

CAF - WORKING PAPER #2025/08

First version: September 8, 2025

Lifting Each Other Up: How Cooperative Firms Foster Local Development

L. Guillermo Woo-Gómez¹ | L. Guillermo Woo-Mora²

¹MSc in Regional and Urban
Planning Studies gwoo@indesac.org

²PhD Candidate, Paris School of
Economics and École des Hautes
Études en Sciences Sociales.
guillermo.woo-mora@psemail.eu

Do cooperative firms foster local economic development? This paper examines Mexico, assembling a new georeferenced panel dataset at the 10×10 km grid-cell level for 2015–2023. Across multiple research designs, we consistently find that cooperative presence boosts local development, measured by nightlight intensity. An event-study design shows persistent extensive-margin gains of 6–8% within four years of entry. To address selection concerns, we implement a shift-share IV strategy based on endogenous lagged-cooperative presence and plausibly exogenous sectoral growth shocks; the results imply that one additional cooperative increases nightlight density by about 2.7%. Complementary census evidence links cooperatives to higher schooling, home asset ownership, and decrease migration pressures. We also document stronger effects in Indigenous communities, where cooperatives have longer survival spells. Aggregate patterns suggest that cooperatives increase agricultural specialization but with clear productivity gains, while redistributive effects raise local disposable income and decrease poverty. These findings provide novel causal evidence that cooperatives can function as engines of inclusive local development.

KEYWORDS

Cooperatives, local development, inclusive growth, place-based policies.

Small sections of text that are less than two paragraphs may be quoted without explicit permission as long as this document is acknowledged. Findings, interpretations and conclusions expressed in this publication are the sole responsibility of its author(s) and cannot be, in any way, attributed to CAF, its Executive Directors or the countries they represent. CAF does not guarantee the accuracy of the data included in this publication and is not, in any way, responsible for any consequences resulting from its use.

CAF - DOCUMENTO DE TRABAJO #2025/08

Primera versión: 8 de septiembre de 2025

Avanzando juntos: Cómo las cooperativas impulsan el desarrollo local

L. Guillermo Woo-Gómez¹ | L. Guillermo Woo-Mora²

¹MSc in Regional and Urban Planning Studies gwoo@indesac.org

²PhD Candidate, Paris School of Economics and École des Hautes Études en Sciences Sociales.
guillermo.woo-mora@psemail.eu

¿Fomentan las cooperativas el desarrollo económico local? Este artículo examina el caso de México, construyendo un nuevo panel de datos georreferenciados a nivel de cuadrícula de 10 × 10 km para el periodo 2015–2023. A través de múltiples estrategias de identificación, encontramos de manera consistente que la presencia de cooperativas impulsa el desarrollo local, medido por la intensidad de las luces nocturnas. Un diseño de estudio de evento muestra ganancias persistentes en el margen extensivo de entre 6 y 8 % dentro de los cuatro años posteriores a la entrada. Para abordar preocupaciones de selección endógena, implementamos una estrategia de variables instrumentales de tipo shift-share basada en la presencia previa de cooperativas (endógena) y en choques de crecimiento sectorial plausiblemente exógenos; los resultados implican que una cooperativa adicional incrementa la densidad de luces nocturnas en alrededor de 2.7 %. Evidencia complementaria de los censos vincula a las cooperativas con mayores niveles de escolaridad, mayor propiedad de activos en los hogares y una reducción en las presiones migratorias. Asimismo, documentamos efectos más fuertes en comunidades indígenas, donde las cooperativas presentan trayectorias de supervivencia más largas. Los patrones agregados sugieren que las cooperativas incrementan la especialización agrícola con ganancias claras de productividad, mientras que los efectos redistributivos elevan el ingreso disponible local y reducen la pobreza. Estos hallazgos aportan evidencia causal novedosa de que las cooperativas pueden funcionar como motores de un desarrollo local inclusivo.

KEYWORDS

Cooperativas, desarrollo local, crecimiento inclusivo, políticas basadas en el territorio.

