WorldPop. We classify a district as treated from the first year its 3G coverage reaches the 2017 sample mean of 91.74 percent, capturing the attainment of near-universal access.[1] We then combine 3G coverage data with the Vietnam Labour Force Survey (LFS) 2010–2017, and exploit variation in the timing and extent of 3G expansion across districts in a staggered difference-in-differences (DiD) framework. Specifically, we compare labour market outcomes in districts that reach the coverage threshold (the *treated*) with those that remain below that threshold (the *never-treated*) throughout the study period.

A key challenge to identification is non-random selection into treatment. Mobile internet providers might have prioritised more developed or urbanised districts, where residents are more likely to own smartphones and demand for mobile internet services is higher. To strengthen the credibility of our identification strategy, we exploit heterogeneity in exposure to mobile internet across demographic groups. We argue that younger workers are more likely to be directly affected by 3G expansion since they tend to adopt new technologies more readily, are quicker to acquire new digital skills, and are more likely to own smartphones (Silver et al., 2019; Albinowski and Lewandowski, 2022). Older workers, by contrast, are less likely to use the (mobile) internet and, as such, provide a useful comparison group whose labour market outcomes should be less responsive to the rollout of 3G (Poushter, 2016; Silver, 2019). We exploit this distinction by estimating separate event-study specifications for younger (aged 20–44) and older (aged 45–64) workers, comparing changes in labour market outcomes between treated and never-treated districts within each age group. Under the assumption that the gap between young and older workers would

[1] The threshold is motivated by the bimodal distribution of district-level coverage.

have evolved similarly across treatment and control groups in the absence of mobile internet rollout, this approach allows us to isolate the impact of mobile internet expansion from pre-existing differences in local economic trajectories.

Our main finding is that the rollout of 3G accelerates the process of structural transformation in Vietnam, reallocating workers away from agriculture, while enabling them to take up manufacturing jobs. In a naïve two-way fixed effects (TWFE) specification, 3G expansion increases the share of the female workforce in manufacturing, while the corresponding effect among men is negligible. Focusing on women, our DiD event study estimates show that this pattern is predominantly driven by young female workers (aged 20–44). Among their older counterparts (aged 45–64), the corresponding effect is much smaller and mostly statistically insignificant, lending support to our identification strategy. Moreover, the effect grows substantially over time: four years after treatment, the share of young women employed in manufacturing increases by around 9 percentage points, accompanied by a similar decline in agricultural employment.

Beyond sectoral reallocation, we find strong evidence of employment formalisation across districts with access to 3G. These effects are again concentrated among young women. Four years after treatment, the share employed in jobs covered by social insurance rises by about 8 percentage points. The share employed in tax-registered firms rises by 11 percentage points two years after treatment. These positive effects are mirrored by a sizeable decline in employment in household businesses and in the share holding a second job, both indicators of informal employment.[2] Together, these patterns point to a substantial shift from informal to formal employment following the arrival of mobile internet.

Leveraging additional household panel data, we show that the movement of women out of agriculture is accompanied by a decline in female labour on family farms. While 3G expansion does not appear to reduce the likelihood that a household operates a farm business, it significantly alters the labour composition of these businesses. In particular, the number of female family members working in the farm business falls by 0.074 per household following the arrival of 3G, consistent with women leaving agriculture.[3] We further show that 3G adoption increases women's individual income and salaried earnings by about 22 and 24 percent respectively and, concurrently, household income and expenditure by about 14 percent.[4] This provides evidence that improved access to labour market information and employment opportunities (e.g., online job advertisements) may have enabled women to take advantage of growing demand for labour in more productive, non-agricultural sectors.[5]

[2] McCaig (2011) also notes that household businesses are a major source of informal employment in Vietnam.

[3] In 2010, households with a farm business in treated districts had on average 1.59 family members working in it, of whom 0.86 were women (2.47 and 1.24 in control districts; see Appendix Table C3).

[4] Wei et al. (2026) find that mobile internet improves household wealth in the Philippines. However, their results indicate a mixed effect on female employment with an increase in seasonal work but a decrease in year-round employment.

[5] The increasing demand for female labour in export-oriented, FDI manufacturing firms has been well documented for Vietnam in the last three decades (McCaig, 2011; McCaig and Pavcnik, 2018; Rotunno et al., 2026; Huynh and Ku, 2025).

Our findings are robust to a range of alternative specifications and datasets. To address concerns raised by recent developments in the staggered DiD literature, we complement our baseline event-study estimates with the approach of Sun and Abraham (2021) and Callaway and Sant'Anna (2021). We further validate our results using the Vietnam Household Living Standards Survey 2010–2018 and the chained DiD estimator developed by Bellégo et al. (2025), which combines short-term changes in employment outcomes observed within individuals across overlapping panels to recover longer-term treatment effects, without requiring a balanced panel. By exploiting within-individual variation rather than relying solely on changes in aggregate employment shares, this approach is less susceptible to bias arising from time-invariant individual heterogeneity and changes in sample composition. Across these exercises, the estimated effects remain strongly consistent with our baseline estimates using LFS data.

Why would mobile internet access facilitate the process of structural transformation? One potential explanation is that improved connectivity reduces labour market frictions and search costs. In developing economies, information about vacancies often circulates through personal networks or informal recruitment channels, limiting workers' access to employment opportunities outside their existing sectors or communities (Beaman and Magruder, 2012; Hensel et al., 2026). By lowering the cost for employers to advertise vacancies and for jobseekers to discover them, mobile internet may expand the set of opportunities available to workers and improve matching between firms and workers. This mechanism may be particularly important for women, whose access to labour market information and professional networks may differ from those of men (Jensen, 2012; Beaman et al., 2018). However, conventional labour force surveys contain little information on the vacancies available to workers, making it difficult to examine this channel directly.

We overcome this limitation by constructing a novel dataset of over 400,000 job roles advertised by over 23,000 recruiters on Facebook between 2009 and 2017. Unlike conventional online job boards, Facebook provides a low-cost recruitment platform widely used by employers and employment agencies. We extract individual vacancies from posts, identify their geographic locations (i.e., districts) where possible, and recover information about job requirements and amenities offered. Consistent with the diffusion of mobile internet, online recruitment activity was almost non-existent during 2009–2012 but expanded rapidly thereafter. By 2017, treated districts recorded over 100,000 advertised roles annually, while posting activity remained minimal in never-treated districts.

Linking Facebook job advertisement data to the staggered expansion of 3G, we find that mobile internet substantially increases online recruitment activity. More specifically, four years after a district gains access to mobile internet, the number of vacancies advertised online is nearly 65 percent higher, while the number of vacancies mentioning social insurance is approximately 30 percent higher two years after access. Together with the worker-side evidence on sectoral reallocation and formalisation, these

findings suggest that mobile internet reduces information frictions in the labour market and facilitates the matching of workers to new employment opportunities, consistent with mechanisms previously documented in developed economies (Goldfarb and Tucker, 2019).

Since gender requirements are prevalent in Vietnamese job advertisements (Pham et al., 2026), we further measure explicit gender preferences from stated requirements. To capture more subtle forms of gender targeting, we employ a Vietnamese sentence-embedding model based on Simple Contrastive Learning of Sentence Embeddings (SimCSE), adapted to the language of Facebook recruitment posts (Gao et al., 2021; Pham et al., 2026).[6] This approach enables us to capture not only advertisements explicitly targeted at female applicants but also implicitly gendered wording which keyword rules cannot detect. We find that 3G expansion has a positive effect on the number of advertised roles targeting female workers, either explicitly or implicitly, which is roughly 30 percent higher two years after treatment. Vacancies offering social insurance also become more numerous as a result of 3G expansion, although we find no clear increase among those that target women.

Overall, our results show that although mobile internet reduces information frictions for all users, in the case of Vietnam, it disproportionately benefits women. These heterogeneous effects across gender are likely to reflect the fact that labour-intensive manufacturing disproportionately recruits women (McCaig, 2011; Huynh and Ku, 2025), and that mobile internet increases the number of online vacancies targeted at women. It may also reflect the fact that women, whose access to job networks is more limited, had the most to gain from a new source of labour market information (Beaman et al., 2018).

This paper contributes to three strands of literature. The first is a nascent but growing body of work investigating the labour market effects of internet access in developing countries.[7] Here, there is broad consensus on the nexus between internet connectivity and economic growth. Internet access has been found to be associated with increased labour force participation in Rwanda, Tanzania and Nigeria (Caldarola et al., 2023; Bahia et al., 2021, 2024). Beyond its effects on aggregate employment, internet connectivity has also been shown to facilitate structural transformation, moving workers out of agriculture and towards the services sector in sub-Saharan Africa (Chiplunkar and Goldberg, 2022). Hjort and Poulsen (2019) exploit variation in the arrival of submarine cables in Africa and demonstrate significant effects of fast internet on employment rates. While this literature provides robust evidence that internet connectivity can increase employment and facilitate labour reallocation away from agriculture, relatively little is known about its implications for formalisation. This distinction is particularly important in developing economies, where a substantial share of workers remain engaged in informal employment (McCaig, 2011; La Porta and Shleifer, 2014). Our paper addresses this gap by examining whether the

[6] The implicit measure is computed from the requirements of the 154,889 roles (35.4 percent) that have requirement text of their own.

[7] For a review of evidence in developed countries, see Goldfarb and Tucker (2019).

expansion of mobile internet facilitates transitions into formal employment, which typically offers greater employment stability and access to job amenities.

More broadly, our paper relates to the literature which sits at the intersection of technology and gender, where existing evidence is mixed. In the context of Mexico, Aguayo-Tellez et al. (2014) show that trade-induced computerisation reduces physically demanding tasks, thereby increasing wages and employment rates of women in blue-collar jobs. A recent study by Azam et al. (2024) finds positive effects of mobile internet on employment and earnings in India, particularly for female workers with higher ICT skills. However, technological adoption does not unequivocally reduce gender inequality. Aksoy et al. (2021) find that technological change can exacerbate gender wage inequality, as men are more likely to benefit from technological innovations in medium- and high-skilled occupations. Additionally, Jones and Sen (2025) find no significant overall employment effects of digital job-matching platforms in Mozambique, with weaker employment benefits for women than men. Particularly relevant to our paper is a study by Tang et al. (2026), who demonstrate that broadband-internet adoption by Vietnamese firms during the 2000s led to an increase in the share of female workers. Exploiting the expansion of ICT backbone nodes in Vietnam in 2007 and geographic variation in last-mile broadband connectivity, the authors demonstrate that this positive effect on female labour demand is stronger in social, customer-facing and service-oriented industries, where women are more likely to have a comparative advantage, and weaker in industries characterised by routine or manual tasks. At the individual level, they find that access to an internet-connected computer reduces the time women spend on housework, while increasing both the number of days they work per month and participation in formal employment. Despite this, the authors find no corresponding improvements in the gender wage gap. Our study complements this work by examining the diffusion of 3G mobile internet beginning in 2010, shifting the focus from firm-level ICT adoption to a technology that achieved substantially greater penetration and which individuals can access and adopt independently of their employment status.

Finally, our paper also contributes to the growing literature using online job advertisements to study labour demand. Job advertisements provide detailed information on employers' skill requirements and recruitment behaviour that is typically unavailable in conventional survey data (Deming and Kahn, 2018; Hershbein and Kahn, 2018; Marinescu and Wolthoff, 2020). A related literature examines how employers communicate gender preferences through job advertisements. Kuhn and Shen (2013) document the prevalence of explicit gender requests, while subsequent studies demonstrate that these requests shape jobseekers' application decisions and recruitment outcomes (Kuhn et al., 2020; Kuhn and Shen, 2023; Card et al., 2025). More recently, advances in natural language processing (NLP) methods have enabled researchers to identify implicit gender preferences embedded in vacancy descriptions, even in the absence of explicit gender requirements (Chaturvedi et al., 2025; Pham et al., 2026). We advance this literature

in two ways. First, we construct a novel dataset of job advertisements from Facebook, an informal, low-cost recruitment channel that potentially captures vacancies overlooked by conventional online job boards. This is especially pertinent for developing economies where recruitment frequently occurs through informal networks (Fernando et al., 2023; Hensel et al., 2026). Second, we exploit the staggered rollout of 3G to move beyond documenting employers' recruitment preferences in job advertisements and investigate how increased internet access shapes both the volume and gender targeting of advertised employment opportunities. By linking these novel measures of recruitment activity to individual-level labour market outcomes, we are able to shed light on how increased digital connectivity alleviates information frictions and facilitates labour reallocation, particularly among women.

The remainder of the paper is organised as follows: Section 2 describes the data sources used to construct district-level 3G coverage and labour market outcomes, and introduces the treatment definition and spatial distribution of treatment across districts and over time. Section 3 outlines the empirical strategy, followed by the main findings in Section 4. Section 5 investigates the underlying mechanisms, discussing the channels through which 3G internet might affect the structural transformation of the labour market. Section 6 presents additional evidence on worker reallocation using household-level data and conducts a range of robustness checks before concluding in Section 7.

2 Background and Data

2.1 Rollout of AAG Submarine Cable and 3G Networks

The introduction of 3G technology marked a significant departure from earlier generations of mobile telecommunications in Vietnam. While 2G networks were primarily designed for voice calls and text messaging, with limited data transmission capabilities through GPRS and EDGE, 3G technology enabled substantially faster mobile internet access, supporting web browsing, social media, video streaming, and other data-intensive applications. The diffusion of 3G was complemented by substantial improvements in Vietnam's international telecommunications infrastructure, particularly the arrival of the Asia-America Gateway (AAG) submarine fibre-optic cable in November 2009. By expanding the country's international bandwidth capacity, the AAG helped alleviate potential bottlenecks in data transmission as mobile internet usage increased. Vietnam's international internet bandwidth grew from just over 100 Gbps in 2009 to more than 340 Gbps in 2012, reaching approximately 3.8 Tbps by the end of 2016. Together, the expansion of international bandwidth and investments in domestic 3G infrastructure facilitated the transition from predominantly voice-based mobile telecommunications towards widespread mobile internet connectivity.

2.2 Data on Mobile Internet Coverage

Our main source of data for reconstructing the rollout of 3G in Vietnam is the **OpenCelliD** (OCI) database.[8] OCI is a global open database of cell towers maintained by Unwired Labs, a geolocation service provider. It is the largest publicly accessible database of its kind and is updated on a daily basis. The dataset contains the geographic coordinates of individual cell towers, together with metadata such as the time and date when signals were recorded.[9] Tower locations are crowdsourced from mobile phone users via applications that collect cell ID information, which implies that data density is higher along major transport corridors and in urban areas. As the *actual* geographic reach of each tower is not detailed in the OCI data, we construct a coverage footprint centred on the tower's coordinates by assigning a coverage radius of 2 kilometres to towers in urban districts and 12 kilometres to towers in rural districts.[10] This distinction reflects differences in cellular network deployment and signal propagation across settlement types. In densely populated urban areas, greater network capacity requirements and physical obstructions typically result in smaller cell coverage areas, whereas rural networks generally rely on more widely spaced base stations with larger coverage footprints (ITU, 2013).

To produce a more precise measure of district-level 3G coverage over time, we overlay these tower footprints with population density data from WorldPop to calculate the share of each district's population covered by 3G. WorldPop provides annual data at a 100-metre resolution, where each pixel records the estimated number of residents. These data are constructed by disaggregating census and survey-based population counts from administrative units down to the pixel level using a Random Forest model that incorporates geospatial covariates to distribute population across space.[11]

Figure 2 shows 3G coverage across districts over time, organised by the year in which each district first recorded a 3G signal. According to the OCI data, the rollout began in 2010 and coverage was near-universal by 2017, when 683 of the 685 districts had recorded a 3G signal and mean district-level coverage was 92 percent. Appendix Figure D1 presents the mean and median district-level 3G coverage by year, while Appendix Figure D2 illustrates the coverage distribution over time. The distribution is bimodal, with most districts having little or no coverage in the early 2010s and converging to nearly full coverage by 2017. Motivated by this pattern, we classify districts whose 3G coverage reaches the 2017 mean district-level coverage (91.74 percent) as treated, while districts that never reach this threshold

[8] https://opencellid.org/

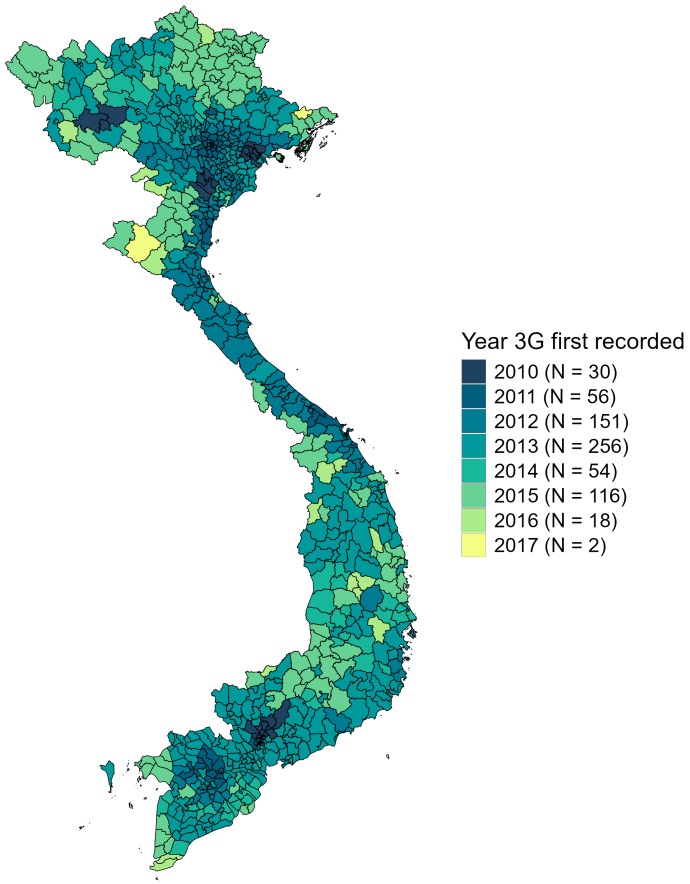
[9] Previous studies such as Chiplunkar and Goldberg (2022) and Pham and Caldarola (2026) use Collins Bartholomew (CB) data which offer more granular cellular coverage at the 1 km × 1 km grid cell level. Such information is not available for Vietnam before 2013, when many of the districts in our sample had already become treated. In addition, local telecommunications companies do not submit their data in certain years, rendering these data unreliable. By contrast, OCI data do not rely on submissions from mobile service providers and instead pick up actual mobile usage. To assess the reliability of our reconstructed coverage measure, we compare district-level OCI coverage with that obtained from CB in 2017. Mean coverage is very similar across the two sources (91.7 and 90.9 percent), and the two measures are positively correlated across districts (correlation of 0.64; rank correlation of 0.82), as shown in Appendix Figure D3.

[10] A district is classified as urban if at least half of its constituent wards are designated as urban under Vietnam's official administrative classification, and rural otherwise.

[11] For further information, please refer to Stevens et al. (2015).

serve as the control group. Figure 3 shows a map of districts by treatment status over time by year first treated, defined as the year in which a district's 3G coverage reaches 91.74 percent. The fastest phase of 3G network expansion took place between 2013–2015, during which nearly 400 out of 685 districts cross the treatment threshold. We exclude the two districts that had already attained this level of mobile internet coverage in 2010, the first year of our study period. The final sample therefore comprises 546 districts treated at some point during the study period, and 137 that remain untreated throughout.

Figure 2: 3G coverage over time by year first recorded



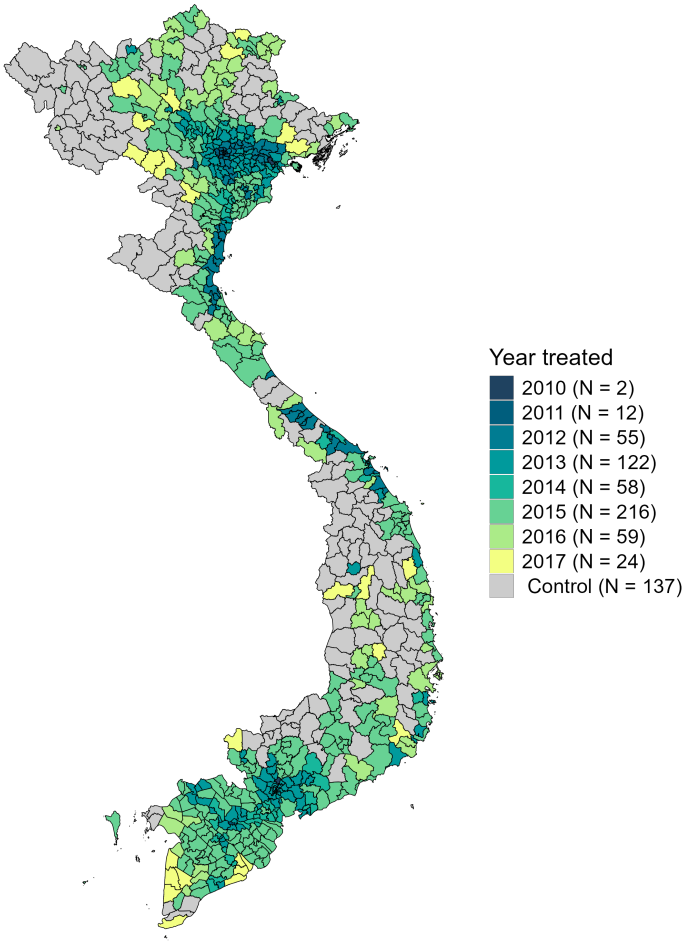
Notes: 3G coverage across districts by the year in which a 3G signal was first recorded. The sample includes 685 districts with consistent boundaries over 2010–2017. Source: Authors' calculations using OpenCelliD data.

2.3 Labour Market Outcomes

Our main source of data comes from the Labour Force Surveys (LFS) covering the period 2010–2017. The LFS contains a nationally representative sample of approximately 800,000 individuals in each survey year.[12] We restrict our attention to the working-age (20–64) population, aggregated to the district level.

[12] In 2010, there were two survey waves. From 2011 onwards, the LFS has been conducted monthly. In this analysis, we only exploit the variation at the yearly level.

Figure 3: Treatment status over time by year first treated



Notes: The year in which each district was first treated. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). The sample includes 685 districts with consistent boundaries over 2010–2017. Source: Authors' calculations using OpenCelliD and WorldPop data.

The LFS provides comprehensive information on individuals' employment status and labour market outcomes. Based on their industry of work, we classify individuals into the agriculture, manufacturing or services sector. Information on employers allows us to distinguish between the formal sector (e.g., firms with a tax identification number) and the informal sector (e.g., household businesses). We then calculate the share of workers in each sector and formality category at the district level accordingly.

Table 1 presents average labour market characteristics at the district level by treatment status in 2010, the first year in our study period. As defined in Section 2.2, a district becomes treated once its 3G coverage reaches the 2017 sample mean. Essentially, treated districts are those with near-universal 3G signal coverage, while the mean population coverage of the never-treated districts is about 62 percent by 2017. The LFP rate is high in both treated and control districts, averaging around 90 percent. However, the proportion of workers holding a second job is considerably lower in treated (23 percent) than in control districts (32 percent). Treated districts also exhibit a lower share of workers employed in household businesses and agriculture, and a higher share in manufacturing and services as well as higher shares working for firms with a tax identification number (tax ID) or covered by social insurance. Taken together, these patterns are indicative of more developed and formalised local economies. Such differences are not unexpected, given that 3G rollout is unlikely to be random across districts. Areas receiving earlier network expansion are generally more urbanised and already on a faster-growing trajectory. Appendix Figures D4 and D5 show how employment shares across sectors and formality evolve by treatment status and age group.

Table 1: Descriptive statistics by treatment status (initially in 2010)

	Control ($N = 137$)				Treated ($N = 546$)				Treated − Control
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Diff.
Panel A. All									
LFP	0.93	0.05	0.65	1.00	0.87	0.07	0.65	1.00	-0.06***
Has a second job	0.32	0.22	0.00	0.94	0.23	0.19	0.00	0.92	-0.08***
Household business share	0.83	0.08	0.60	0.99	0.76	0.16	0.18	1.00	-0.07***
Agriculture share	0.66	0.17	0.12	0.99	0.41	0.23	0.00	0.96	-0.25***
Manufacturing share	0.04	0.04	0.00	0.25	0.14	0.11	0.00	0.82	0.09***
Service share	0.26	0.13	0.01	0.58	0.37	0.17	0.04	0.89	0.11***
Share with a tax ID (2011)	0.21	0.18	0.00	0.86	0.31	0.22	0.00	0.90	0.10***
Share with social insurance (2011)	0.16	0.14	0.00	0.70	0.24	0.18	0.00	0.87	0.08***
Panel B. Female									
LFP	0.91	0.09	0.39	1.00	0.83	0.11	0.43	1.00	-0.08***
Has a second job	0.32	0.23	0.00	0.94	0.24	0.21	0.00	0.92	-0.08***
Household business share	0.84	0.08	0.63	1.00	0.77	0.16	0.14	1.00	-0.07***
Agriculture share	0.67	0.19	0.07	1.00	0.43	0.25	0.00	1.00	-0.24***
Manufacturing share	0.04	0.05	0.00	0.25	0.14	0.12	0.00	0.85	0.10***
Service share	0.28	0.16	0.00	0.76	0.41	0.19	0.00	0.89	0.12***
Share with a tax ID (2011)	0.20	0.19	0.00	0.92	0.30	0.22	0.00	0.83	0.09***
Share with social insurance (2011)	0.16	0.14	0.00	0.60	0.23	0.18	0.00	0.81	0.07***

*Source: Authors' calculations using LFS 2010 (2011 for tax ID and social insurance). Significance of the differences is based on separate OLS regressions of each variable on a treatment indicator, with standard errors clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Districts first treated in 2010 are excluded.*

2.4 Household Panel Data

We additionally rely on data from the Vietnam Household Living Standards Survey (VHLSS) for 2010–2018. The surveys are conducted every two years by the General Statistics Office (GSO) of Vietnam, with technical assistance from the World Bank. The VHLSS is nationally representative and by far the most comprehensive microdata in Vietnam on the living standards of the population. Similarly to the LFS, the VHLSS records individual-level information about labour force participation and other employment outcomes. The advantage of the VHLSS is its rotating panel feature, which allows us to follow individuals over two to three consecutive rounds (corresponding to two to four years). We will come back to this in Section 6, where we exploit the data structure to perform an identification exercise using the chained DiD estimator.[13]

3 Empirical Strategy

3.1 Two-Way Fixed Effects Model

To understand the aggregate effect of 3G mobile internet on the labour market, for each district d in year t, we exploit district-level variation in 3G treatment status and estimate the following TWFE model:

$$Y_{dt} = \gamma \,\text{Mobile Internet}_{dt} + \delta_d + \theta_t + \eta \ln \text{Province Export}_{pt} + \mathbf{X}'_{d,2009}\boldsymbol{\lambda}_t + \epsilon_{dt} \tag{1}$$

where Y_{dt} are the outcome variables of interest including district-level share of adults aged 20 to 64 who report having worked in the last 7 days, share reporting holding a second job, share of workers in the agriculture, manufacturing and services sectors, and share of workers in the formal and informal sectors. $\text{Mobile Internet}_{dt}$ takes the value of 1 if 3G coverage of district d in year t reaches the 2017 mean district-level coverage (91.74 percent) as discussed in Section 2. We additionally include district (δ) fixed effects and year (θ) fixed effects (FEs). To understand the heterogeneous effects of 3G access by gender, we estimate equation 1 separately for men and women.

A key challenge to the identification strategy is non-random selection into treatment. In particular, the rollout of 3G infrastructure might have begun earlier in more developed or urbanised districts, where residents are more likely to own smartphones and demand mobile internet services. If early-treated districts were already on a faster-growing trajectory, pre-existing differences might confound the effects of 3G access when comparing treated with never-treated districts. As shown in Table 1, treated districts

[13] The indicator of LFP in the VHLSS slightly differs from that in the LFS as the recall period for having done any work is in the last 12 months.

tend to have a lower share of workers employed in agriculture or in household businesses—sectors typically associated with lower productivity, lower wages and a high degree of informality. The inclusion of district FEs purges away time-invariant district characteristics. In addition, year FEs absorb nationwide trends that are common to all districts in a given year. Therefore, identification comes from within-district changes before and after having 3G access relative to that of the control group.

Importantly, we control for log provincial export exposure (ln Province Export$_{pt}$).[14] The export measure is a shift-share Bartik-style construction that combines the economy-wide growth of exports in each industry with the province's initial industrial composition. Specifically,

$$\ln \text{Province Export}_{pt} = \ln\left(\sum_i s_{pi}^{2009} \cdot \frac{X_{it}}{L_i^{2009}}\right), \tag{2}$$

where s_{pi}^{2009} is the share of province p's employment in industry i in 2009, X_{it} is Vietnam's total export value of industry i in year t, and L_i^{2009} is national employment in industry i in 2009. Data on industrial and provincial employment compositions are calculated using the 2009 Vietnam Population and Housing Census.[15] By holding initial industry employment shares fixed, this measure captures differences in provinces' exposure to trade shocks according to their pre-existing labour market composition. This is particularly relevant in Vietnam, where trade liberalisation and the expansion of export-oriented manufacturing have been important drivers of structural transformation and female employment. Including this measure therefore helps disentangle the effects of 3G expansion from changes in labour demand associated with export growth.

We further control for a set of district characteristics in 2009—shares of employment in manufacturing, FDI firms, information technology (IT), as well as the shares of high-school-educated population and migrants—interacted with year FEs. These district characteristics are likely to be strongly correlated with the structural transformation process already in place, so controlling for them should help isolate the effect of mobile internet on the local labour market from pre-existing trends.

3.2 Event Study: Young vs. Old Workers

Despite flexibly controlling for trends in treated and control districts (by interacting district characteristics in 2009 with year FEs and including log provincial exports), our identification strategy might still be susceptible to selection into treatment. In particular, districts treated earlier may have been on a faster-growing trajectory, with expanding employment in non-agricultural sectors, and our preferred set of controls may not fully account for these differences.

[14] Provinces (level 1) are the administrative divisions above districts (level 2) in Vietnam.
[15] For a more detailed discussion of the construction of this measure and its validity, see Huynh and Ku (2025).

To further assess the credibility of our findings, we exploit differences in the expected responsiveness of younger and older workers to mobile internet. We argue that 3G expansion, like many technological changes, is more likely to affect younger workers. These are people who tend to be more technologically adept, quicker to acquire new skills, and more likely to own smartphones. Older workers, by contrast, may adopt these technologies more slowly and thus be less directly affected. If this is the case, labour market outcomes for older workers should evolve similarly across treated and never-treated districts, providing a useful benchmark.

This approach introduces an additional comparison dimension, conceptually related to a triple-differences design, without imposing a formal DDD specification. If the estimated effects primarily reflect broader district-level economic shocks unrelated to mobile internet, we might expect to observe similar changes in employment outcomes among both younger and older workers. Conversely, effects concentrated among younger workers, together with the absence of differential pre-treatment trends, would provide additional evidence consistent with the interpretation that mobile internet expansion contributed to the observed labour market adjustments.

To test for pre-trends and understand the dynamic effects of 3G on the local labour market across age groups, we implement the following event study separately for workers aged 20–44 ('young workers') and workers aged 45–64 ('old workers'):

$$Y_{dt} = \sum_{\substack{j=-6 \\ j\neq -1}}^{6} \beta_j D_{dt}^{j} + \delta_d + \theta_t + \eta \ln \text{Province Export}_{p(d)t} + \mathbf{X}'_{d,2009}\boldsymbol{\lambda}_t + \epsilon_{dt} \tag{3}$$

where d indexes district and t indexes year. Y_{dt} captures the same outcomes as those given by the TWFE model. D_{dt}^{j} are leads and lags for when district d first reached the mean district-level coverage threshold and *never-treated* districts take the value of 0 for all leads and lags. As an alternative empirical strategy, we estimate the event study using Sun and Abraham (2021), in which the control group for each treatment cohort consists of the *never-treated*.

4 Results

4.1 Aggregate Effects of 3G Expansion on Local Labour Markets

Labour force participation and sectoral reallocation. We start by documenting the overall effects of 3G mobile internet on labour market outcomes at the district level using data from the LFS in the period 2010–2017. Table 2 reports the estimated impacts on LFP and sectoral composition of employment across agriculture, manufacturing and services following equation 1. Panel A represents the aggregate

effects, while Panel B and Panel C show separate estimates for women and men, respectively. All specifications control for baseline district-level characteristics interacted with year dummies and include district FEs and year FEs, and standard errors are clustered at the district level.

In column 1, we report the results for labour force participation, where the outcome $Work$ is the share of individuals who worked in the last 7 days. The results here indicate that there is a small negative effect of 3G access on labour force participation, albeit only marginally significant. This is unsurprising given the already high levels of LFP in Vietnam, where approximately 90 percent of the working-age population reports being employed.

On the intensive margin, the results in columns 2–4 indicate that access to mobile internet is associated with an expansion of manufacturing employment. Specifically, treated districts experience a 0.5 percentage point (pp) increase in the share of workers in manufacturing, while the estimated effects on agriculture and services are negative but statistically insignificant. This aligns with Vietnam's broader pattern of structural change driven by large inflows of FDI and rapid export expansion in low-skilled, labour-intensive manufacturing sectors in recent decades (McCaig, 2011).

Previous research has shown that structural transformation in Vietnam tends to benefit female workers more than their male counterparts (McCaig, 2011; Huynh and Ku, 2025; Rotunno et al., 2026). Our results suggest that technology-induced structural transformation exhibits a similar gendered pattern. The reallocation effects associated with 3G rollout appear to be primarily driven by female workers. As shown in Panel B, column 3, 3G mobile internet increases the share of female workers employed in manufacturing by 1 pp, significant at the 1 percent level. The effects on male workers are virtually absent.

The concentration of employment gains in manufacturing is particularly noteworthy when compared with the existing literature on mobile internet. Using data from 14 developing countries in sub-Saharan Africa, Chiplunkar and Goldberg (2022) find that 3G expansion increases employment, particularly among women, but does not generate a comparable movement out of agriculture. Our findings for Vietnam reveal a different pattern, whereby improved connectivity is associated with the movement of women out of agriculture and into manufacturing. One possible explanation is that the effects of mobile internet depend on labour demand in the local labour market. In Vietnam, where export-oriented manufacturing expanded rapidly over the study period, improved access to information may have enabled women to take advantage of growing demand for manufacturing labour. In economies where such opportunities are less prevalent, the benefits of mobile connectivity may instead materialise through self-employment or service-sector activities.

Table 2: 3G rollout and LFP and sectoral reallocation

	LFP	Sector		
	(1) Work	(2) Agriculture	(3) Manufacturing	(4) Service
Panel A. Overall effects				
Mobile Internet	-0.005**	-0.003	0.005**	-0.008
	(0.002)	(0.007)	(0.003)	(0.006)
Observations	5,370	5,370	5,370	5,370
R^2	0.864	0.883	0.875	0.808
Panel B. Effects on Female				
Mobile Internet	-0.005*	-0.003	0.010***	-0.010
	(0.003)	(0.008)	(0.003)	(0.007)
Observations	5,370	5,370	5,370	5,370
R^2	0.873	0.874	0.865	0.805
Panel C. Effects on Male				
Mobile Internet	-0.005**	-0.002	0.001	-0.007
	(0.002)	(0.007)	(0.003)	(0.006)
Observations	5,370	5,370	5,370	5,370
R^2	0.768	0.881	0.839	0.794

Notes: All columns control for district FEs, year FEs, interactions of year dummies with district characteristics in 2009 (share employment in manufacturing, IT service, FDI firms, share with high school education and share of migrants) and log provincial export. Standard errors are clustered at the district level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Formalisation of employment. Panel A of Table 3 presents the overall effects of 3G rollout on several proxies for (in)formal employment. In treated districts, there is a 0.8 pp reduction in the share of workers employed in household businesses (column 2), significant at the 10 percent level.[16] In contrast, the estimated effects of 3G on second-job holding (column 1), the share of workers employed by registered firms (i.e., firms with a tax ID) and the share of workers covered by social insurance (columns 3 and 4, respectively) are small and statistically insignificant.

The separate effects by gender in Panel B and Panel C reveal noteworthy heterogeneity. In column 2, the decline in informal employment is larger for women, with a 1.1 pp reduction in household business employment among women (Panel B), significant at the 5 percent level, compared with a statistically insignificant 0.5 pp decline among men (Panel C). The estimates for the share of women employed in registered firms (1.3 pp, column 3) and covered by social insurance (0.4 pp, column 4) are positive but statistically insignificant. These results are consistent with the broader pattern of structural transformation in Vietnam, where women have disproportionately benefited from the expansion of export-oriented, FDI-driven manufacturing (McCaig and Pavcnik, 2018; Huynh and Ku, 2025; Rotunno et al., 2026). Our findings suggest that mobile internet may have played a complementary role in this process. We come back to this in Section 5.1.

[16] For a detailed discussion on household businesses and informality in Vietnam, see McCaig and Pavcnik (2018).

Table 3: 3G rollout and formalisation of work

	Informal		Formal	
	(1) Second job	(2) Household Business	(3) Tax ID	(4) Social Insurance
Panel A. Overall effects				
Mobile Internet	-0.002	-0.008*	0.006	0.002
	(0.008)	(0.004)	(0.009)	(0.005)
Observations	5,370	5,370	2,606	4,619
R^2	0.791	0.869	0.821	0.813
Panel B. Effects on Female				
Mobile Internet	-0.003	-0.011**	0.013	0.004
	(0.008)	(0.004)	(0.010)	(0.005)
Observations	5,370	5,370	2,606	4,619
R^2	0.806	0.853	0.805	0.790
Panel C. Effects on Male				
Mobile Internet	-0.003	-0.005	-0.000	-0.001
	(0.008)	(0.004)	(0.010)	(0.005)
Observations	5,370	5,370	2,606	4,619
R^2	0.752	0.858	0.807	0.797

Notes: All columns control for district FEs, year FEs, interactions of year dummies with district characteristics in 2009 (share employment in manufacturing, IT service, FDI firms, share with high school education and share of migrants) and log provincial export. Standard errors are clustered at the district level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Although the estimated effects in Tables 2 and 3 are modest in magnitude, they represent average effects over the study period and may conceal important heterogeneity in treatment effects over time. Moreover, conventional TWFE estimates may be biased under staggered treatment adoption when treatment effects vary across cohorts or with exposure duration.

4.2 Young vs. Old Workers

In this section, we present results of the event study given by equation 3 for the young and old cohorts. We define young workers as those aged 20–44, and old workers as those aged 45–64. The old workers, presumably less exposed to new technologies, effectively provide a third comparison layer in the spirit of a triple-differences design (DDD). Rather than estimating a formal DDD model, we instead run separate event-study regressions for each age group to examine whether our main results have a causal interpretation. Following recent advances in the DiD literature, we recognise the limitation of the naïve TWFE estimator, which can generate biased estimates in the presence of heterogeneous and dynamic treatment effects—most notably through negative weighting and 'forbidden comparisons', where early-treated units serve as controls for later-treated ones. To address these concerns, we implement the event-study approach proposed by Sun and Abraham (2021) (hereafter, SA estimates), in which the

control group for each treatment cohort consists of the *never-treated* units.[17] Here, we choose to focus on **labour market outcomes of women** given that the effects on sectoral reallocation and formalisation appear to be concentrated among female workers, as shown in Section 4.1.