Pequeñas secciones del texto, menores a dos párrafos, pueden ser citadas sin autorización explícita siempre que se cite el presente documento. Los resultados, interpretaciones y conclusiones expresados en esta publicación son de exclusiva responsabilidad de su(s) autor(es), y de ninguna manera pueden ser atribuidos a CAF, a los miembros de su Directorio Ejecutivo o a los países que ellos representan. CAF no garantiza la exactitud de los datos incluidos en esta publicación y no se hace responsable en ningún aspecto de las consecuencias que resulten de su utilización.

1 | INTRODUCTION

Poverty has a geography—and it is overwhelmingly rural. As of 2023, the global rural poverty rate stood at 16 percent, compared to just 5 percent in urban areas (World Bank, 2024). Addressing this rural–urban divide is a central challenge for low- and middle-income countries. Conventional development strategies often rely on large-scale infrastructure projects or external investments, which can generate substantial gains but also entail high fiscal costs, long implementation lags, and uneven spatial benefits. These limitations have motivated a growing search for locally embedded, cost-effective institutions that can promote inclusive development and complement broader place-based policies.

Cooperative firms represent one such institution. Organized around principles of collective ownership and democratic governance, they are enterprises in which workers are also owners and decision-makers, sharing in both management responsibilities and the distribution of profits. As labor-managed firms, cooperatives offer a structural alternative to conventional capitalist enterprises and are widespread in many low-, middle-, and high-income settings, often operating in agriculture, fishing, and other community-based activities.

In theory, they can foster inclusive development by expanding access to credit and risk-sharing, improving bargaining power in markets, generating local employment, redistributing income, and reinvesting in the communities where they operate. Critics, however, emphasize potential inefficiencies, limited scale, and mixed evidence on long-term sustainability. Despite their prominence, long history, and normative appeal, there is limited rigorous evidence on whether and how cooperatives contribute to local development. This gap leaves open a central question: are cooperatives primarily symbolic alternatives to capitalism, or can they function as genuine engines of local growth? Moreover, through what mechanisms might these effects occur, and which characteristics are most critical to their success?

This paper examines whether and how cooperative firms foster local economic development. We focus on Mexico, where poverty is concentrated in rural and Indigenous communities (CONEVAL, 2019b,a) and where cooperatives are widespread across agriculture, fishing, and other community-based activities. Using newly assembled georeferenced data and fine-grained measures of economic activity, we assess whether cooperative presence and growth translate into measurable development gains. We further analyze the channels through which cooperatives operate and the conditions under which their effects are strongest, combining multiple quasi-experimental strategies with rich spatial and census data to provide new causal evidence on their developmental role.

To study the role of cooperatives in local development, we build a balanced panel at the 10×10 km grid-cell level for Mexico between 2015 and 2023. Cooperative presence is identified from the FIDESUR Directory of Cooperatives and Social Firms, which builds on INEGI's DENUE registry and identifies co-ops by legal and commercial designation under Mexico's Social and Solidarity Economy Law. After trimming unpopulated areas, the final sample covers about 12,000 populated cells, 16% of which contained at least one cooperative during the period.

The data allow us to characterize non-*ejido* cooperative firms along several dimensions.¹ Co-ops are geographically widespread but unevenly distributed: most cells host only one, with higher concentrations in the South–Southeast. They operate across nearly all sectors, though they are most prevalent in agriculture, livestock, and fishing, where they account for nearly one-fifth of establishments. Most are micro or small firms with fewer than 50

¹*Ejid*os are communal landholdings where groups of farmers collectively own and manage land for agricultural purposes, granted by the government following the Mexican Revolution.

workers, and survival analysis shows they remain active longer than comparable non-cooperatives—especially in Indigenous localities where traditions of collective work may support them.