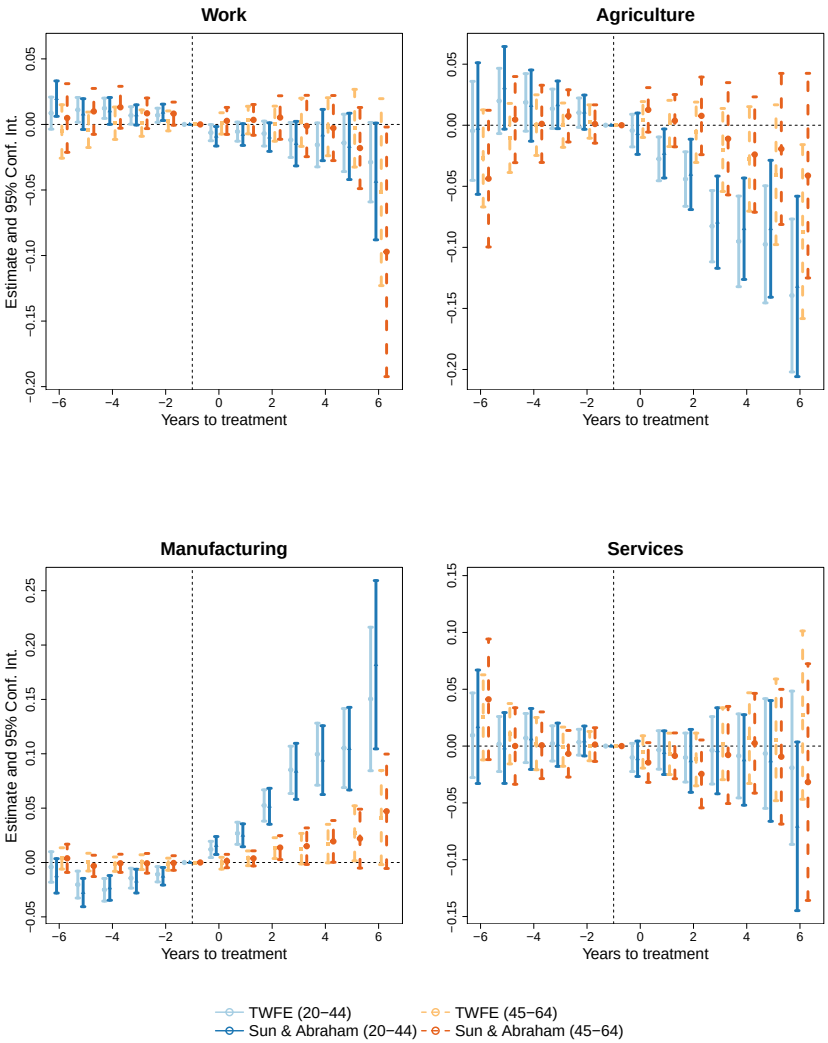
Labour force participation and sectoral reallocation. Figure 4 presents the dynamic effects of 3G coverage on LFP and the shares of employment in agriculture, manufacturing, and services over time. The dashed orange lines represent the estimated effects on older workers, while the solid blue lines correspond to younger workers. The light and dark shaded coefficients correspond to TWFE and SA estimates, respectively. The upper-left panel of Figure 4 indicates that there is no meaningful change in LFP across female workers of both age groups. However, we observe a clear effect of 3G on sectoral reallocation of young female workers—an effect that is detectable almost immediately after treatment and becomes more pronounced over time. Consistent with Table 2, treated districts experience a sizeable decline in the share of young women working in agriculture, accompanied by a corresponding steady increase in manufacturing. More specifically, one year after treatment, agricultural employment declines by 2 pp and, by the fourth year, this effect increases to 9 pp. Concurrently, we find mirror-image patterns for the reallocation of young female workers into the manufacturing sector. By contrast, the effects on services are relatively muted. Across all panels, the naïve TWFE and SA estimates are broadly consistent.

Parallel trends. Importantly, the coefficients in the pre-treatment periods for the young group (blue lines) are generally small and statistically insignificant, supporting the parallel trends assumption that in the absence of 3G expansion, the composition of the young female workforce in treated and control districts would have followed similar trends. By comparison, the estimated effects for older women (orange lines) are small and mostly statistically insignificant, the main exception being a modest increase in manufacturing employment in some post-treatment years, which is much smaller than that among young women. The much weaker response among the older workforce is consistent with our hypothesis that younger workers are more responsive to technological change, particularly mobile internet expansion. More broadly, the lack of pre-treatment differences and the limited post-treatment responses among the older cohorts suggest that the estimated effects are specific to the population most likely to adopt and benefit from mobile internet, rather than reflecting broader district-level shocks coinciding with 3G rollout.

Formalisation of employment. Figure 5 corroborates the finding in Table 3, showing that 3G mobile internet reduces the share of female workers in informal employment. Here again, we see that these effects

[17] In Section 6.2, we show robustness exercises using SA's *last-treated*, as well as Callaway and Sant'Anna (2021)'s combination of the *not-yet-treated* and *never-treated* as the alternative control groups.

Figure 4: 3G rollout and LFP and sectoral composition of female workers, by age group



Notes: Event-study estimates of the effect of 3G coverage on female labour force participation and sectoral employment. Work is the share of women who worked in the last 7 days; agriculture, manufacturing and services are the shares of working women employed in each sector. Women aged 20–44 are shown in blue (solid) and women aged 45–64 in orange (dashed). Light markers show two-way fixed effects (TWFE) estimates and dark markers estimates from the Sun and Abraham (2021) estimator, with never-treated districts as the control group. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Specifications include district and year fixed effects, log provincial exports and 2009 district characteristics interacted with year dummies. The sample covers 683 districts over 2010–2017 and excludes districts first treated in 2010. Vertical bars are 95 percent confidence intervals based on standard errors clustered at the district level. Source: Authors' calculations using Labour Force Survey and OpenCelliD data.

strengthen over time. Four years after the onset of 3G expansion, the declines in the shares holding a second job and employed in household businesses reach approximately 5 pp and 8 pp respectively. At the same time, our event study estimates confirm the shift towards formal employment, proxied by working for a registered firm or being covered by social insurance. This reinforces the narrative of increasing formalisation in the labour market. Similarly to the previous set of results on sectoral composition, the pre-treatment coefficients for all outcomes are negligible, reassuring against pre-trend concerns. Moreover, the absence of comparable effects among older women, whose estimated coefficients remain close to zero throughout the study period, is consistent with the effects being concentrated among younger workers rather than reflecting broader district-level shocks affecting both age groups. While some evidence of pre-trends appears for the tax ID variable, the coefficients are not statistically significant and may reflect data limitations: the variable is available in fewer years and is more likely to be subject to measurement error, as individuals might not know accurately whether their employer is formally registered for tax purposes.[18]

5 Mechanisms

5.1 Mobile Internet as a Complement to Industrial Growth

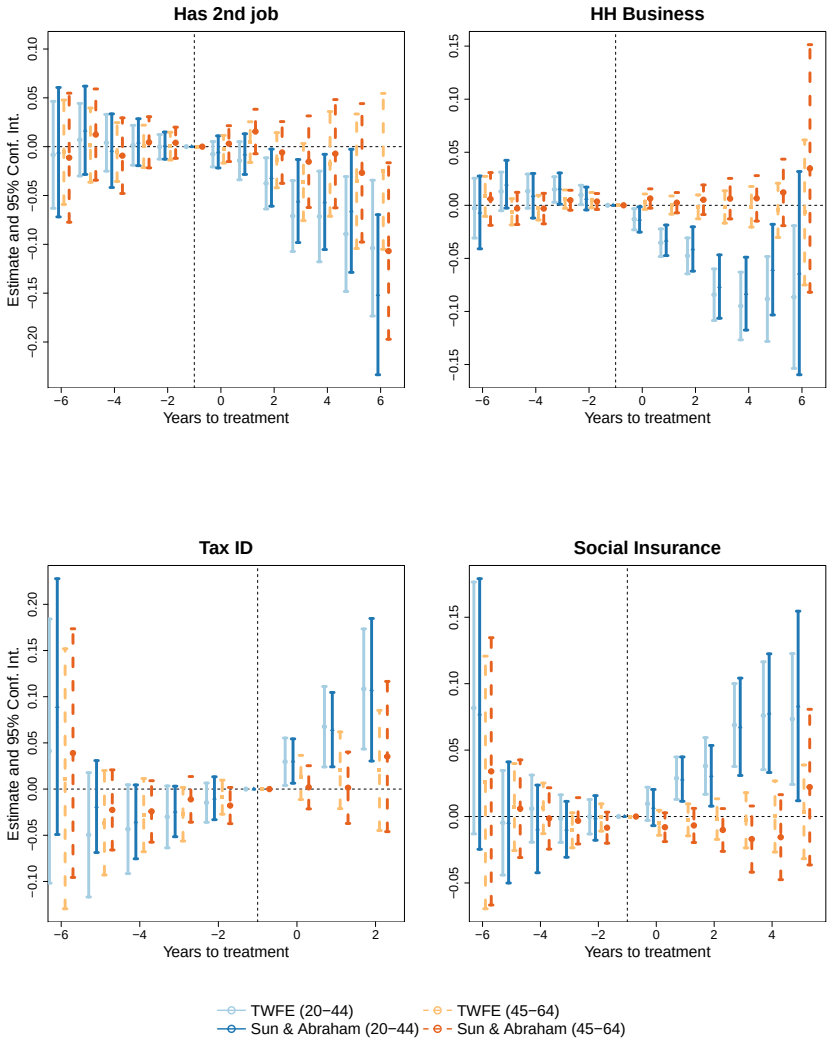
Distance to industrial zones and the spatial reach of mobile internet. Figure 6 examines the complementarity between 3G expansion and industrialisation by exploiting variation in districts' proximity to pre-existing industrial zones.[19] Specifically, districts are grouped into 5-kilometre bands based on the distance between the district's centroid and that of the nearest district hosting an industrial or economic zone (hereafter, industrial zone) established in 2009 or earlier. If mobile internet facilitates the matching of workers to employment opportunities created by manufacturing firms, its effects should be strongest where such jobs are geographically accessible.

The results support this prediction. Interestingly, the effects do not decline monotonically with distance. Instead, they follow a hump-shaped pattern, reaching their maximum in districts located 5–15 kilometres from the nearest industrial zone. If these the results documented in Section 4 are driven entirely by trade shocks, we would expect the strongest response in the districts closest to industrial

[18] Tax ID is recorded in the LFS only for 2011–2014 and social insurance coverage for 2011–2017. In 2011 both questions were asked only in August, and in 2012 only in March and October; from 2013 they are asked in all months. District shares for 2011 and 2012 are therefore computed from respondents in these months only, and 65 districts in 2011 and 13 in 2012 are missing in the female sample because no woman was interviewed in the relevant months.

[19] Data on the location of industrial zones, including coastal and cross-border economic zones, and the year in which each was approved or established are taken from Tafese et al. (2025). To calculate the distance between a district and the nearest industrial zone, we measure the straight-line distance from the district's centroid to the centroid of the nearest district hosting a zone, so that the distance is zero for host districts. We retain only zones in place before 2010, the first year of our study period, so that their location predates the rollout of 3G and cannot have been determined by it. Of the 610 zones in the data, 295 were in place before 2010, and are located in 163 districts.

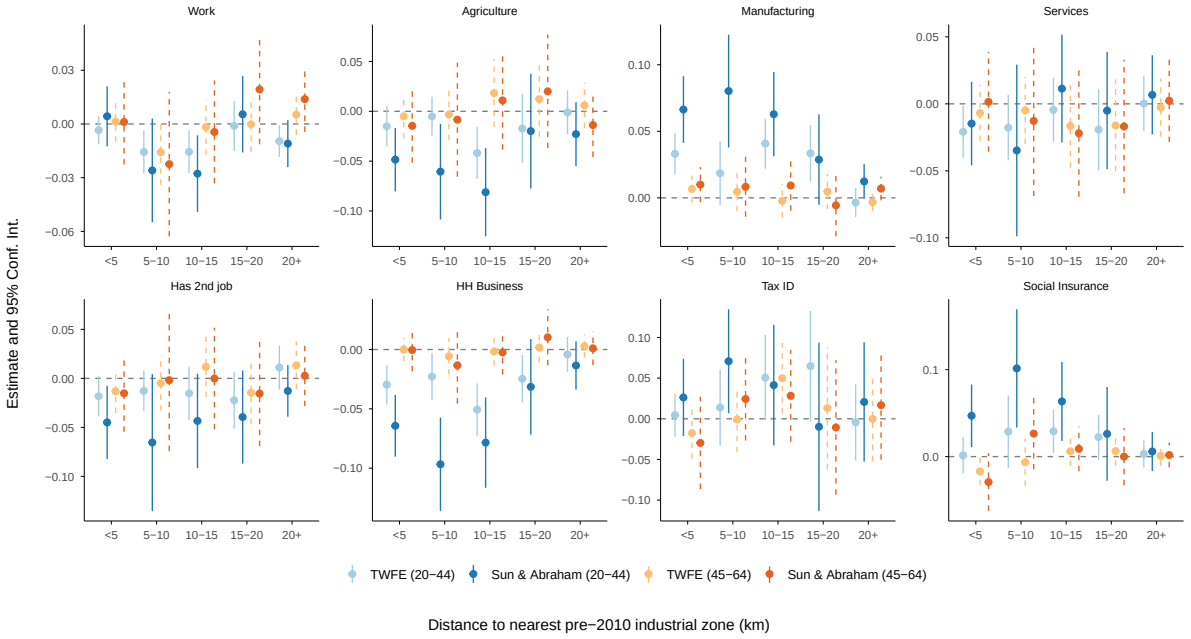
Figure 5: 3G rollout and formalisation of female workers, by age group



Notes: Event-study estimates of the effect of 3G coverage on female informal and formal employment. The outcomes are the shares of working women with a second job, employed in a household business, working for a firm with a tax ID, and covered by social insurance. Women aged 20–44 are shown in blue (solid) and women aged 45–64 in orange (dashed). Light markers show two-way fixed effects (TWFE) estimates and dark markers estimates from the Sun and Abraham (2021) estimator, with never-treated districts as the control group. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Specifications include district and year fixed effects, log provincial exports and 2009 district characteristics interacted with year dummies. The sample covers 2010–2017; tax ID is observed for 2011–2014 and social insurance for 2011–2017. Districts first treated in 2010 are excluded from the TWFE estimates for second-job holding and household businesses; the corresponding Sun and Abraham estimates, and all tax ID and social insurance estimates, retain them. The tax ID and social insurance samples are restricted to event years −6 to 2 and −6 to 5, respectively, plus never-treated districts. Vertical bars are 95 percent confidence intervals based on standard errors clustered at the district level. Source: Authors' calculations using Labour Force Survey and OpenCelliD data.

zones, where export-related labour demand is most concentrated. The hump-shaped pattern suggests that proximity to export-oriented jobs alone cannot explain our estimates. One possible explanation is that workers in districts that host an industrial zone, or whose centroid lies within 5 kilometres of that of a host district, already face relatively low information frictions and therefore benefit less from improved access to mobile internet. By contrast, workers living slightly further away may face greater search and matching costs, leaving more scope for mobile internet to improve access to information about employment opportunities. Beyond 20 kilometres, however, the effects largely disappear, suggesting that physical proximity to industrial jobs remains an important constraint even when information frictions are reduced.

Figure 6: 3G rollout and reallocation of labour, by distance to the nearest industrial zone



Notes: Estimates of the effect of 3G coverage on female employment outcomes by distance to the nearest industrial or economic zone (hereafter, industrial zone) in place by 2009. Outcomes are defined as in Figures 4 and 5. Distance is measured in a straight line from the district's centroid to that of the nearest district hosting a zone, so it is zero for host districts. Zone locations are compiled from provincial government, zone management authority and industrial property websites. A zone is dated by its year of approval or, where this is missing, its year of establishment or the first year it is visible on Google Earth; 295 zones in 163 districts were in place by 2009. Women aged 20–44 are shown in blue (solid) and women aged 45–64 in orange (dashed). Light markers show two-way fixed effects (TWFE) estimates of 3G treatment interacted with each distance band. Dark markers show the average treatment effect from the Sun and Abraham (2021) estimator, estimated separately for each band using the treated districts in that band and all never-treated districts. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Specifications include district and year fixed effects, log provincial exports and 2009 district characteristics interacted with year dummies. Districts first treated in 2010 are excluded for work and the three sectors. The tax ID and social insurance samples are restricted to event years −6 to 2 and −6 to 5, respectively, plus never-treated districts. Vertical bars are 95 percent confidence intervals based on standard errors clustered at the district level. Source: Authors' calculations using Labour Force Survey, OpenCelliD and industrial zone data.

A large literature shows that trade liberalisation generates substantial employment growth in the FDI manufacturing sector and contributes to the reallocation of workers towards more productive firms (McCaig, 2011; McCaig and Pavcnik, 2018; Huynh and Ku, 2025; Rotunno et al., 2026). Our results

suggest that mobile internet may enable workers to take greater advantage of these opportunities by lowering information frictions that otherwise limit access to emerging job opportunities. In an economy undergoing rapid export-led industrialisation, the benefits of digital connectivity may therefore arise not only from generating new economic activities, but also from facilitating the movement of workers towards employment opportunities created by broader structural changes. The fact that the effects are concentrated in districts located within commuting distance of industrial zones, yet largely disappear beyond 20 kilometres, indicates that digital connectivity and local labour demand act as complements.

Heterogeneous effects by provincial export intensity. As a robustness check of the same mechanism, Appendix Table A2 examines whether the effects of mobile internet are stronger in provinces experiencing faster export growth. In particular, we re-estimate an augmented version of equation (1), adding an interaction term between 3G treatment and log provincial exports. If 3G facilitates the matching of workers to employment opportunities generated by export-oriented manufacturing firms, its effects should be amplified in areas with stronger export expansion. The results support this prediction, with larger effects on movement out of agriculture, into manufacturing, and into formal employment in provinces with higher export intensity. Consistent with our baseline results, the effects are nearly twice as large and more precisely estimated for women than for men. Moreover, the female workforce experiences a statistically significant increase in manufacturing employment and a sizeable decline in household-business employment even in provinces with average export intensity (reflected in the main Mobile Internet coefficients).[20]

5.2 Online Recruitment Boom: Job Advertisements on Facebook

A central channel through which mobile internet may reshape the labour market is a reduction in search frictions. By lowering the cost of obtaining and spreading information, 3G can make vacancies easier for jobseekers to find and easier for employers to advertise, particularly where information about jobs would otherwise travel mainly through informal channels (Goldfarb and Tucker, 2019; Hjort and Tian, 2025). Using the 2012 Vietnam STEP Household Survey, Hensel et al. (2026) find that almost all jobseekers use formal methods (e.g., employment agencies, school career offices, job advertisements, internet searches, etc.), while only approximately 60 percent rely on informal search methods (e.g., through friends and relatives). This is particularly true for young and more-educated workers. A large volume of job information now circulates on Facebook, which has emerged as one of the most visited sites in Vietnam. It is increasingly used by jobseekers to obtain information about new opportunities,

[20] A one-standard-deviation increase in log provincial exports (0.837, equivalent to 130 percent higher exports) amplifies the effects of mobile internet on sectoral reallocation by around 2.6 pp. Columns 5 to 8 similarly show that export exposure amplifies the formalisation effects of 3G, with significant interaction effects for second-job holding, household-business employment, and social insurance coverage.

and by employers to post vacancies that can reach a large pool of potential applicants (Lindgren et al., 2021; To et al., 2022). This represents an important channel through which search frictions are reduced in the labour market, and the advertisements themselves also provide valuable information about what employers decide to advertise, and to whom.

To test the mechanisms that may explain the results documented in Section 4, we ask three questions. First, does 3G coverage increase the volume of job information available to jobseekers? Second, since our main results show particularly strong effects for women, is this information directed at women, either explicitly or implicitly? Third, do the vacancies entail formal job amenities, in the sense that they offer social insurance, so that the channel can contribute to the shift towards formal employment documented in the main analysis?

Our job advertisement data were downloaded from the Meta Content Library (MCL), a research platform that provides researchers with access to public Facebook content. To assemble the Facebook job advertisement data, we searched for posts on Vietnam-based Pages containing *tuyen dung* and *tim viec*—the phrases associated with recruitment—covering 1 January 2009 to 31 December 2017. While the MCL allows researchers to access the universe of public Facebook content on its secure research platform, downloads are limited to a subset of posts which includes those posted on pages with 15,000 or more likes or followers, or by profiles that are either verified or with 25,000 or more followers. Our sample thus represents the more visible segment of Facebook recruitment activity: advertisements published by large and established pages and by high-profile accounts, rather than every vacancy advertised on Facebook. In total, after filtering out non-job advertisements (e.g., career-advice posts, course promotions, contests, news and administrative notices), our sample comprises 293,776 job advertisements published by 23,012 Facebook pages between 2009 and 2017. Each record contains the post text, the time of creation, and the publishing page. For 159,198 advertisements (54.2 percent), we are able to locate the district of the workplace based on the work location stated in the post text, allowing us to understand the differences in posting behaviour between treated and control districts. Since a single post often advertises more than one position, we split each advertisement into the roles it contains, giving 438,004 roles across all job posts.

Following extraction of the individual positions being advertised, we identify the job titles and descriptions. We associate (gender) requirements and workplace amenities with individual positions wherever the relevant text can be reliably attributed to a particular vacancy. Attaching the measures to the individual position matters for the search-friction interpretation, since a jobseeker responds to a specific vacancy and to its stated requirements and terms, not to the Facebook post as a whole.

To measure gender biases in job advertisement targeting, we identify explicit gender requests through a dictionary-based method which employs transparent pattern-matching rules whose matched

wording we retain for verification. Implicit gendering, by contrast, is conveyed through the way required skills and characteristics are described, which keyword rules cannot capture. For this component, we use an NLP model, a Vietnamese sentence-embedding model based on SimCSE that we train on the text of the advertisements. For further information on this process, please refer to Appendix B. We also identify references to formal employment arrangements with pattern-matching rules. In particular, we classify a vacancy as providing *social insurance* if its text, or the text shared by all roles of its post, mentions social, health, unemployment, labour or accident insurance (including the abbreviations BHXH, BHYT and BHTN), lists insurance among the job's benefits, or refers to benefits under the Labour Code, such as severance or unemployment allowances.

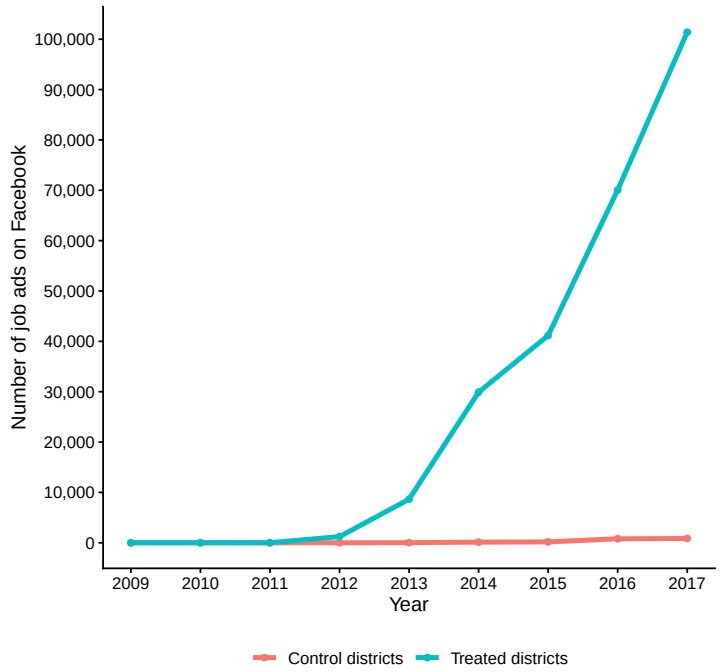
We then aggregate the positions advertised to the district-year level and employ the same DiD framework as in the main analysis. Our outcomes are the (asinh) number of advertised roles, the number of formal roles, and the number of roles explicitly and/or implicitly targeting women. Together, these shed light on whether lower search frictions are accompanied by more vacancies, whether those vacancies are directed at women, and whether they facilitated women's transition into formal roles. Since Facebook advertisements are posted by employers, these outcomes describe the labour-demand side of the information channel. They therefore complement the household-survey results on workers' reallocation, which cannot distinguish whether employers advertise more or whether jobseekers find the same vacancies more easily.

Table 4 presents summary statistics for job advertisements posted on Facebook pages in treated and control districts between 2009 and 2017. While almost no job advertisements were observed in 2009, recruitment activity increased over the subsequent years (see Figure 7). In line with the rollout of 3G, online job recruitment was virtually non-existent before 2012. Notably, recruitment activity on Facebook remained negligible between 2009 and 2012. By 2013, 191 of the 685 districts (28 percent) had reached the 3G coverage threshold, coinciding with the boom in Facebook recruitment activity in treated districts.

Averaged over all district-years, 5.6 percent of the advertised roles in a treated district-year explicitly state a requirement or preference for female candidates, against 2.6 percent in control districts. Including advertisements that target women implicitly through gender-coded language, the shares rise to 10.2 percent in treated and 5.0 percent in control districts.[21] The explicit share in treated districts is comparable to that documented elsewhere. Approximately 6 percent of online vacancies in Pakistan express an explicit preference for women (Matsuda et al., 2019), and 4.2 percent of job advertisements in India do so (Chaturvedi et al., 2025). In China, Kuhn and Shen (2013) similarly document the prevalence of gender-specific recruitment, and highlight that employers' preferences for male and female

[21] We find a similar share of job advertisements targeting men either explicitly or implicitly.

Figure 7: Total number of job advertisements on Facebook pages, by year



Notes: Number of job advertisements on Facebook pages in treated and control districts, 2009–2017. Each advertised role counts as one job advertisement and is assigned to one district. The figure includes the roles in districts that can be assigned to a treated or control district (about 58 percent of all roles). A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Source: Authors' calculations using Facebook job advertisement data and OpenCelliD data.

workers are highly occupation-specific. Among district-years with at least one advertisement, about one in five advertised roles offers social insurance in both treated and control districts (20.3 and 19.1 percent).

Table 4: Summary statistics of job advertisements on Facebook pages

	Control $N = 137$				Treated $N = 546$			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Number of job ads	2.85	10.19	0.00	128.00	65.71	315.39	0.00	6,495.00
Of which								
Female labour – explicit	0.026	0.118	0.000	1.000	0.056	0.130	0.000	1.000
Female labour – explicit or implicit	0.050	0.163	0.000	1.000	0.102	0.188	0.000	1.000
Mention social insurance	0.055	0.185	0.000	1.000	0.095	0.190	0.000	1.000

Notes: The unit of observation is district-year, 2009–2017. A job advertisement is an advertised role. Shares are averaged over all district-years, with district-years without any advertisement set to zero. A role from a post that names several districts is counted in each of them. A role explicitly mentions female labour if it requires or prefers women, and implicitly if its requirements score (Vietnamese SimCSE) is above zero. Districts first treated in 2010 are excluded. Source: Authors' calculations using Facebook job advertisement data.

Table 5 demonstrates that the roles advertised on Facebook tend to be skewed towards skilled, non-agricultural occupations. Pooling all roles with an assigned occupation, 51 percent are in managerial, professional or technical occupations (ISCO-08 major groups 1–3), 44 percent are in clerical, service, sales, craft and operator occupations (groups 4–8), and only 5 percent are elementary occupations. Explicit requests for female candidates are most common in clerical (16 percent) and service and sales (20 percent) occupations, and least common in managerial, technical and craft occupations (4–5 percent), which is consistent with the occupation-specific gender preferences documented by Kuhn and Shen (2013). However, this occupational distribution should be interpreted with caution, as advertisements on Facebook are likely to capture the more skill-intensive segment of recruitment activity, rather than the full spectrum of vacancies available in the labour market. Rather, we interpret these advertisements as providing evidence of how mobile internet changes the dissemination of labour market information and employers' recruitment behaviour, without assuming that the vacancies observed on Facebook are representative of overall labour demand.

5.3 Evidence on Gender-Biased Online Vacancies

Figure 8 presents the effects of 3G connectivity on the volume of job advertisements posted on Facebook, including those targeting female applicants. We find an immediate and persistent increase in online vacancy postings following the introduction of 3G in treated districts. By the fourth year following treatment, treated districts recorded 65 percent more job advertisements relative to control districts, suggesting that improved mobile internet connectivity facilitated the dissemination of labour market information, potentially by reducing the costs of advertising vacancies.

Table 5: Summary statistics of occupations on Facebook pages

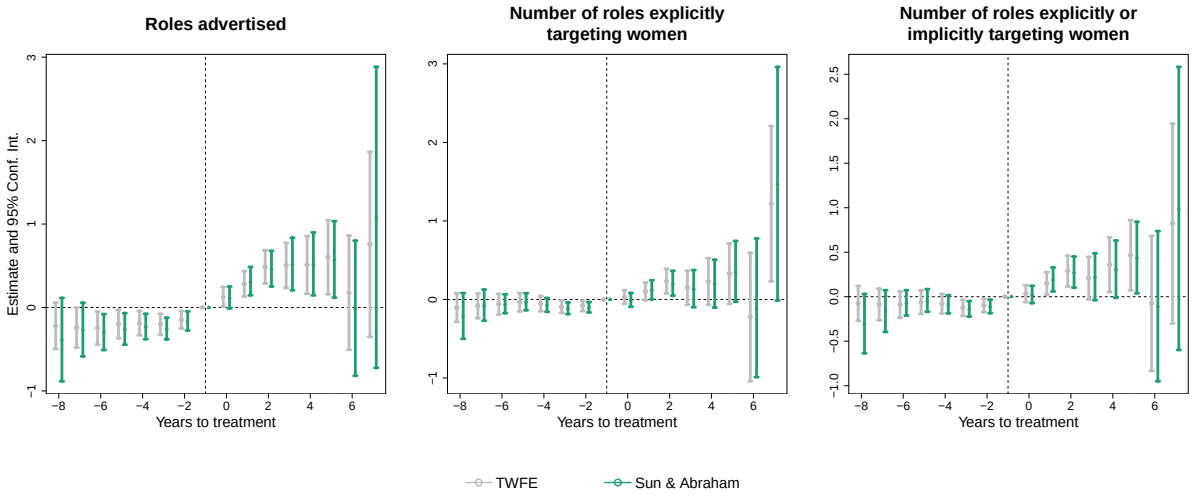
	Control $N = 137$				Treated $N = 546$			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Managers	0.039	0.114	0.000	1.000	0.057	0.108	0.000	1.000
Professionals	0.149	0.263	0.000	1.000	0.156	0.204	0.000	1.000
Technicians and associate professionals	0.149	0.250	0.000	1.000	0.171	0.200	0.000	1.000
Clerical support workers	0.096	0.186	0.000	1.000	0.108	0.139	0.000	1.000
Service and sales workers	0.220	0.291	0.000	1.000	0.220	0.228	0.000	1.000
Skilled agricultural, forestry and fishery workers	0.003	0.054	0.000	1.000	0.001	0.014	0.000	0.333
Craft and related trades workers	0.011	0.044	0.000	0.500	0.023	0.072	0.000	1.000
Plant and machine operators and assemblers	0.017	0.083	0.000	1.000	0.031	0.079	0.000	1.000
Elementary occupations	0.070	0.190	0.000	1.000	0.036	0.086	0.000	1.000

Notes: The unit of observation is district-year, 2009–2017. A job advertisement is an advertised role. Shares are computed over district-years with at least one ad. Shares are the proportion of a district-year's roles in each ISCO-08 major group; roles whose occupation could not be assigned and armed forces (3 roles) are not shown. In total, 345,261 of the 438,004 roles (78.8 percent) are matched to an ISCO-08 major group, through either a VSCO match or the keyword lexicon. Districts first treated in 2010 are excluded. Source: Authors' calculations using Facebook job advertisement data.

The number of advertised roles targeting female applicants also increases, although by less. The number targeting women either explicitly or implicitly is roughly 30 percent higher two years after treatment, while the increase in roles explicitly targeting women is smaller, at around 20 percent in the second year, and is not statistically significant in most later years. The steady rise in the combined measure may reflect the gradual adoption of online recruitment by employers, particularly against the backdrop of Vietnam's ongoing export-led industrialisation and the associated expansion of employment opportunities for women. As demand for female labour increased in export-oriented industries, employers may have increasingly taken advantage of mobile internet connectivity to reach a wider pool of potential female applicants, reducing recruitment frictions that might otherwise have constrained their ability to fill vacancies. Together with our findings from Section 4, these results provide evidence that mobile internet facilitated women's transition into non-agricultural and formal employment by increasing the availability of information about employment opportunities for women.

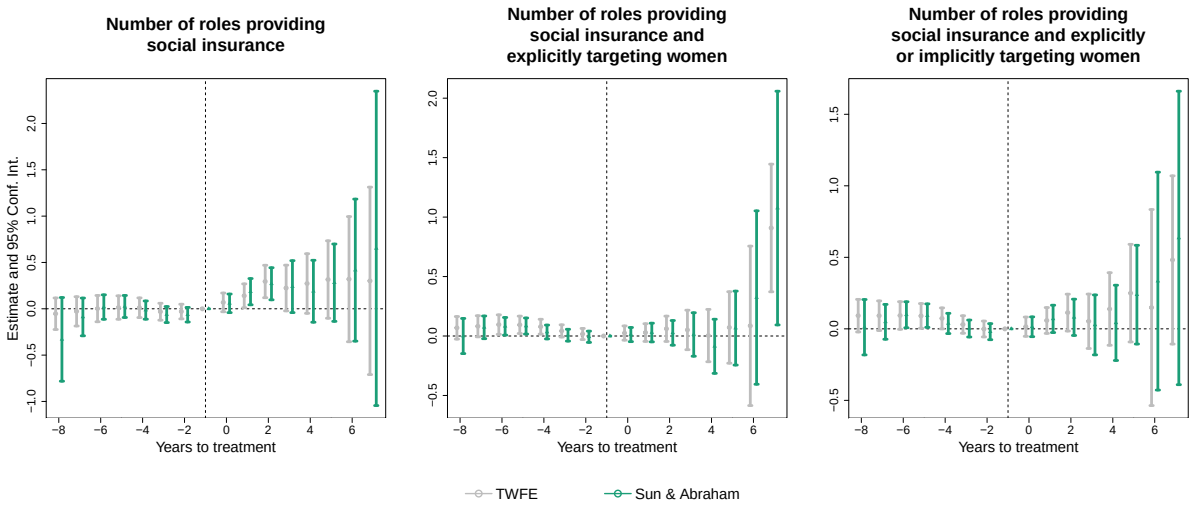
While Figure 8 shows that job advertisement volume increased following 3G expansion, Figure 9 shows that the number of *formal* job advertisements also increased. Relative to control districts, job advertisements mentioning the provision of social insurance were 30 percent higher in treated districts by the second year and remained so throughout the study period. While we do not find that roles mentioning social insurance disproportionately target women, 3G may nevertheless facilitate women's transition into formal employment. This is because formal job advertisements are less likely to specify gender preferences, potentially making these opportunities accessible to a broader pool of jobseekers regardless of gender. By reducing the costs of obtaining information about formal vacancies, mobile internet may therefore have enabled women to access employment opportunities beyond those traditionally advertised to female workers.

Figure 8: 3G rollout and the number of job advertisements and of job advertisements targeting women on Facebook pages



Notes: Event-study estimates of the effect of 3G coverage on the number of roles advertised on Facebook pages. The outcomes are the inverse hyperbolic sine of the number of roles in a district-year: all roles advertised (left), roles that explicitly target women by requiring or preferring female candidates (middle), and roles that explicitly or implicitly target women (right). Implicit targeting is measured with a Vietnamese SimCSE sentence-embedding model, which scores the wording of each role's requirements by its similarity to roles that explicitly require women relative to roles that explicitly require men; a role is implicitly female-coded if this score is positive. Each advertised role counts as one job advertisement, once in every district its post names. Grey markers show two-way fixed effects (TWFE) estimates and green markers estimates from the Sun and Abraham (2021) estimator, with never-treated districts as the control group. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Specifications include district and year fixed effects, log provincial exports and 2009 district characteristics interacted with year dummies. The sample covers district-years over 2009–2017. Vertical bars are 95 percent confidence intervals based on standard errors clustered at the district level. Source: Authors' calculations using Facebook job advertisement data and OpenCelliD data.

Figure 9: 3G rollout and the number of job advertisements providing social insurance on Facebook pages



Notes: Event-study estimates of the effect of 3G coverage on the number of roles on Facebook pages that provide social insurance. The outcomes are the inverse hyperbolic sine of the number of roles in a district-year that provide social insurance (left), that also explicitly target women (middle), and that also explicitly or implicitly target women (right). A role provides social insurance if its own text, or the text shared by all roles of its post, mentions social, health, unemployment, labour or accident insurance (including the abbreviations BHXH, BHYT and BHTN), lists insurance among the job's benefits, or refers to benefits under the Labour Code, such as severance or unemployment allowances. Each advertised role counts as one job advertisement, once in every district its post names. Grey markers show two-way fixed effects (TWFE) estimates and green markers estimates from the Sun and Abraham (2021) estimator, with never-treated districts as the control group. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Specifications include district and year fixed effects, log provincial exports and 2009 district characteristics interacted with year dummies. The sample covers district-years over 2009–2017. Vertical bars are 95 percent confidence intervals based on standard errors clustered at the district level. Source: Authors' calculations using Facebook job advertisement data and OpenCelliD data.

6 Robustness Checks

6.1 Household Panel Data

As a robustness check to our results in Section 4, we employ the Vietnam Household Living Standards Survey (VHLSS) of 2010–2018 and exploit its rotating panel feature. Since the LFS is a repeated cross-section, changes in district averages can reflect changes in the composition of the district's workers, rather than actual changes in individuals' labour market outcomes.

The VHLSS 2010–2018 overcomes this problem because it follows households over two or three consecutive rounds. The VHLSS is conducted every two years and, in each round, re-interviews approximately 50 percent of the households surveyed in the previous round while adding new ones. Appendix Table C1 shows the resulting rotation structure. In total, 36,442 distinct households are observed in at least two rounds. Of these, 23,152 are observed in two consecutive rounds and 13,290 in three. No household is observed in more than three rounds, so the longest span over which a household is followed is four years (e.g., 2014, 2016 and 2018). Our individual-level analysis focuses on women aged 20–64, as in Section 4.

As we do not observe the same households across all five waves of the VHLSS, a standard DiD estimator with individual fixed effects is not feasible. We instead use the chained DiD developed by Bellégo et al. (2025) in which effects for each treatment cohort and survey wave are recovered from individuals observed in consecutive waves, and these short-run changes are combined using two-step Generalized Method of Moments (GMM). A key assumption of the chained DiD is that there must be no selective survival into the next survey period. Appendix Table C2 largely supports this assumption, with treatment status and household income being uncorrelated with being observed again in the next round. Among women, attrition is more likely for those who are younger, those who are not employed and those with at least a high school education.

Appendix Table C3 presents the summary statistics for households and individuals in the VHLSS at baseline. Similarly to the LFS, women in treated districts are less likely to work. Conditional on working, women in treated districts are more likely to be in the manufacturing or services sector. They are also less likely to be employed in household businesses, although, among wage workers, they are not significantly different from control women in terms of coverage by social insurance, work contract, or paid leave. Panel B shows the same pattern for treatment and control households. Treated households are less likely to run a farm business, have substantially higher income and expenditure, and are more likely to own a mobile phone or a computer at baseline.

Household technology adoption. Since the VHLSS provides information on household assets and expenditures, we first verify that treated districts experienced a significant increase in digital technology use. Appendix Figure C1 shows a substantial rise in mobile phone ownership over time, while computer ownership stagnates. Interestingly, in treated districts, the share of households reporting internet-related expenditures increases from below 10 percent to over 40 percent by 2018, with growth accelerating after 2014. This timing is consistent with the nationwide rollout of 3G, as most districts become treated between 2013 and 2015. The observed pattern also closely mirrors the rapid expansion of mobile internet users documented in Figure 1, providing further evidence that our treatment measure captures meaningful improvements in internet access.

Table 6 shows that 3G coverage raises the probability that a household owns a mobile phone by 6.1 pp, and this estimate is significant at the 1 percent level. The effect on computer ownership is smaller (4.5 pp) and not statistically significant. These results are consistent with households accessing the internet primarily through mobile devices rather than computers, and provide reassurance that 3G coverage translated into actual adoption of mobile technology by households. Appendix Figure C2 presents the corresponding event-study estimates. The effects on mobile phone ownership emerge immediately after 3G rollout and continue to grow over time, reaching roughly 10 pp after four years and 20 pp after six years.