We measure local development using VIIRS nighttime light intensity per capita, a standard proxy for economic activity (Henderson et al., 2011, 2012; Donaldson and Storeygard, 2016; Pinkovskiy and Sala-I-Martin, 2016; Michalopoulos and Papaioannou, 2018). We provide evidence that, in Mexico, nightlights closely track municipal GDP per capita, household income, and poverty rates, making them a relevant and reliable outcome measure.

We first exploit the panel structure of our data, linking annual variation in cooperative presence to changes in nightlight intensity per capita across 10×10 km grid cells from 2015 to 2023. Exploiting within-cell variation and conditioning on the size distribution of non-cooperative establishments and controls selected via double-LASSO (Belloni et al., 2014), we find a robust positive association: in our preferred specification, one additional cooperative is linked to a 0.6% increase in local nightlight density, suggesting stronger economic performance in areas with more cooperative activity.

To strengthen identification, we complement the OLS results with two designs exploiting spatial and temporal variation. First, a border design (BD) focuses on the *intensive margin*, comparing treated cells hosting cooperatives with adjacent untreated neighbors; it shows that one additional cooperative raises nightlight density by about 0.7%. Second, a difference-in-differences (DiD) with event-study design captures the *extensive margin*, comparing cells before and after their first cooperative to not-yet-treated cells. The event-study estimates show no evidence of differential pre-trends between treated and untreated cells, supporting the validity of the parallel trends assumption. Following cooperative entry, we observe persistent post-entry gains of 6–8% within two to four years. Both approaches reinforce the benchmark findings under stronger identification assumptions.

While consistent across methods, these findings remain vulnerable to endogeneity. Cooperative presence may correlate with unobserved factors like political mobilization, social capital, or public investment, and cooperatives may also emerge endogenously in response to local economic conditions. Hence, the estimates cannot be interpreted as fully causal.

To address endogeneity concerns, we implement a shift–share instrumental variables (SSIV) strategy in the *many shocks* framework of Borusyak et al. (2022, 2025). The instrument interacts each cell’s pre-period sectoral composition of cooperatives, classified by legal name in the 2013 DENU, with growth shocks in non-cooperative medium and large establishments located in nearby—but non-adjacent—municipalities between 2015 and 2023. This strategy recognizes that exposure weights are endogenous: cooperative entry often follows agglomeration or “demonstration” dynamics, whereby past successes provide visible proof of feasibility and organizational know-how, making new formations more likely in areas with prior cooperative presence (Conte, 1986; Arando et al., 2012; Conte and Jones, 2015). By contrast, the shocks capture spatially proximate demand-side shifts in sectoral activity that are plausibly exogenous to cooperative presence. Identification therefore comes from the quasi-random *shifts*, net of national sectoral trends and excluding the focal municipality. This design isolates variation in cooperative growth driven by external sectoral dynamics rather than local conditions or reverse causality.

We validate this strategy along three dimensions: (i) shocks are strongly predictive of cooperative presence, (ii) the identifying variation is broad-based, with an effective number of shocks above 140 (comparable to Autor et al. (2013)), and (iii) balance and orthogonality tests show no systematic relationship with baseline covariates such as nightlights, infrastructure, or demographics. Taken together, these diagnostics support the validity of the SSIV as a source of plausibly exogenous variation in cooperative activity.

The SSIV estimates show that cooperative firms have a positive and economically meaningful impact on local development. In our preferred specification—controlling for baseline exposure to cooperatives, changes in the size distribution of non-cooperative establishments, *ejidos*, and infrastructure—one additional cooperative firm at the grid-cell level raises nighttime light intensity per capita by about 2.7% between 2015 and 2023.

We complement these findings with socio-economic indicators from the 2010 and 2020 Population and Housing Census at the locality level. Increases in cooperative presence are associated with higher mean years of schooling, greater household asset ownership, and lower overcrowding and unemployment rates. We also find reduced out-migration pressures, with more residents remaining in the same state. Together, these results corroborate the nighttime evidence and indicate that cooperative expansion fosters broad-based improvements in living standards.

We further assess the SSIV results through robustness exercises. Estimates remain stable when excluding medium and large cooperatives, down-weighting influential sectors such as fishing, or controlling for infrastructure and firm composition. Balance tests on time-varying covariates and a zero first-stage test confirm that shocks affect outcomes only through cooperatives. A decomposition shows that the OLS–IV gap reflects endogeneity rather than weighting or measurement artifacts. Taken together, these checks, along with the consistent positive effects across our different research designs under varying identification assumptions, reinforce a causal interpretation of the results.

The effect of cooperative expansion is consistently positive but varies by context. Impacts are stronger in cells with greater sectoral diversity, where complementarities with other activities are higher, and in areas with larger Indigenous or Catholic populations, consistent with traditions of collective work and external support. Overall, the development potential of cooperatives depends not only on economic structure but also on local social and cultural environments.

We interpret cooperative presence as a *bundle treatment*: cooperatives can simultaneously expand access to credit and risk-sharing, raise agricultural productivity, and redistribute income through collective ownership. Lacking firm-level data, we cannot isolate micro-level channels. Instead, we use aggregate evidence to trace broad pathways linking cooperative expansion to local development.

Cooperative growth increases the local concentration of economic activity, shifting resources toward agriculture and away from services. This specialization is accompanied by clear productivity gains: municipalities with more cooperatives achieve higher yields, greater production value per hectare, and increased crop diversity. These results highlight productivity improvements in primary activities as one key channel.

Finally, we find that cooperatives do not directly expand infrastructure. However, they do raise household income and reduce extreme and multidimensional poverty. These redistributive effects reinforce our baseline findings from nightlights, suggesting that higher disposable income and local consumption are another pathway through which cooperatives foster development.

The main contribution of this paper is to provide rigorous new evidence on how cooperative firms shape local economic development. Much of the theoretical literature on cooperatives has emphasized the trade-offs between efficiency and equity under alternative ownership structures (Ward, 1958; Domar, 1966; Sen, 1966; Bonin, 1977; Putterman, 1980; Holmstrom, 1982; Kandel and Lazear, 1992; Bonin et al., 1993; Kremer, 1997; Brzustowski and Caselli, 2024), while empirical research has largely examined firm-level dynamics. This work compares cooperative and employee-owned firms to conventional enterprises in terms of productivity, organizational practices, wage dispersion, job stability, and worker welfare (Craig and Pencavel, 1992; Blasi et al., 1996; Pencavel et al., 2006; Burdín and Dean, 2009,

2012; Clemente et al., 2012; Fakhfakh et al., 2012; Casaburi and Macchiavello, 2015; Alves et al., 2016; Burdín, 2016; Magne, 2017; Alves et al., 2022; Caselli et al., 2022), as summarized in reviews by Pencavel and Craig (1994); Kruse et al. (2010); Pencavel (2013); Jones (2018).

By contrast, little is known about the broader developmental impacts of cooperatives, especially in low- and middle-income countries. Beyond studies of FairTrade certification (Dragusanu et al., 2014, 2022), land tenure reforms (Besley and Burgess, 2000; Banerjee et al., 2002; Montero, 2022), and cooperative traditions in specific historical or cultural settings (Abramitzky, 2008, 2011), few contributions examine their local economy-wide effects.² A notable exception is Sukhtankar (2016), who exploits a regression discontinuity design across command-area borders in India to compare cooperative and private sugar mills, and finds that privately owned mills generate higher agricultural productivity and farmer income. These results underscore that ownership structure can significantly shape local development outcomes.

We contribute to this debate with new evidence from a different context, providing new causal evidence that cooperatives can foster local development through agricultural productivity gains and redistribution effects that raise incomes and reduce poverty. In doing so, we underscore the developmental role of cooperatives beyond niche markets or institutional reforms, and highlight that the effects of ownership structure may be context-dependent.