Table 6: 3G rollout and household technology adoption, VHLSS

	Has mobile phone	Has computer
ATT	0.061***	0.045
	(0.013)	(0.030)

*Notes: Each column reports the average treatment effect of 3G coverage estimated using the chained DiD estimator of Bellégo et al. (2025) and the 2010–2018 VHLSS rotating panel. The dependent variables are indicators for whether the household owns a mobile phone or a computer. The estimator exploits changes within households observed in consecutive survey waves, chaining these short-run changes across overlapping panels using two-step GMM. The reported coefficient is the simple average of post-treatment cohort-by-wave treatment effects. Treatment cohorts are defined by the year in which a district first reaches the 2017 mean population-weighted 3G coverage of 91.74 percent. As the VHLSS is conducted biennially, districts first treated in odd-numbered years are assigned to the subsequent survey wave. Districts already treated in 2010 are excluded, and not-yet-treated and never-treated districts serve as the comparison group. All specifications control for baseline (2009) district characteristics interacted with survey-year indicators. Standard errors, clustered at the district level and computed from the influence functions of the estimator, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Labour force participation and sectoral reallocation. Table 7 reports the effects on female labour force participation (FLFP) and sectoral composition. Consistent with the LFS, we find no significant effect on the probability that a woman has worked in the last 12 months (column 1). On the other hand, the results for women's sector of work are large and precisely estimated (columns 2–3). Conditional on working, 3G coverage reduces the share of women employed in agriculture by 5.7 pp and increases the share employed in manufacturing by 4.7 pp, significant at the 5 and 1 percent levels respectively, providing support for our results in Section 4. Relative to the 2010 levels in treated districts, this is a

12 percent decline in agricultural employment and a 26 percent increase in manufacturing employment. We continue to obtain small and insignificant results for the effect of 3G on work in the services sector. The VHLSS estimates for women's structural transformation are considerably larger than the TWFE estimates in Table 2, which average over the whole period and are attenuated by the staggered design. They are closer to the longer-run effects in Figure 4. The corresponding event-study figures in Appendix C show that the effects grow steadily with time since treatment. For agriculture, the decline is about 3 pp in the year of treatment and reaches roughly 9 pp after four years, which is in line with the LFS event-study estimates for young women.

Table 7: 3G rollout and LFP and sectoral reallocation of female workers, VHLSS

		Sector		
	(1) Work	(2) Agriculture	(3) Manufacturing	(4) Service
ATT	0.015	-0.057**	0.047***	-0.006
	(0.013)	(0.028)	(0.016)	(0.017)

*Notes: Each column reports the average treatment effect of 3G coverage estimated using the chained DiD estimator of Bellégo et al. (2025) and the 2010–2018 VHLSS rotating panel. The sample comprises women aged 20–64. Column 1 reports the effect on the probability of having worked in the preceding 12 months. Columns 2–4 report the effects on employment in agriculture, manufacturing and services, respectively, conditional on working. The estimator exploits changes within individuals observed in consecutive survey waves, chaining these short-run changes across overlapping panels using two-step GMM. The reported coefficient is the simple average of post-treatment cohort-by-wave treatment effects. Treatment cohorts are defined by the year in which a district first reaches the 2017 mean population-weighted 3G coverage of 91.74 percent. As the VHLSS is conducted biennially, districts first treated in odd-numbered years are assigned to the subsequent survey wave. Districts already treated in 2010 are excluded, and not-yet-treated and never-treated districts serve as the comparison group. All specifications control for baseline (2009) district characteristics interacted with survey-year indicators. Standard errors, clustered at the district level and computed from the influence functions of the estimator, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Formalisation of employment. Table 8 shows that the reallocation away from agriculture and towards manufacturing is accompanied by a meaningful shift towards formal employment. The share of working women employed in household businesses falls by 4.1 pp, significant at the 1 percent level. Among wage workers, the share covered by social insurance rises by 6.4 pp (significant at the 1 percent level) and the share with a written work contract by 4.7 pp (significant at the 5 percent level). The effect on paid leave among wage workers is positive at 2.9 pp but not statistically significant. These results corroborate the formalisation findings of Table 3 and Figure 5. The VHLSS effects on household business employment and social insurance coverage are also larger than the TWFE estimates using the LFS, which we attribute to the averaging over time in the TWFE specification. One difference from the LFS is that we do not find a decline in second-job holding in the VHLSS.

A natural question is whether this formalisation is merely a by-product of leaving agriculture. To benchmark this, we apply the estimated sectoral shifts to the pre-treatment (2010) sector-specific rates of formality among women. In agriculture, 99 percent of female workers are in household businesses, compared with 67 percent in manufacturing. Among wage workers, 9 percent of those in agriculture are covered by social insurance and 11 percent have a contract; in manufacturing the shares are 50 percent

and 66 percent. The sector shift alone would imply a 2.9 pp fall in household business employment, about 70 percent of the estimated 4.1 pp, but only a 1.4 pp rise in social insurance coverage and a 2.0 pp rise in contract coverage, about one fifth and two fifths of the estimated effects. The decline in household business employment is therefore largely a mechanical consequence of leaving agriculture, whereas the sector shift explains only a fraction of the gains in social insurance and contracts. This suggests that, beyond moving out of agriculture, women moved into more formal jobs within sectors, which is consistent with the increase in vacancies offering social insurance in treated districts documented in Section 5.2.

Table 8: 3G rollout and formalisation of female workers, VHLSS

	Informal		Formal		
	(1) Second job	(2) Household business	(3) Social insurance	(4) Contract	(5) Paid leave
ATT	-0.005	-0.041***	0.064***	0.047**	0.029
	(0.031)	(0.013)	(0.015)	(0.020)	(0.019)

*Notes: Each column reports the average treatment effect of 3G coverage estimated using the chained DiD estimator of Bellégo et al. (2025) and the 2010–2018 VHLSS rotating panel. The sample comprises working women aged 20–64. Social insurance, written employment contract and paid leave are observed for wage workers only, so columns 3–5 are estimated on wage workers. The dependent variables are indicators for holding a second job, employment in a household business, coverage by social insurance, having a written employment contract, and entitlement to paid leave, as indicated by the column headings. The estimator exploits changes within individuals observed in consecutive survey waves, chaining these short-run changes across overlapping panels using two-step GMM. The reported coefficient is the simple average of post-treatment cohort-by-wave treatment effects. Treatment cohorts are defined by the year in which a district first reaches the 2017 mean population-weighted 3G coverage of 91.74 percent. As the VHLSS is conducted biennially, districts first treated in odd-numbered years are assigned to the subsequent survey wave. Districts already treated in 2010 are excluded, and not-yet-treated and never-treated districts serve as the comparison group. All specifications control for baseline (2009) district characteristics interacted with survey-year indicators. Standard errors, clustered at the district level and computed from the influence functions of the estimator, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Household businesses. Turning now to whether households cease operating their businesses or whether these businesses simply employ fewer household members, Table 9 shows no significant effect on the probability that a household operates a farm business (column 1). On the other hand, the number of family members working in the farm business declines slightly (column 2), but the number of *female* family members working in it falls by 0.074 per household (column 3, significant at the 10 percent level). The pattern suggests that the exit from agriculture documented above occurs mainly through women leaving the family farm and not through households closing their farm business altogether.

Income, household income and expenditure. Table 10 reports the effects of women's technology-induced sectoral reallocation on incomes. Individual income of women rises by approximately 22 percent and earnings from salaried work by 24 percent in treated districts, both significant at the 1 percent level (columns 1–2).[22] These findings suggest that the sectoral reallocation and employment formalisation documented earlier are accompanied by substantial improvements in women's economic outcomes, consistent with improved access to more remunerative employment opportunities. The increase in income

[22] Income and earnings are only observed for women who work. Earnings are observed only for women who receive a wage.

Table 9: 3G rollout and household farm businesses, VHLSS

	Operates a Farm Business	No. of family members	No. of female family members
ATT	0.017	-0.072	-0.074*
	(0.019)	(0.075)	(0.043)

*Notes: Each column reports the average treatment effect of 3G coverage estimated using the chained DiD estimator of Bellégo et al. (2025) and the 2010–2018 VHLSS rotating panel. Column 1 reports the effect on the probability that a household operates a farm business. Columns 2 and 3 report the effects on the number of household members and female household members working in the farm business, respectively. The estimator exploits changes within households observed in consecutive survey waves, chaining these short-run changes across overlapping panels using two-step GMM. The reported coefficient is the simple average of post-treatment cohort-by-wave treatment effects. Treatment cohorts are defined by the year in which a district first reaches the 2017 mean population-weighted 3G coverage of 91.74 percent. As the VHLSS is conducted biennially, districts first treated in odd-numbered years are assigned to the subsequent survey wave. Districts already treated in 2010 are excluded, and not-yet-treated and never-treated districts serve as the comparison group. All specifications control for baseline (2009) district characteristics interacted with survey-year indicators. Standard errors, clustered at the district level and computed from the influence functions of the estimator, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

extends beyond the individual level, as columns 3–4 show that 3G coverage raises household income by about 14 percent and household expenditure by a commensurate amount. This is in line with Wei et al. (2026) and Bahia et al. (2024), who also find that mobile internet raises household welfare by increasing household wealth and consumption.[23]

Table 10: 3G rollout and income and expenditure, VHLSS

	log(Income)	log(Earnings)	log(Household income)	log(Household expenditure)
ATT	0.196***	0.217***	0.128***	0.128***
	(0.054)	(0.050)	(0.044)	(0.047)

*Notes: Each column reports the average treatment effect of 3G coverage estimated using the chained DiD estimator of Bellégo et al. (2025) and the 2010–2018 VHLSS rotating panel. Columns 1 and 2 report the effects on women's individual income and earnings from salaried employment, respectively. These outcomes are observed only among employed women and wage-employed women, respectively. Columns 3 and 4 report the effects on household income and expenditure. The estimator exploits changes within individuals and households observed in consecutive survey waves, chaining these short-run changes across overlapping panels using two-step GMM. The reported coefficient is the simple average of post-treatment cohort-by-wave treatment effects. Treatment cohorts are defined by the year in which a district first reaches the 2017 mean population-weighted 3G coverage of 91.74 percent. As the VHLSS is conducted biennially, districts first treated in odd-numbered years are assigned to the subsequent survey wave. Districts already treated in 2010 are excluded, and not-yet-treated and never-treated districts serve as the comparison group. All specifications control for baseline (2009) district characteristics interacted with survey-year indicators. Standard errors, clustered at the district level and computed from the influence functions of the estimator, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

6.2 Alternative Control Groups

We assess the sensitivity of our results to the choice of comparison group in two ways. First, we employ the Callaway and Sant'Anna (2021) estimator, using both the *never-treated* and the *not-yet-treated* districts as the control group. The corresponding event-study estimates for women aged 20–44 and 45–64 are reported in Appendix Figures A1 (with covariates) and A2 (without covariates).[24] For younger women, the effects build up gradually after treatment. Two years after treatment, the share employed

[23] We report all the corresponding event-study results using the VHLSS data in Appendix Figures C3 to C6.

[24] The Callaway and Sant'Anna (2021) estimator is doubly robust, combining outcome regression and inverse-probability weighting. Because treatment timing is non-random (see Table 1 in Section 2), conditioning on district-level characteristics reveals substantial differences between early- and late-treated districts, leading to violations of the common-support assumption in some cohort-time comparisons. As a result, specifications with covariates only identify treatment effects up to two years after treatment. For completeness, we also report estimates without covariates, for which event-study effects can be estimated for up to six years post-treatment.

in agriculture is lower by about 4 pp and the share employed in manufacturing is higher by a similar magnitude. The effect grows four years after treatment, with the share in manufacturing increasing to about 6 pp. Employment in household businesses falls by about 5 pp two years after treatment and by about 10 pp after four years, while we also observe an increase in social insurance coverage and employment in firms with a tax ID. The pre-treatment coefficients are small, although they are slightly positive for agriculture and household business and slightly negative for manufacturing in the earlier periods. For older women, we do find evidence of reallocation into the manufacturing sector (by approximately 3 pp after four years), but no effect on employment in household businesses, employment in firms with a tax ID or coverage by social insurance.

Second, we re-estimate the event studies using the Sun and Abraham (2021) estimator with the *last-treated* cohort (districts first treated in 2017) instead of the baseline's *never-treated*. Results are reported in Appendix Figure A3. The effects on the young female workforce remain strongly consistent with our baseline. Older female workers show little response to 3G expansion, with the exception of agricultural and services employment. All in all, these exercises confirm our main findings on the 3G-induced structural transformation in the labour market, particularly among young female workers.

6.3 Alternative Specifications

A remaining concern for our identification strategy is that the spatial rollout of 3G was not random, as factors attracting investment in mobile network infrastructure may also independently drive structural transformation. For instance, provinces experiencing greater inflows of FDI, industrial development, or public infrastructure spending may have attracted earlier investment in telecommunications infrastructure, while simultaneously generating new employment opportunities in manufacturing. Although our baseline event-study specification controls for time-varying provincial export exposure and allows districts with different pre-treatment characteristics to follow differential trends, these controls may not fully account for broader changes in provincial economic conditions. We therefore re-estimate the event-study specification in equation (3), replacing year fixed effects and the provincial export control with province-by-year fixed effects, $\theta_{p(d)t}$. These absorb all time-varying shocks common to districts within the same province, so that identification relies on variation in the timing of 3G expansion across districts within the same province, conditional on the remaining controls.

As shown in Appendix Figure A4, the estimated effects retain their sign and dynamic pattern after the inclusion of province-by-year fixed effects. The decline in the share of young women in agriculture is essentially unchanged (about -0.08 four years after treatment), and the increase in manufacturing remains large and statistically significant, although it is smaller than in the baseline (0.07 against 0.09 four years after treatment). The effects on household business employment are likewise smaller but

remain significant, whereas the estimates for second-job holding, tax ID and social insurance coverage are less precisely estimated and lose some of their statistical significance. This provides further reassurance that our findings are not driven by broader provincial economic developments, particularly the expansion of export-oriented manufacturing, which may have simultaneously influenced the rollout of 3G infrastructure and the demand for female labour.

The estimates for women aged 45–64, shown by the dashed lines in the same figure, are small and mostly statistically insignificant in both specifications, apart from modest increases in manufacturing employment in some years, and are not materially affected by the inclusion of province-by-year fixed effects. That older women respond much less is consistent with the young women's results reflecting an effect of 3G specific to their labour market, not a province-wide shock that would also have moved older women's employment.

7 Conclusion

This paper examines whether the expansion of mobile internet can facilitate structural transformation and improve women's labour market outcomes in developing economies. Using the LFS, and exploiting the staggered rollout of 3G networks across districts in Vietnam between 2010 and 2017, we find that improved mobile internet connectivity accelerates the reallocation of labour away from agriculture and into manufacturing, while promoting the transition from informal household-based activities towards formal employment. These effects are particularly pronounced among younger women.

Using the rotating panel structure of the VHLSS, we show that households reduce their reliance on female family labour in farm businesses, without a corresponding decline in the likelihood of operating a farm business. These changes are accompanied by substantial improvements in economic outcomes, with increases in women's individual income and salaried earnings, as well as household income and expenditure. Together, these findings suggest that improved connectivity can facilitate not only the movement of workers towards more productive sectors, but also improvements in household economic welfare.

To investigate the mechanisms underlying these changes, we construct a novel dataset of over 400,000 advertised job roles extracted from Facebook recruitment posts. We find that 3G expansion substantially increases online recruitment activity, including advertisements targeting female applicants and vacancies offering formal employment benefits such as social insurance. By applying NLP techniques to identify both explicit and implicit gender preferences, we provide new evidence on how digital connectivity may shape the information available to female jobseekers. These findings are consistent with mobile internet reducing labour market search frictions by expanding the visibility of employment opportunities,

particularly for workers seeking to move beyond traditional agricultural and household-based activities. While the advertisement data do not allow us to directly observe worker–firm matches, the patterns in online recruitment complement our individual-level evidence of sectoral reallocation and employment formalisation.

Our results have broader implications for understanding the drivers of structural transformation in developing economies. Vietnam's transition from agriculture towards manufacturing has traditionally been attributed to trade liberalisation, FDI, and the expansion of export-oriented industries. Our findings suggest that improvements in digital connectivity may play an important complementary role in this process. While trade integration and industrialisation generate new employment opportunities, workers must also be able to learn about and access these jobs. By reducing the costs of disseminating and obtaining labour market information, mobile internet can help workers take advantage of the opportunities created by broader economic transformation. This mechanism may be particularly important for women, whose access to employment information and recruitment networks can be more constrained.

As mobile internet continues to expand across developing economies, our findings highlight the potential for digital infrastructure to complement industrial development and promote more inclusive structural transformation. Policies that expand affordable internet connectivity may therefore generate benefits extending beyond digital participation itself, by facilitating access to formal employment and enabling workers, particularly women, to participate more fully in the opportunities created by economic growth.

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A Additional Results from LFS

Table A1: Effects of 3G Rollout on Female Labour Market Outcomes using Trimmed Samples

	LFP	Sectoral Reallocation			Formalisation			
	(1) Work	(2) Agriculture	(3) Manufacturing	(4) Service	(5) Second job	(6) Household Business	(7) Tax ID	(8) Social Insurance
Panel A. Drop early treated (before 2013)								
Mobile Internet	-0.005	-0.009	0.011***	-0.004	-0.008	-0.013***	0.007	0.006
	(0.003)	(0.008)	(0.003)	(0.008)	(0.009)	(0.005)	(0.011)	(0.005)
Observations	4,838	4,838	4,838	4,838	4,838	4,838	2,349	4,161
R^2	0.870	0.865	0.874	0.781	0.801	0.837	0.784	0.767
Panel B. Drop the bottom 5 percent								
Mobile Internet	-0.004	-0.005	0.009**	-0.007	-0.006	-0.012***	0.012	0.005
	(0.003)	(0.008)	(0.003)	(0.007)	(0.008)	(0.004)	(0.010)	(0.005)
Observations	5,129	5,129	5,129	5,129	5,129	5,129	2,489	4,416
R^2	0.870	0.878	0.860	0.814	0.812	0.859	0.805	0.793
Panel C. Drop the bottom 10 percent								
Mobile Internet	-0.003	-0.004	0.007*	-0.006	-0.003	-0.010**	0.013	0.005
	(0.003)	(0.008)	(0.004)	(0.007)	(0.008)	(0.005)	(0.010)	(0.005)
Observations	4,865	4,865	4,865	4,865	4,865	4,865	2,366	4,194
R^2	0.868	0.879	0.855	0.818	0.820	0.864	0.806	0.798

Notes: In panel A, the sample excludes districts that are treated before 2013. Panels B and C exclude districts whose 3G coverage in 2017 is below the 5th percentile (34.9%) and below the 10th percentile (56.7%). The number of districts excluded from each panel is 67, 34 and 68, respectively. Dependent variables are specified in the column header. All columns control for time FEs interacting with district characteristics in 2009, log provincial export, district FEs and year FEs. Standard errors are clustered at the district level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: CSDID estimates with covariates



Notes: Event-study estimates of the effect of 3G coverage on female employment outcomes using the Callaway and Sant'Anna (2021) estimator. Women aged 20–44 are shown in blue (solid) and women aged 45–64 in orange (dashed). A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). The estimation conditions on 2009 district characteristics (employment shares in manufacturing, IT and FDI firms, the share of high-school-educated population and the share of migrants) and log provincial exports. Districts first treated in 2010 are excluded. Because common support is limited, post-treatment effects are reported only up to two years after treatment. Vertical bars are 95 percent confidence intervals based on standard errors clustered at the district level. Source: Authors' calculations using Labour Force Survey and OpenCelliD data.