Our second contribution is to the literature on local economic development and place-based policies (Kline and Moretti, 2014; Neumark and Simpson, 2015). A growing body of research has documented the transformative effects of transportation, electrification, and other large-scale infrastructure investments on regional growth and welfare (Dinkelman, 2011; Donaldson and Storeygard, 2016; Donaldson, 2018; Asher and Novosad, 2020; Borusyak and Hull, 2023; Asher et al., 2024; Gertler et al., 2024). While such projects can generate substantial gains, they typically involve large upfront costs, depend on complementary private-sector responses, and may produce uneven spatial outcomes (Duranton and Venables, 2021). Our results suggest that cooperative firms provide a market-oriented alternative or complement to these policies, expanding the toolkit for fostering inclusive and sustainable local development. This perspective is particularly relevant for policy debates in developing countries, where fiscal space is limited and traditional “big push” infrastructure strategies are often difficult to sustain.

Our third contribution is to the emerging literature on how cultural contexts mediate economic development outcomes (Nunn, 2019; Ashraf et al., 2020; Lowes and Montero, 2021; McGuirk and Nunn, 2024; Moscona and Seck, 2024; Bau et al., 2025). We show that cooperative firms exhibit longer survival spells and stronger local development effects in communities with higher Indigenous presence, including significant reductions in poverty. This finding suggests that cooperatives may align with traditions of communal labor and collective governance, making them particularly well-suited as inclusive development institutions in such settings. More broadly, our results illustrate how locally rooted, market-based organizations can complement cultural preferences for collective forms of economic activity, amplifying developmental gains and supporting poverty reduction. These findings highlight the potential of cooperatives as a culturally appropriate tool for fostering inclusive development in Indigenous and marginalized communities, where conventional market mechanisms and top-down interventions often prove less effective.

The rest of the paper is structured as follows. Section 2 provides background on the history and legal status of cooperative firms in Mexico. Section 3 describes our data sources,

²A small set of papers examines the correlation between cooperatives and development, but none employs quasi-experimental research designs (Ma and Abdulai, 2017; Coccorese and Shaffer, 2021; Costa et al., 2023; Costa and Delbono, 2023; Terzo et al., 2024).

including the identification of cooperatives and the construction of local development measures. Section 4 outlines the empirical framework and identification strategies used to estimate the effects of cooperatives on local development. Section 5 presents the main results, robustness checks, and heterogeneity analysis. Section 6 explores potential mechanisms at the aggregate level. Finally, Section 7 concludes.

2 | CONTEXT

| Cooperatives and the Global Social and Solidarity Economy.

Cooperative firms are part of the broader Social and Solidarity Economy (SSE)—a form of economic organization grounded in solidarity, reciprocity, and democratic governance. Unlike conventional enterprises that prioritize shareholder value, SSE entities are collectively owned and managed, with members often participating in both day-to-day labor and strategic decision-making (Coraggio, 2015; Utting, 2015). This institutional logic combines economic viability with equity and community development, distinguishing SSE organizations from both capitalist firms and public institutions. Rooted in nineteenth-century reformist and socialist thought (Owen, King, Fourier, Mill), the SSE today encompasses cooperatives, mutual societies, community enterprises, and associations that combine economic activity with social objectives.

Despite cross-country variation in legal frameworks, they typically share common features: one-member-one-vote governance, autonomy from the state, limited profit distribution, and the reinvestment of surpluses into collective goals. Their growing recognition underscores their policy relevance: in 2023, the United Nations General Assembly adopted Resolution 77/281, urging member states to promote the SSE as a pathway toward the Sustainable Development Goals (SDGs), while proclaiming 2025 as the International Year of Cooperatives (United Nations General Assembly, 2023; International Labour Organization, 2014).