Table A2: Heterogeneous Effects of 3G Rollout by Provincial Export Intensity

	LFP	Sectoral Reallocation			Formalisation			
	(1) Work	(2) Agriculture	(3) Manufacturing	(4) Service	(5) Second job	(6) Household Business	(7) Tax ID	(8) Social Insurance
Panel A. Overall effects								
Mobile Internet	-0.005**	-0.001	0.004*	-0.009	-0.000	-0.006	0.011	0.001
	(0.002)	(0.007)	(0.003)	(0.007)	(0.008)	(0.004)	(0.010)	(0.005)
Mobile Internet × ln Province Export	-0.010	-0.031	0.032***	-0.009	-0.033	-0.027**	-0.053	0.022
	(0.006)	(0.021)	(0.009)	(0.019)	(0.025)	(0.013)	(0.049)	(0.020)
Observations	5,370	5,370	5,370	5,370	5,370	5,370	2,606	4,619
R^2	0.864	0.884	0.875	0.808	0.792	0.869	0.821	0.813
Panel B. Effects on Female								
Mobile Internet	-0.005*	-0.001	0.009***	-0.010	-0.001	-0.010**	0.017	0.003
	(0.003)	(0.008)	(0.003)	(0.007)	(0.009)	(0.004)	(0.011)	(0.005)
Mobile Internet × ln Province Export	-0.000	-0.020***	0.011***	0.009	-0.024***	-0.014***	-0.012	0.012**
	(0.003)	(0.007)	(0.004)	(0.007)	(0.007)	(0.004)	(0.010)	(0.005)
Observations	5,370	5,370	5,370	5,370	5,370	5,370	2,606	4,619
R^2	0.873	0.875	0.865	0.806	0.806	0.854	0.805	0.790
Panel C. Effects on Male								
Mobile Internet	-0.005**	-0.001	-0.000	-0.007	-0.001	-0.004	0.005	-0.001
	(0.002)	(0.007)	(0.003)	(0.006)	(0.008)	(0.004)	(0.011)	(0.005)
Mobile Internet × ln Province Export	-0.004*	-0.012*	0.006**	0.005	-0.025***	-0.012***	-0.015	0.012**
	(0.002)	(0.006)	(0.003)	(0.006)	(0.006)	(0.004)	(0.011)	(0.005)
Observations	5,370	5,370	5,370	5,370	5,370	5,370	2,606	4,619
R^2	0.768	0.881	0.840	0.794	0.753	0.858	0.808	0.797

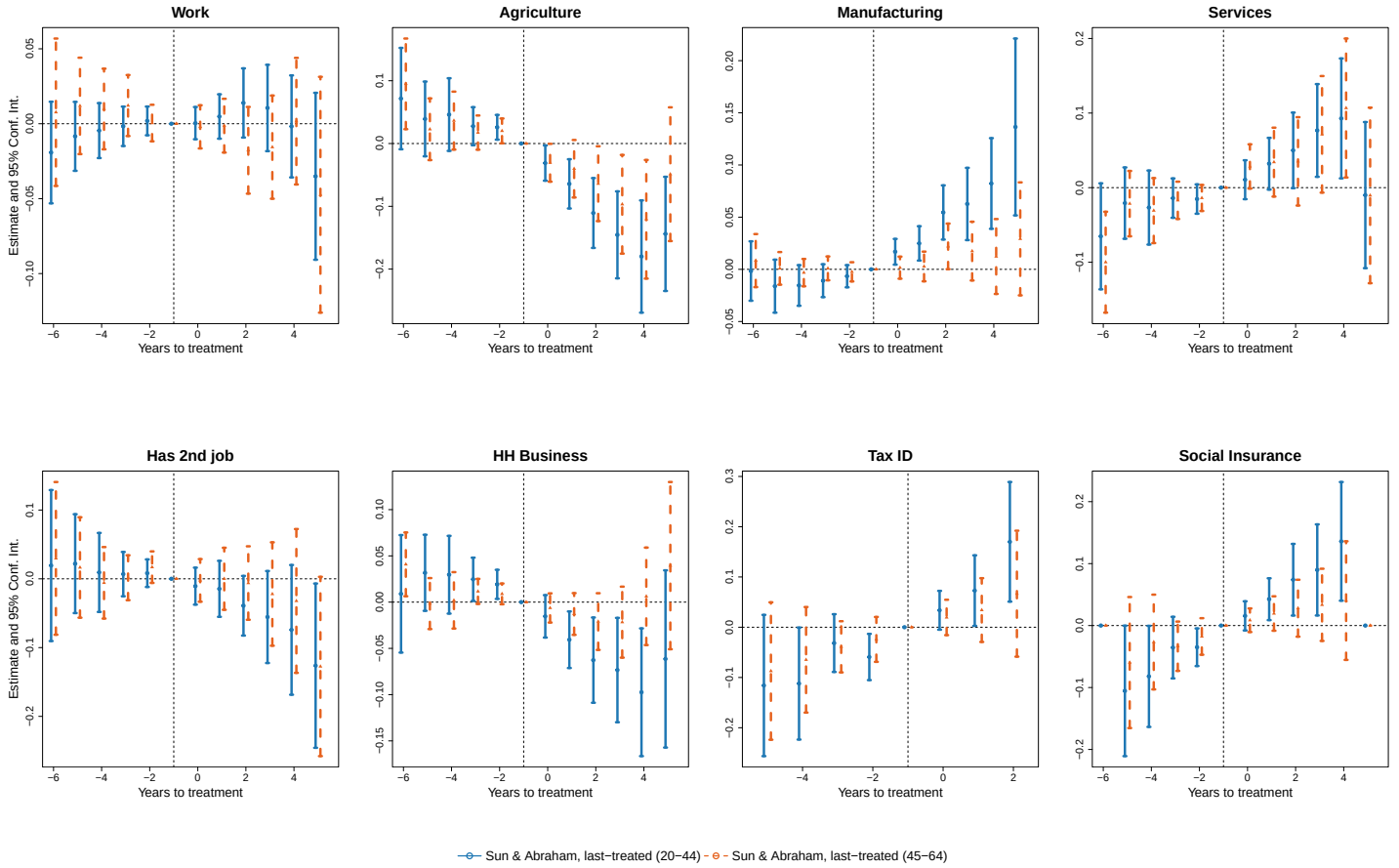
Notes: Log province export is re-centred with mean zero. All columns control for district FEs, year FEs, interactions of year dummies with district characteristics in 2009 (share employment in manufacturing, IT service, FDI firms, share with high school education and share of migrants) and log province export. Standard errors are clustered at the district level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A2: CSDID estimates without covariates



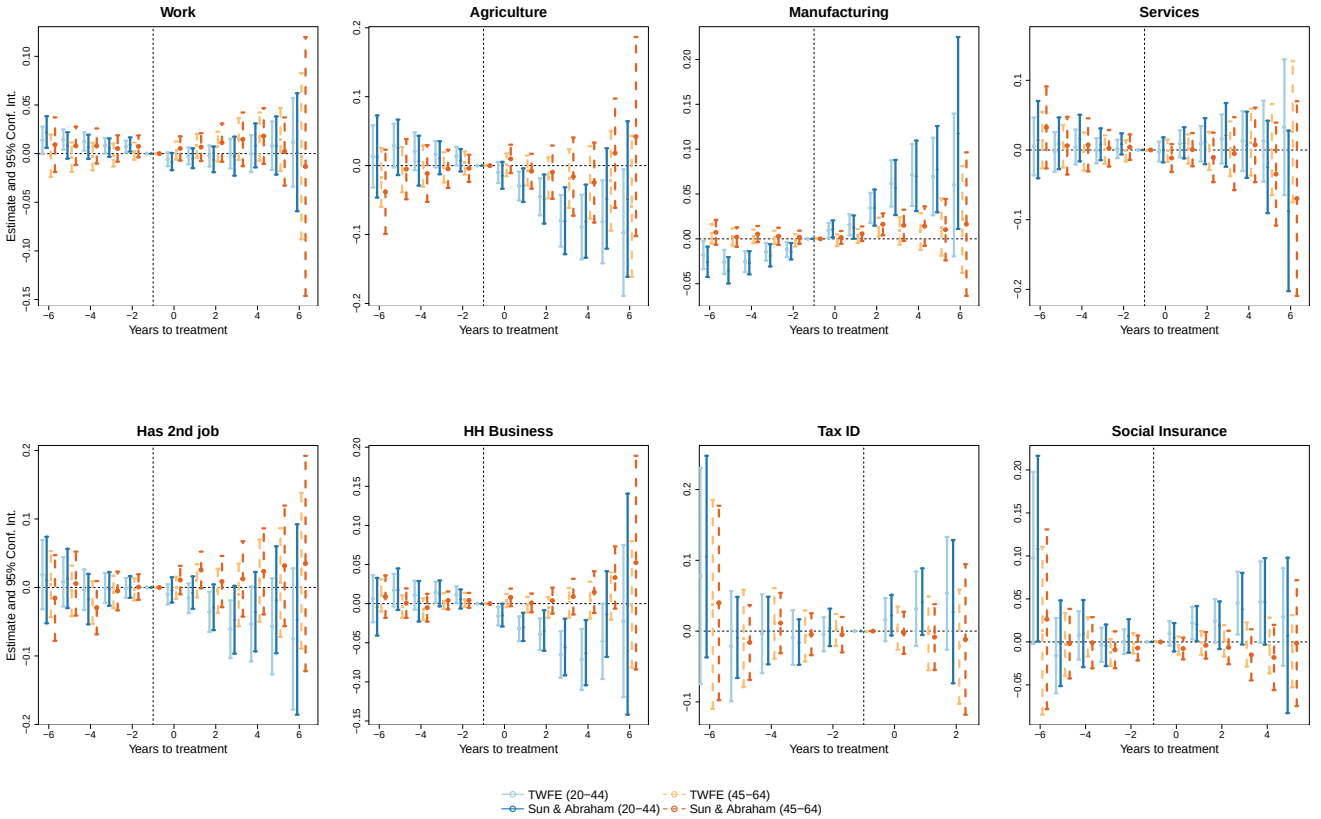
Notes: Event-study estimates of the effect of 3G coverage on female employment outcomes using the Callaway and Sant'Anna (2021) estimator, without covariates. Women aged 20–44 are shown in blue (solid) and women aged 45–64 in orange (dashed). A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Districts first treated in 2010 are excluded. Vertical bars are 95 percent confidence intervals based on standard errors clustered at the district level. Source: Authors' calculations using Labour Force Survey and OpenCelliD data.

Figure A3: SA estimates using the last-treated cohort as the control group



Notes: Event-study estimates of the effect of 3G coverage on female employment outcomes using the Sun and Abraham (2021) estimator, with the last-treated cohort (the 24 districts first treated in 2017) as the control group. Women aged 20–44 are shown in blue (solid) and women aged 45–64 in orange (dashed). A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Specifications include district and year fixed effects, log provincial exports and 2009 district characteristics interacted with year dummies. The sample covers districts first treated between 2011 and 2017 over 2010–2016; never-treated districts and districts first treated in 2010 are excluded. Tax ID is observed for 2011–2014 and social insurance from 2011. Vertical bars are 95 percent confidence intervals based on standard errors clustered at the district level. Source: Authors' calculations using Labour Force Survey and OpenCelliD data.

Figure A4: 3G rollout and LFP, sectoral composition and formalisation of female workers, by age group: province-by-year fixed effects



Notes: Event-study estimates of the effect of 3G coverage on female labour force participation, sectoral employment and informal and formal employment, with province-by-year fixed effects. Outcomes are defined as in Figures 4 and 5. Women aged 20–44 are shown in blue (solid) and women aged 45–64 in orange (dashed). Light markers show two-way fixed effects (TWFE) estimates and dark markers estimates from the Sun and Abraham (2021) estimator, with never-treated districts as the control group. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Specifications include district and province-by-year fixed effects and 2009 district characteristics interacted with year dummies. The sample covers 2010–2017. Districts first treated in 2010 are excluded for work and the three sectors, and from the TWFE estimates for second-job holding and household businesses; the corresponding Sun and Abraham estimates, and all tax ID and social insurance estimates, retain them. The tax ID and social insurance samples are restricted to event years −6 to 2 and −6 to 5, respectively, plus never-treated districts. Vertical bars are 95 percent confidence intervals based on standard errors clustered at the district level. Source: Authors' calculations using Labour Force Survey and OpenCelliD data.

B Measuring Gender Preferences and Employment Formality in Job Advertisements

Identifying the intended audience of a job advertisement and the terms on which the job is offered requires information that is not recorded in any structured field. We therefore extract it from the text of the posts, using the approaches described below.

A. Stated gender preferences. First, we identify explicit gender requests through a dictionary-based method which employs transparent pattern-matching rules. A position is coded *female required* when the text explicitly restricts applicants to women, and *female preferred* when it prioritises women without excluding men. We code *male required* and *male preferred* in the same way, which provides corresponding measures of employers' stated preferences for male workers. Statements that open a position to both men and women are treated as gender-neutral. As the rules rely on explicit wording, they do not capture implied recruitment language that does not state a gender requirement or preference. The indicators therefore capture *explicitly stated* gender preferences communicated in advertisements rather than employers' *implicit* preferences.

B. Implicit gender-coded job requirements. Implicit gendering, by contrast, is conveyed through the way required skills and characteristics are described, which keyword rules cannot capture. To measure gendered recruitment language that does not explicitly reference applicants' gender, we construct a separate measure of implicit gender-coded job requirements. Our approach builds on the use of contextual sentence embeddings to measure gendered language in Vietnamese recruitment advertisements, similar to Pham et al. (2026). We restrict this analysis to vacancies for which a job requirements section can be identified and reliably attributed to the advertised position. Following Pham et al. (2026), we preprocess the requirements text to exclude sentences referring primarily to formal educational qualifications, experience thresholds, age, and explicit demographic criteria, including gender, in order to ensure that the resulting measure captures implicit gender associations in the language used to describe desirable skills and personal attributes, rather than preferences or observable qualifications that may differ systematically across male- and female-targeted occupations. We retain statements describing skills, abilities, behavioural characteristics, physical appearance, and personality traits. Conceptually, this measure addresses whether, when more jobseekers can be reached at low cost, employers convey whom they wish to attract not only through explicit requests, which are common in Vietnamese job advertisements, but also through the characteristics they ask for (Pham et al., 2026).

To this end, we employ a Vietnamese sentence-embedding model based on Simple Contrastive Learning of Sentence Embeddings (SimCSE) to represent the retained requirements text as numerical

vectors capturing its contextual meaning (Gao et al., 2021). Semantically similar requirements are mapped to nearby locations in the embedding space, allowing us to identify similarities in recruitment language beyond predefined gender-coded dictionaries. We start from a publicly available Vietnamese SimCSE model and continue its unsupervised contrastive training on the requirement and job-description clauses of our advertisements, which adapts the representation to the informal language of Facebook recruitment posts. The SimCSE approach has three main advantages for measuring implicit gendering in this setting.

First, the representation is learned without labelled examples of gendered language. In its unsupervised form, SimCSE treats two encodings of the same sentence, produced under different dropout masks, as a positive pair and treats the other sentences in the training batch as negatives. This contrastive objective pulls together representations of the same meaning while spreading unrelated text across the embedding space, which Gao et al. (2021) show yields better sentence representations than the hidden states of pre-trained encoders such as BERT.

Second, the representation is semantic rather than lexical. Requirements worded differently but conveying similar meaning are placed close together, which is important for Facebook recruitment text, where the same characteristic may appear as an abbreviation, a synonym, a spelling variant, a version without diacritics, or a typographical error. A dictionary of gendered words, as used in much of the existing literature (e.g., Gaucher et al., 2011), would miss such variants unless it is updated continuously. Dictionaries also score each word independently and are typically constructed for a different language and institutional context, whereas the embedding captures the combination of attributes expressed in the full requirements text of a vacancy.

Third, the direction of the measure is anchored in how employers themselves recruit. Instead of assuming in advance which skills or traits are gendered, we locate each vacancy relative to the language of vacancies in which employers explicitly request men or women. A requirement is female-leaning if it resembles the requirements that accompany explicit requests for women, and male-leaning if it resembles those that accompany explicit requests for men. The measure therefore has a transparent interpretation, namely similarity to explicit gender-targeting language, and does not rely on external stereotypes.

To construct a directional measure of gender association, we use the requirements of roles that explicitly require women only and of roles that explicitly require men only, identified by the rules described above, as reference groups. Each distinct requirement text enters a reference group once, and a role is never compared with reference roles from its own post or with reference roles whose text is identical to its own. For each role, we compute the similarity of its requirement embedding to the average embedding of the female reference group, subtract its similarity to the average embedding of the male reference group, and standardise the result across scored roles to have mean zero and standard

deviation one. The result is a continuous measure of the relative association of the role's requirements with female-targeted versus male-targeted recruitment language: positive values indicate wording that leans more towards female-request roles than the average role does, negative values indicate wording that leans more towards male-request roles than the average role does, and the scale is measured in standard deviations across roles, so that zero marks the average role rather than a neutral point. Pham et al. (2026) use the corresponding index as a continuous variable; for our district-year counts of roles, we convert it into a binary indicator, so that a role is implicitly female-coded if its score is above zero and implicitly male-coded if the score is below zero. Roles without requirement text of their own remain unscored.

As explained above, a role is implicitly female-coded if its requirements score is above zero. Figure B1 shows which requirement phrases distinguish these roles, and Figure B2 shows the corresponding job titles. The strongest words associated with female-coded jobs relate to appearance, voice, and manner. Of the 50 phrases most strongly associated with female-coded roles, 20 describe physical appearance and grooming, 16 describe voice and speech, 10 describe a friendly and polite manner, and 4 describe an interest in customer service, beauty or fashion. Roles with such wording are overwhelmingly female-coded: about 89 percent of the roles whose requirements mention appearance, voice, or height are female-coded, against 47 percent of all scored roles, and about 43 percent of female-coded roles contain such wording, against about 5 percent of the other roles. By contrast, the traits that appear in most advertisements, such as being agile, diligent, or honest, lie closer to the overall share (between 50 and 61 percent) and do much less to distinguish female-coded roles. At the other end of the score, requirements mentioning good health and independent, analytical or managerial work are female-coded in only 13 to 16 percent of the roles that contain them.

C. Formal employment arrangements. We identify whether a vacancy offers social insurance using pattern-matching rules. A role *provides social insurance* if its own text, or the text shared by all roles of its post, mentions social, health, unemployment, labour or accident insurance (including the abbreviations BHXH, BHYT and BHTN), lists insurance among the job's benefits, or refers to benefits under the Labour Code, such as severance or unemployment allowances. We record which of the two sources the cue comes from.

Figure B1: Job requirements associated with explicitly and implicitly female-coded advertisements

(a) Explicitly female-coded jobs



(b) Implicitly female-coded jobs



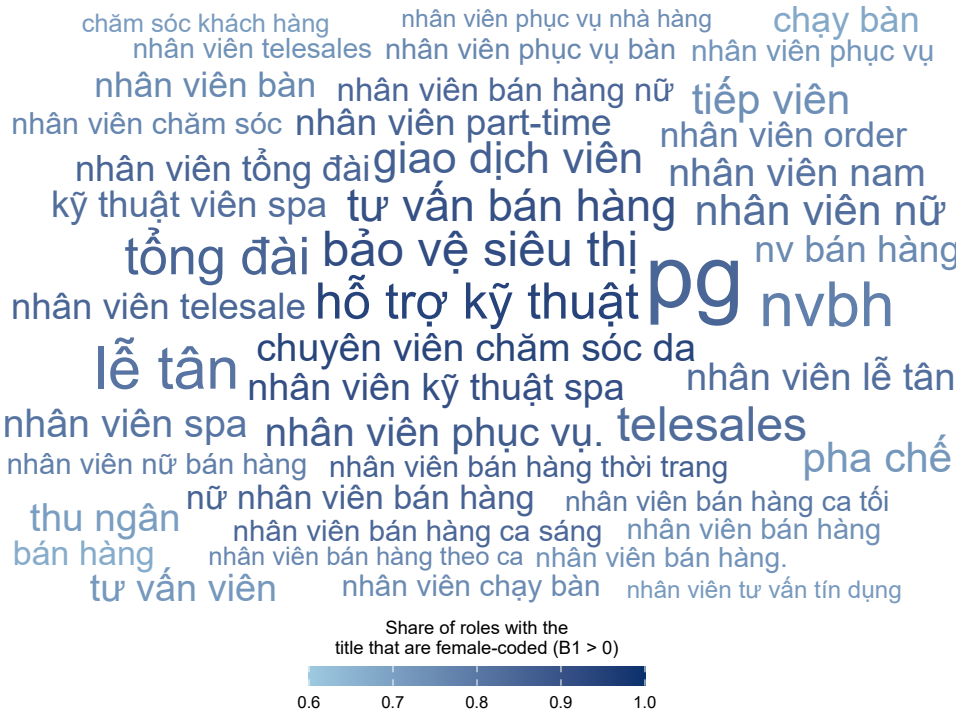
Notes: Job-requirement phrases disproportionately associated with explicitly female-targeted roles (a) and implicitly female-coded roles (b), relative to their respective comparison groups. Explicit targeting is identified from stated requirements or preferences for female applicants, and implicit gender coding from the Vietnamese SimCSE requirements score, with positive values indicating female-coded language. Word size reflects the smoothed log-odds ratio of each phrase relative to its comparison group. Phrases appearing in at least 150 roles and with a z-score of at least 4 are retained, and the 50 highest-ranked phrases are displayed in each panel. Source: Authors' calculations using Facebook job advertisement data.