Globally, the SSE plays a significant role in employment and value creation. According to the *World Cooperative Monitor*, there are more than 3 million cooperatives worldwide, with at least 12% of the world's population participating as members. Cooperatives provide jobs or work opportunities for roughly 10% of the employed population, while the 300 largest cooperatives and mutuals together generate over 2.4 trillion USD in annual turnover (International Cooperative Alliance and Euricse, 2023; Eum, 2017). Prominent examples include cooperative enterprises in Emilia Romagna, Italy; banks such as Crédit Agricole in France; retail groups like REWE in Germany; and agricultural federations such as ZENNOH in Japan. A particularly emblematic case is the Mondragón Corporation in Spain, a network of more than 90 cooperatives spanning manufacturing, retail, finance, and education. Together, these cases demonstrate that cooperative models can scale effectively and compete across diverse sectors, from finance and agriculture to retail and services.

| Cooperative firms in Mexico.

In Mexico, the SSE has deep historical roots. Some historians trace cooperative practices back to pre-colonial indigenous traditions of communal labor and resource sharing (de la Fuente, 1944), while forms closer to modern cooperatives emerged in the nineteenth century. From the mid-1800s, artisans and workers in Mexico City and other urban centers established production and credit cooperatives, influenced by European socialist thought and local

reformist movements (Illades, 1996; Bautista Pérez, 2022).³

The Mexican Revolution and subsequent agrarian reforms expanded the space for collective organization, though cooperatives occupied an ambivalent position in state policy. The 1927 Cooperative Law sought to institutionalize them, and by the early 1930s, Mexico counted nearly 800 cooperatives with more than 30,000 members (Rojas Coria, 1952; Bautista Pérez, 2022). Yet relations with the state were often shaped by corporatist politics. Some presidents (Obregón) sought to attract cooperatives into political alliances, while others (Calles) promoted their formalization. Finally, President Cárdenas incorporated them into broader state-building strategies. Still, within the corporatist structure of the PRI regime, cooperatives received less attention than labor unions, peasant syndicates, or agrarian *ejidos*, which became the privileged channels of state support (Bautista Pérez, 2022). Historical accounts highlight both the expansion and the cooptation of cooperatives, limiting their autonomy. A well-known twentieth-century case was the newspaper *Excelsior*, whose cooperative governance ultimately clashed with the PRI regime (Leñero, 2015).

Today, cooperatives are legally recognized and regulated by two main instruments: the *Ley General de Sociedades Cooperativas* (LGSC) and the 2012 *Ley de la Economía Social y Solidaria* (LESS). The LESS defines the social economy as a set of organizations based on solidarity and reciprocity, encompassing cooperatives, *ejidos*, communal land associations, and savings unions. Within this framework, the LESS distinguishes three types of cooperatives: consumption cooperatives that pool member demand, production cooperatives where members contribute labor or capital to jointly produce goods and services, and savings-and-loan cooperatives that function as member-owned credit institutions under financial regulation. All share core features of democratic governance, limited liability, and indivisible reserves, alongside prerogatives such as tax exemptions on surplus distributions.⁴

According to INEGI, the social economy contributed 1.6% of Mexico's GDP in 2018, with more than three-quarters of value added concentrated in primary activities such as agriculture and fishing (Instituto Nacional de Estadística y Geografía (México), 2022). In employment terms, the sector represented about 4.5% of all remunerated jobs, with an additional 2.6 million people engaged in unpaid but economically relevant activities, mostly within communal landholding systems. While cooperatives are widespread, their distribution is uneven, with stronger presence in southern states and within agriculture, livestock, and fishing.

Mexico also offers emblematic case studies. Longstanding examples include *Caja Popular Mexicana*, the country's largest savings and credit cooperative, as well as the cement producer *Cruz Azul* and the beverage company *Pascual*, which illustrate the ability of cooperatives to scale nationally. More recently, a new generation of smaller cooperatives has emerged in rural and Indigenous regions, where their developmental contributions are particularly salient. One prominent case is *Tosepan Titataniske*, founded in the Sierra Norte of Puebla, which has grown into Mexico's largest Indigenous cooperative, integrating more than 35,000 members across multiple productive activities while advancing sustainable and solidarity-based development (Herrera and Rojas, 2020; Deutsche Welle, 2020; El País México, 2025). Another example is *Capeltic*, a cooperative of Tseltal coffee growers in Chiapas that, in partnership with the Jesuit network, successfully exports to international markets while combining fair-trade principles with community-driven reinvestment (El

³Notable experiments include the Topolobampo colony in Sinaloa, initiatives inspired by Plotino Rhodakanaty, and the 1876 Workers' Congress, which explicitly debated cooperatives as part of the labor agenda (Bautista Pérez, 2022).