Figure B2: Job titles associated with explicitly and implicitly female-coded advertisements

(a) Explicitly female-coded jobs



(b) Implicitly female-coded jobs



Notes: Job-title terms disproportionately associated with explicitly female-targeted roles (a) and implicitly female-coded roles (b), relative to other scored roles. Explicit targeting is identified from stated requirements or preferences for female applicants, and implicit gender coding from the Vietnamese SimCSE requirements score, with positive values indicating female-coded language. Word size reflects the smoothed log-odds ratio of each term relative to the comparison group. Terms appearing in at least 150 roles and with a z-score of at least 4 are retained, and the 50 highest-ranked terms are displayed in each panel. Source: Authors' calculations using Facebook job advertisement data.

C Additional Results from the Household Rotating Panel Data

Table C1: VHLSS rotating panel structure

	2010	2012	2014	2016	2018	
Panel A. Sample size by round						
Households surveyed	9,402	9,399	46,995	46,350	45,839	
Individuals surveyed	37,012	36,655	180,992	175,142	170,529	
Households in the panel	4,126	6,383	23,497	31,938	20,230	
Individuals in the panel	15,140	23,344	82,978	112,970	69,222	
Panel B. Panel households observed in both rounds						
2010	4,126	4,126	1,898	0	0	
2012	4,126	6,383	4,155	1,879	0	
2014	1,898	4,155	23,497	21,221	9,513	
2016	0	1,879	21,221	31,938	20,230	
2018	0	0	9,513	20,230	20,230	
Panel C. Panel individuals observed in both rounds						
2010	15,140	15,140	6,346	0	0	
2012	15,140	23,344	14,549	5,977	0	
2014	6,346	14,549	82,978	74,396	30,648	
2016	0	5,977	74,396	112,970	69,222	
2018	0	0	30,648	69,222	69,222	
Panel D. Rotation pattern of panel households						
Rounds observed	2010	2012	2014	2016	2018	Households
Two rounds	•	•				2,228
Two rounds		•	•			378
Two rounds			•	•		9,829
Two rounds				•	•	10,717
Three rounds	•	•	•			1,898
Three rounds		•	•	•		1,879
Three rounds			•	•	•	9,513
All panel households						36,442

Notes: Authors' calculations using the VHLSS data.

Table C2: Attrition in VHLSS by observables

	Observed again in the next round			
	2010 → 2012	2012 → 2014	2014 → 2016	2016 → 2018
Panel A. Households				
Treated district	0.008	0.004	-0.009	-0.003
	(0.015)	(0.018)	(0.017)	(0.018)
Urban	-0.045***	0.023	-0.023	-0.042***
	(0.016)	(0.017)	(0.015)	(0.015)
Household size	0.016***	0.007	0.003	0.006***
	(0.004)	(0.004)	(0.002)	(0.002)
log household income	-0.006	-0.013	0.007	-0.001
	(0.009)	(0.008)	(0.006)	(0.006)
Head: age (years)	0.001***	0.000	0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Head: female	-0.012	-0.018	-0.011*	-0.006
	(0.013)	(0.013)	(0.006)	(0.007)
Head: ≥ high school education	0.001	-0.005	-0.003	0.016*
	(0.013)	(0.013)	(0.009)	(0.008)
Head: ethnic majority	0.001	-0.005	0.012	-0.011
	(0.017)	(0.020)	(0.018)	(0.018)
R^2	0.006	0.001	0.001	0.002
Observations	9,402	9,399	46,995	46,350
Panel B. Women aged 20–64				
Treated district	0.013	-0.011	-0.005	-0.023
	(0.013)	(0.016)	(0.016)	(0.016)
Age (years)	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
≥ high school education	-0.036***	-0.014	-0.014	-0.023***
	(0.013)	(0.013)	(0.009)	(0.008)
Works	0.034**	0.028*	0.035***	0.060***
	(0.014)	(0.016)	(0.008)	(0.008)
log income	-0.013	-0.002	-0.000	-0.007
	(0.008)	(0.008)	(0.005)	(0.005)
R^2	0.009	0.008	0.009	0.009
Observations	11,009	10,967	54,842	53,133

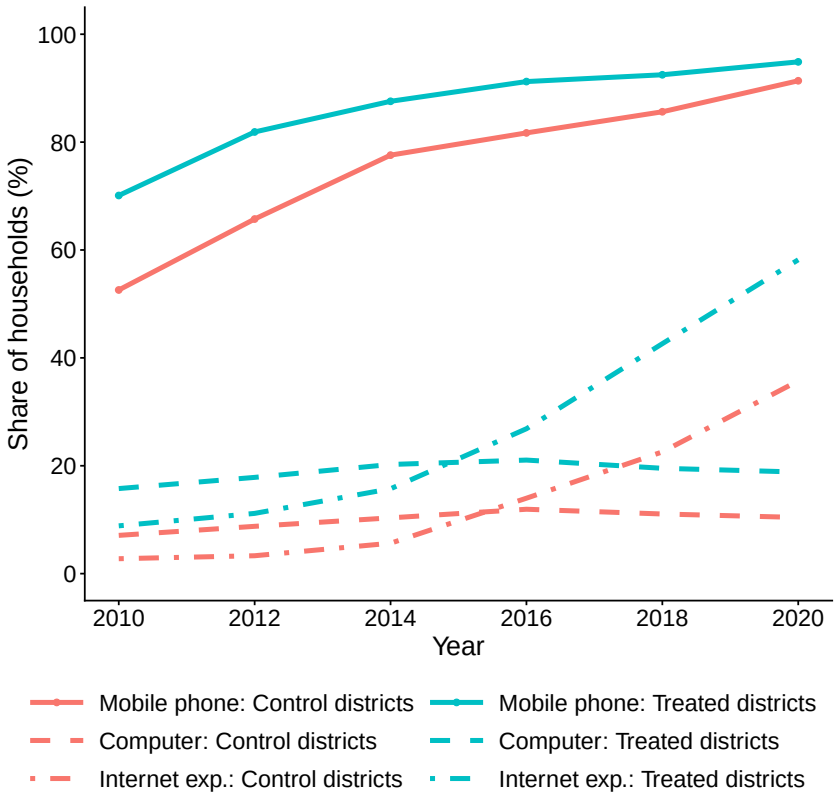
*Notes: Each column reports coefficients from an OLS in which the dependent variable equals one if the household (Panel A) or woman (Panel B) surveyed in the first round of the column heading is observed again in the second round. The regressors are measured in the first round and the sample includes all units surveyed in that round, whether or not they are part of the panel. A district is treated if it reaches the 2017 mean population-weighted 3G coverage of 91.74 percent. Panel A covers households and the characteristics of the household head; Panel B covers women aged 20–64. Standard errors, clustered at the district level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Table C3: Descriptive statistics by treatment status (initially in 2010), VHLSS

	Control				Treated				Treated − Control
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Diff.
Panel A. Individual-level outcomes, women aged 20–64 (control $N = 581$, treated $N = 3,838$)									
Age	37.77	11.33	20.00	64.00	40.57	11.83	20.00	64.00	2.80***
≥ high school education	0.146	0.354	0.000	1.000	0.260	0.438	0.000	1.000	0.113***
Urban	0.091	0.288	0.000	1.000	0.302	0.459	0.000	1.000	0.210***
Work	0.941	0.235	0.000	1.000	0.860	0.347	0.000	1.000	-0.081***
Has 2nd job	0.611	0.488	0.000	1.000	0.472	0.499	0.000	1.000	-0.139***
Agriculture	0.788	0.409	0.000	1.000	0.462	0.499	0.000	1.000	-0.325***
Manufacturing	0.079	0.269	0.000	1.000	0.178	0.383	0.000	1.000	0.099***
Service	0.132	0.338	0.000	1.000	0.337	0.473	0.000	1.000	0.206***
Household business	0.918	0.275	0.000	1.000	0.812	0.391	0.000	1.000	-0.105***
Has social insurance	0.549	0.501	0.000	1.000	0.520	0.500	0.000	1.000	-0.029
Has contract	0.592	0.495	0.000	1.000	0.631	0.483	0.000	1.000	0.040
Has paid leave	0.549	0.501	0.000	1.000	0.527	0.500	0.000	1.000	-0.022
Income (thousand dong)	14,430.7	16,442.3	300.0	68,550.0	21,177.1	19,684.0	200.0	207,000.0	6,746.5***
Earnings from salary (thousand dong)	25,291.7	16,468.2	4,800.0	68,400.0	22,904.1	17,020.9	960.0	204,000.0	-2,387.6
Panel B. Household-level outcomes (control $N = 537$, treated $N = 3,323$)									
Operates a farm business	0.922	0.269	0.000	1.000	0.681	0.466	0.000	1.000	-0.241***
Number of family members working	2.47	1.56	0.00	9.00	1.59	1.24	0.00	7.00	-0.88***
Number of female family members working	1.24	0.88	0.00	5.00	0.86	0.74	0.00	5.00	-0.39***
Household income (thousand dong)	45,860.0	43,875.0	3,973.0	447,080.0	69,413.6	69,717.1	1,130.0	2,140,093.0	23,553.6***
Household expenditure (thousand dong)	42,370.9	36,495.1	5,623.0	428,134.0	60,547.8	59,832.4	3,126.0	1,325,730.0	18,176.9***
Has mobile phone	0.475	0.500	0.000	1.000	0.717	0.450	0.000	1.000	0.243***
Has computer	0.061	0.240	0.000	1.000	0.160	0.367	0.000	1.000	0.099***

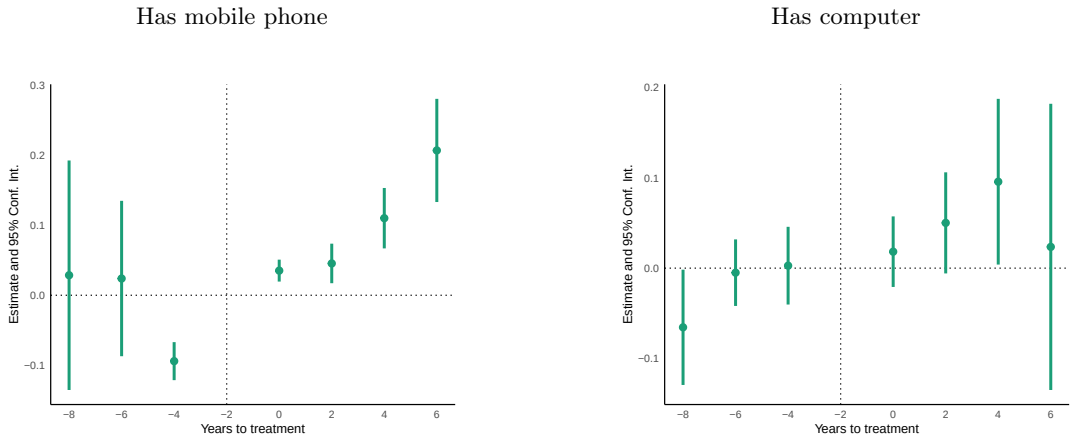
*Notes: Authors' calculations using the 2010 wave of the VHLSS. Panel A covers women aged 20–64 who are part of the VHLSS panel (i.e. linked to at least one other round); Panel B covers the households of all panel adults aged 20–64. Second job, sector and household business are defined for women who work; social insurance, contract and paid leave are defined for wage workers only; income and earnings exclude zeros, and earnings are salary income covering wage workers only. Farm-business outcomes are defined for households with a farm business. The last column is the coefficient from a regression of the variable on treatment status, with standard errors clustered by district. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Figure C1: Household ownership of mobile phones and computers in Vietnam



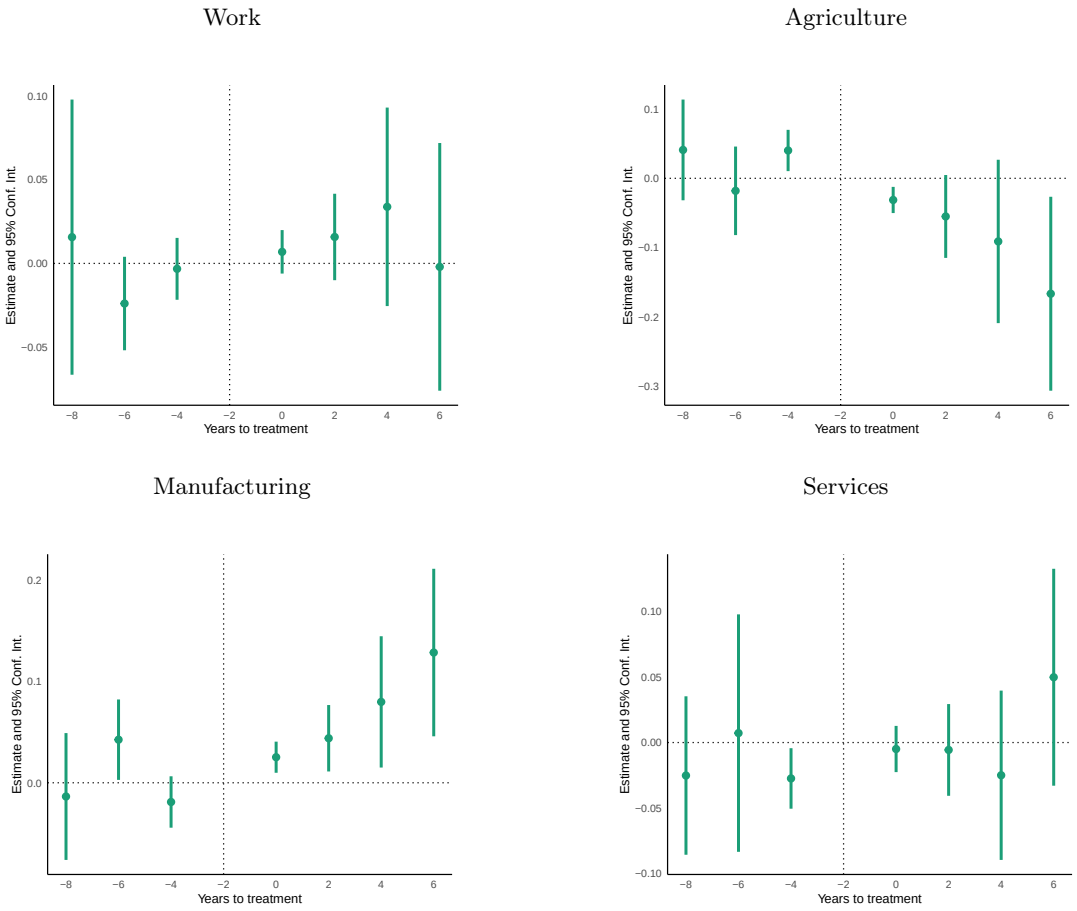
Notes: Share of households that own a mobile phone, own a computer, and report spending on the internet, in treated and control districts, 2010–2020. Shares are unweighted. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Source: Authors' calculations using VHLSS and OpenCelliD data.

Figure C2: 3G rollout and household technology adoption, VHLSS: event-study estimates



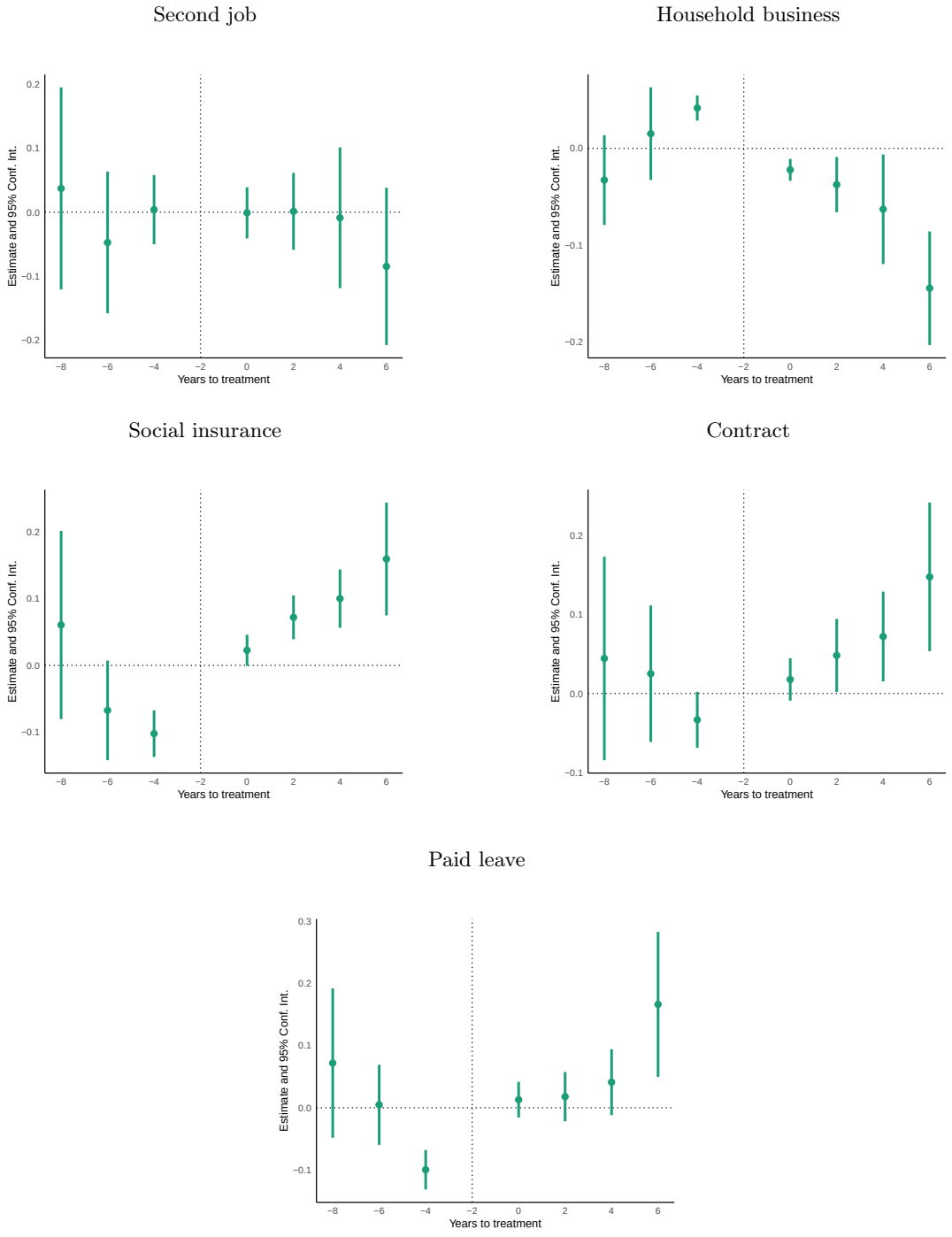
Notes: Dynamic average treatment effects of 3G coverage on the probability that a household owns at least one mobile phone or computer, estimated with the chained difference-in-differences estimator of Bellégo et al. (2025) on the 2010–2018 VHLSS rotating panel. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Districts first treated in 2010 are excluded, and not-yet-treated and never-treated districts serve as the comparison group. As the VHLSS is biennial, districts first treated in odd-numbered years are assigned to the next survey wave. All specifications control for 2009 district characteristics interacted with survey-year indicators. Vertical bars are 95 percent confidence intervals based on standard errors clustered at the district level. Source: Authors' calculations using VHLSS and OpenCelliD data.

Figure C3: 3G rollout and FLFP and sectoral reallocation of female workers, VHLSS: event-study estimates



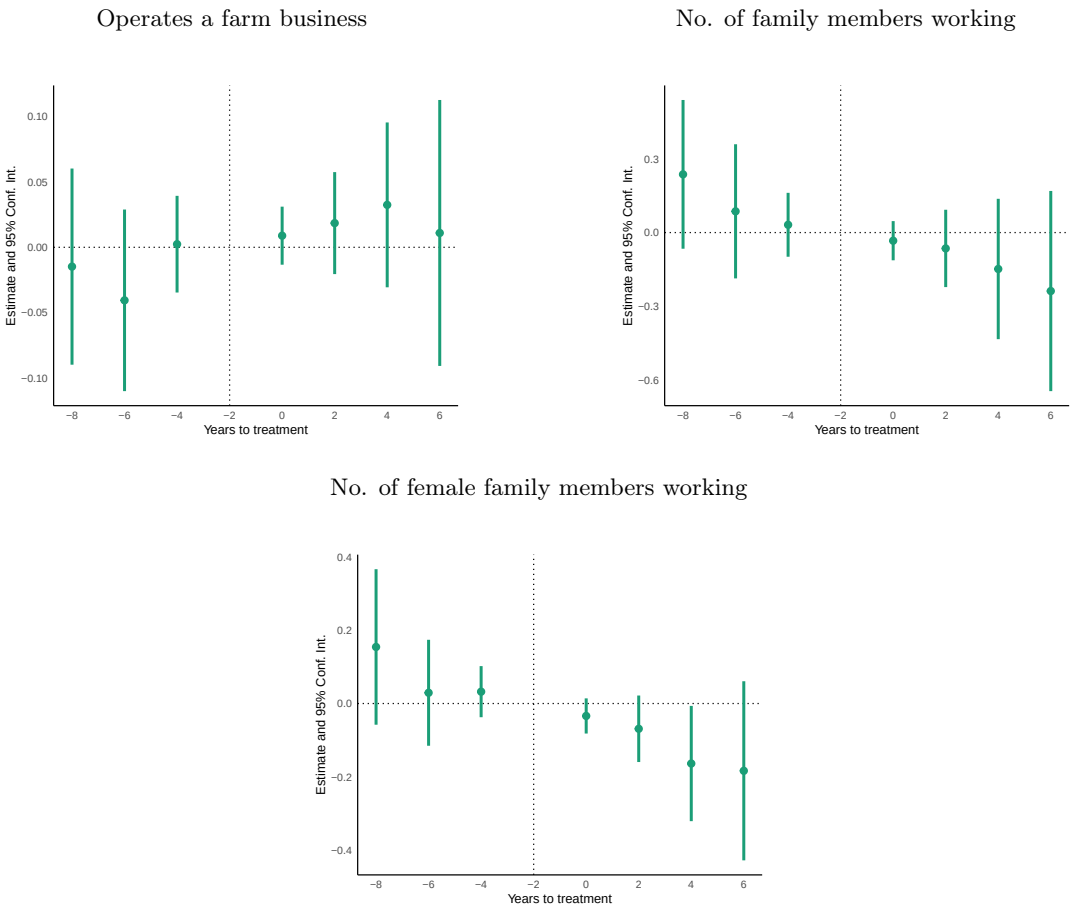
Notes: Dynamic average treatment effects of 3G coverage on outcomes of women aged 20–64, estimated with the chained difference-in-differences estimator of Bellégo et al. (2025) on the 2010–2018 VHLSS rotating panel. Work equals one if the woman has worked in the preceding 12 months; agriculture, manufacturing and services are the shares of working women employed in each sector. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Districts first treated in 2010 are excluded, and not-yet-treated and never-treated districts serve as the comparison group. As the VHLSS is biennial, districts first treated in odd-numbered years are assigned to the next survey wave. All specifications control for 2009 district characteristics interacted with survey-year indicators. Vertical bars are 95 percent confidence intervals based on standard errors clustered at the district level. Source: Authors' calculations using VHLSS and OpenCelliD data.

Figure C4: 3G rollout and formalisation of female workers, VHLSS: event-study estimates



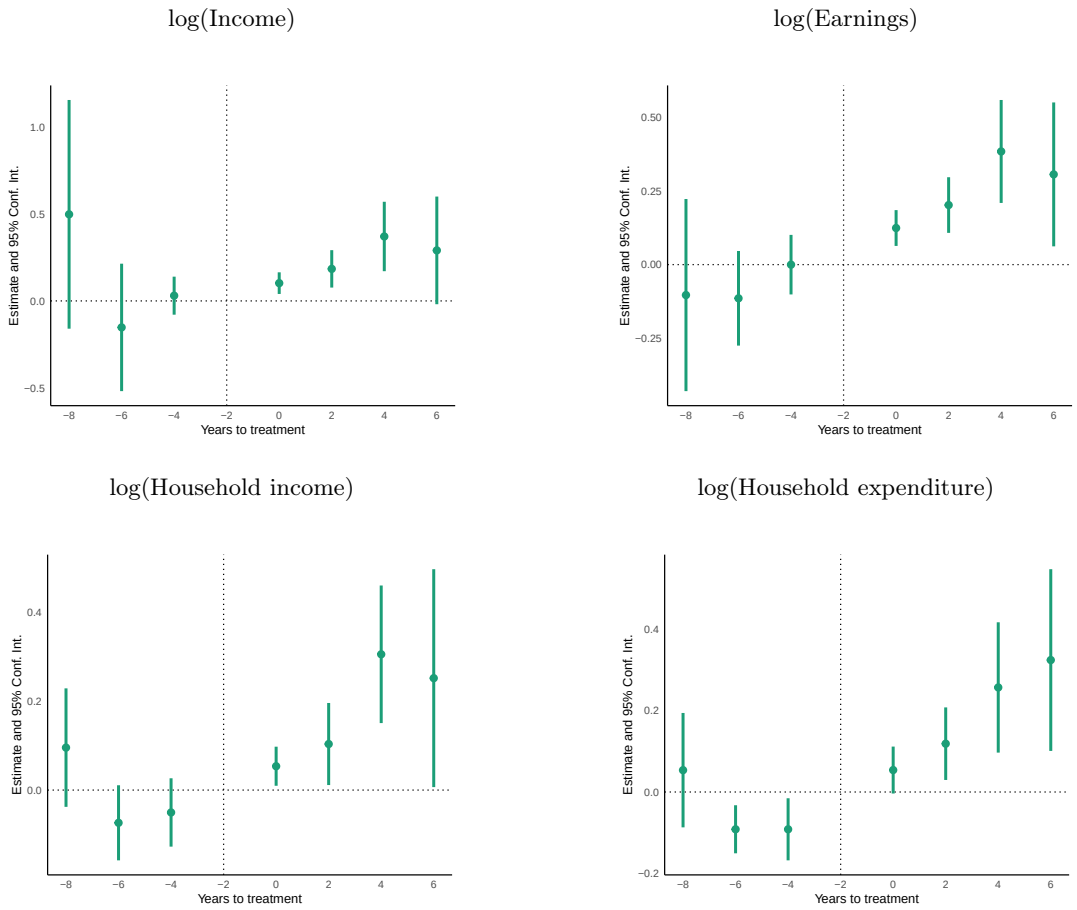
Notes: Dynamic average treatment effects of 3G coverage on outcomes of working women aged 20–64, estimated with the chained difference-in-differences estimator of Bellégo et al. (2025) on the 2010–2018 VHLSS rotating panel. The outcomes are indicators for holding a second job, working in a household business, being covered by social insurance, having a written employment contract, and being entitled to paid leave. Social insurance, written employment contract and paid leave are observed for wage workers only, so these three panels are estimated on wage workers. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Districts first treated in 2010 are excluded, and not-yet-treated and never-treated districts serve as the comparison group. As the VHLSS is biennial, districts first treated in odd-numbered years are assigned to the next survey wave. All specifications control for 2009 district characteristics interacted with survey-year indicators. Vertical bars are 95 percent confidence intervals based on standard errors clustered at the district level. Source: Authors' calculations using VHLSS and OpenCelliD data.

Figure C5: 3G rollout and household farm businesses, VHLSS: event-study estimates



Notes: Dynamic average treatment effects of 3G coverage on household farm businesses, estimated with the chained difference-in-differences estimator of Bellégo et al. (2025) on the 2010–2018 VHLSS rotating panel. The first panel reports the probability that the household operates a farm business. The second and third panels report the number of household members, and of female household members, working in the farm business; these counts are defined only for households that operate a farm business in both waves of a pair. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Districts first treated in 2010 are excluded, and not-yet-treated and never-treated districts serve as the comparison group. As the VHLSS is biennial, districts first treated in odd-numbered years are assigned to the next survey wave. All specifications control for 2009 district characteristics interacted with survey-year indicators. Vertical bars are 95 percent confidence intervals based on standard errors clustered at the district level. Source: Authors' calculations using VHLSS and OpenCelliD data.

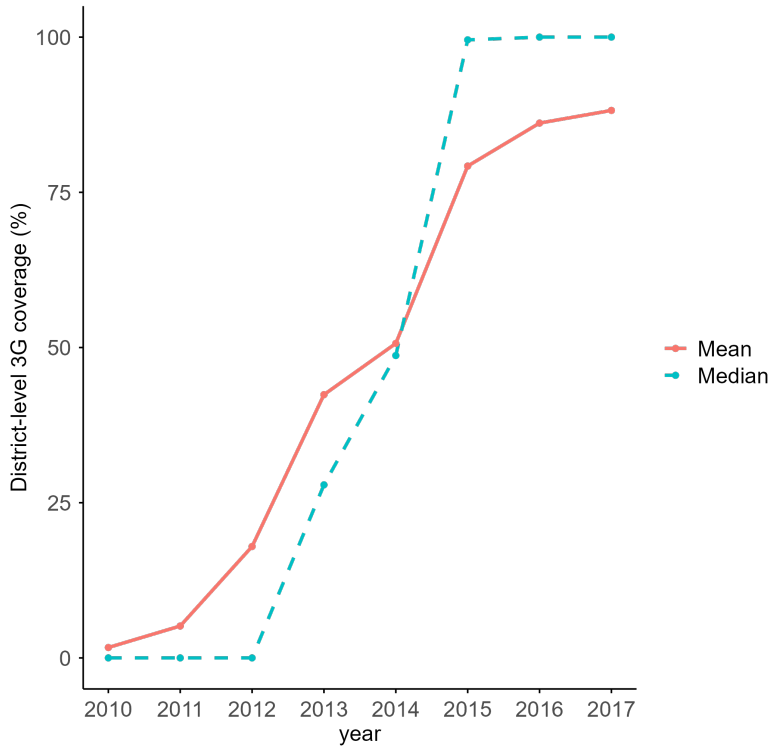
Figure C6: 3G rollout and income and expenditure, VHLSS: event-study estimates



Notes: Dynamic average treatment effects of 3G coverage on income and expenditure, estimated with the chained difference-in-differences estimator of Bellégo et al. (2025) on the 2010–2018 VHLSS rotating panel. The outcomes are log individual income, observed for employed women with positive values; log earnings from salaried employment, observed for wage-employed women with positive values; log household income; and log household expenditure. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Districts first treated in 2010 are excluded, and not-yet-treated and never-treated districts serve as the comparison group. As the VHLSS is biennial, districts first treated in odd-numbered years are assigned to the next survey wave. All specifications control for 2009 district characteristics interacted with survey-year indicators. Vertical bars are 95 percent confidence intervals based on standard errors clustered at the district level. Source: Authors' calculations using VHLSS and OpenCelliD data.

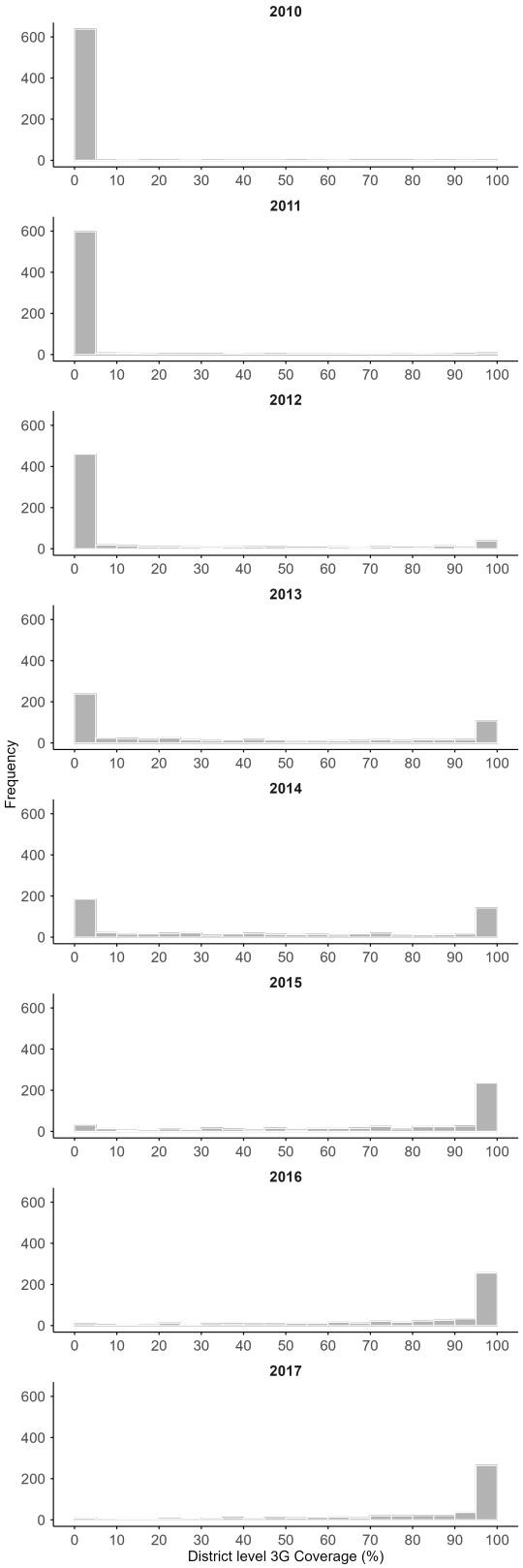
D 3G Coverage Distribution and Outcome Trends

Figure D1: Mean and median district-level 3G coverage, by year



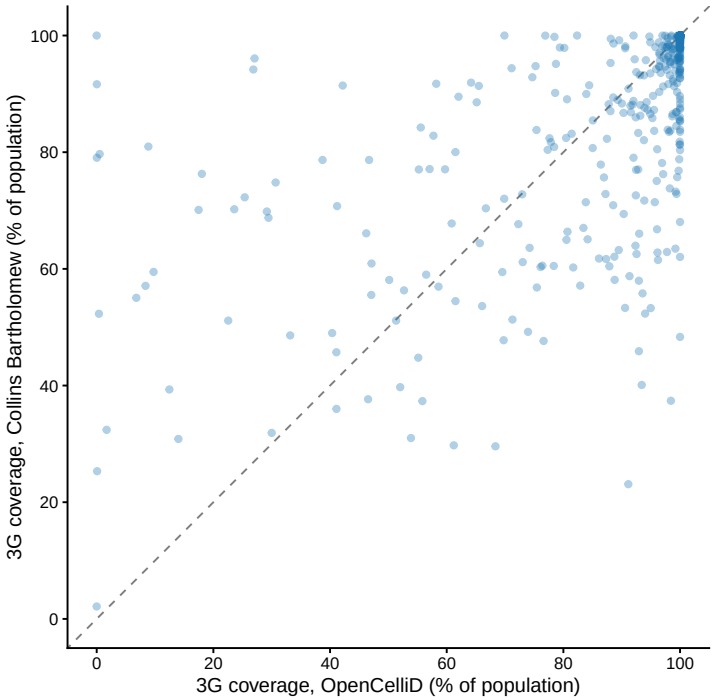
Notes: Mean and median district-level 3G coverage by year. The sample includes 685 districts with consistent boundaries over 2010–2017. Source: Authors' calculations using OpenCelliD and WorldPop data.

Figure D2: Histogram of district-level 3G coverage, by year



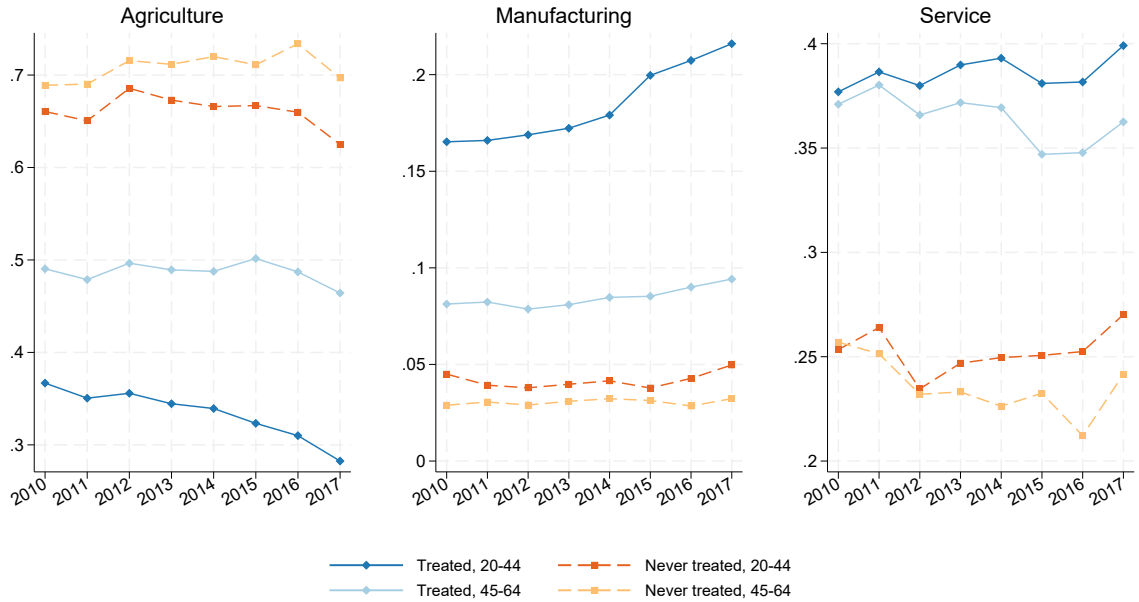
Notes: Distribution of district-level 3G coverage by year. The sample includes 685 districts with consistent boundaries over 2010–2017. Source: Authors' calculations using OpenCelliD and WorldPop data.

Figure D3: District-level 3G coverage in 2017: OpenCelliD and Collins Bartholomew



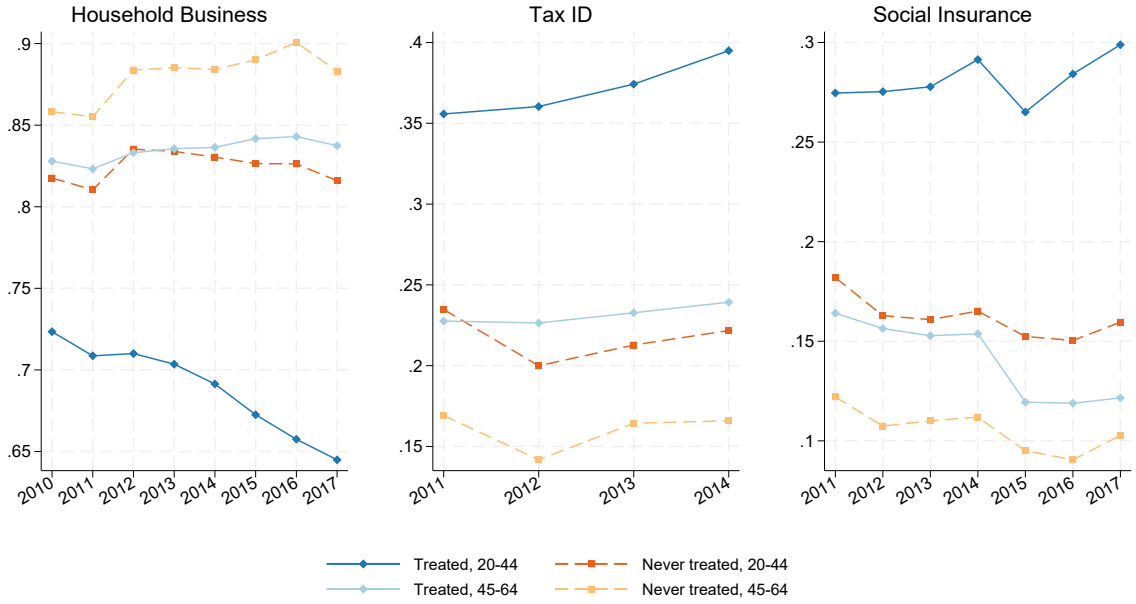
Notes: Each point is one of 685 districts. The axes show the share of the district's population covered by 3G in 2017 according to OCI (horizontal) and CB (vertical), both weighted by population using WorldPop data. The dashed line is the 45-degree line. The correlation between the two measures is 0.64 and the rank correlation is 0.82. Source: Authors' calculations using OCI, CB and WorldPop data.

Figure D4: Employment shares across sectors by treatment status and age group



Notes: Average district-level shares of workers (men and women) employed in agriculture, manufacturing and services, by treatment status and age group, 2010–2017. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Source: Authors' calculations using Labour Force Survey and OpenCelliD data.

Figure D5: Employment formality by treatment status and age group



Notes: Average district-level shares of workers (men and women) employed in household businesses, working for a firm with a tax ID (2011–2014) and covered by social insurance (2011–2017), by treatment status and age group. A district is treated from the first year its population-weighted 3G coverage, measured with OpenCelliD, reaches the 2017 mean district-level coverage (91.74 percent). Source: Authors' calculations using Labour Force Survey and OpenCelliD data.