⁴For instance, many cooperatives are exempt from paying *Impuesto sobre la Renta* (ISR) –income tax– when they fall under the regime for non-profit legal entities. See Placencia Alarcón (2022) for a detailed account of the fiscal conditions under which different types of cooperatives are subject to exemptions or obligations.

[Financiero, 2023](#)). These cases highlight how cooperatives, particularly in marginalized areas, can generate income, strengthen collective organization, and foster inclusive forms of development.

3 | DATA AND DESCRIPTIVE STATISTICS

To study the local and heterogeneous impacts of cooperative firms on economic development, we compile fine-grained administrative, census, and remotely sensed data for Mexico and build a balanced panel of 10×10 km cells for 2015–2023. This section describes the data sources and construction of the panel, then presents descriptive evidence on the geography, sectoral and size composition, and survival of cooperative firms.

3.1 | Data sources

Cooperative Firms. Our primary source for identifying cooperatives is the *Directorio Estadístico Nacional de Unidades Económicas* (DENUE), managed by INEGI.⁵ The DENUE is a statistical directory that enumerates active economic establishments across Mexico. Firms are legally required to register and update their information, and INEGI maintains the directory through a combination of administrative records, field verification, and quinquennial Economic Censuses.

DENUE provides standardized identifiers and georeferenced information on each unit, including its location, sector of activity (six-digit NAICS), employment-size category, and legal or commercial name. Updates occur annually for large firms and strategic sectors, periodically for micro, small, and medium-sized enterprises, and comprehensively every five years through the Economic Census. Importantly, the DENUE does not record internal firm dynamics such as revenues, capital, or sales.

The directory's geographical coverage includes all establishments in urban localities of 2,500 inhabitants or more, as well as rural localities deemed economically significant (e.g., industrial parks or mining sites), and it fully covers units in strategic activities such as mining, construction, transport, finance, and utilities.⁶

We measure the local presence of cooperative firms using the *Fideicomiso para el Desarrollo Regional del Sur Sureste* (FIDESUR) Directory of Cooperatives and Social Firms,⁷ which compiles establishment-level data from INEGI's DENUE for 2015–2023.

FIDESUR identifies cooperatives within DENUE by matching the legal structure (*razón social*) or commercial name of each unit to entities recognized under the Mexican Social and Solidarity Economy Law. In practice, this involves flagging firms whose identifiers contain terms such as “*Sociedad Cooperativa*” (Cooperative Society) or simply “*Cooperativa*” (Cooperative). Broader categories are also included: for instance, “*Unión de Ejidos*” (Union of Ejidos) and “*Unión de Comunidades*” (Union of Communities) reflect collective land or community-based ownership, while “*Sociedades de Producción Rural*” (Rural Production Societies) and “*Sociedades Cooperativas de Ahorro y Préstamo*” (Cooperative Savings and Loan Societies) capture production- and finance-oriented cooperatives.⁸ We include in our counts

⁵For details, see INEGI: [Metodología del DENUE](#).

⁶Economic units located in rural areas that are only captured through the rural sample of the Economic Census are not included in the DENUE. This implies that our analysis primarily reflects the presence of cooperatives in urban and economically relevant rural localities, potentially underrepresenting small-scale cooperatives in remote areas. As a result, estimated effects of cooperatives on local development should be interpreted as lower bounds, since omitted remote cooperatives are more likely to be located in disadvantaged contexts.

⁷The 2022 directory is available at [Directorio de Empresas Sociales](#).

⁸Additional recognized designations include “SC de RL” (Limited Liability Cooperative Society), “SC de RS”

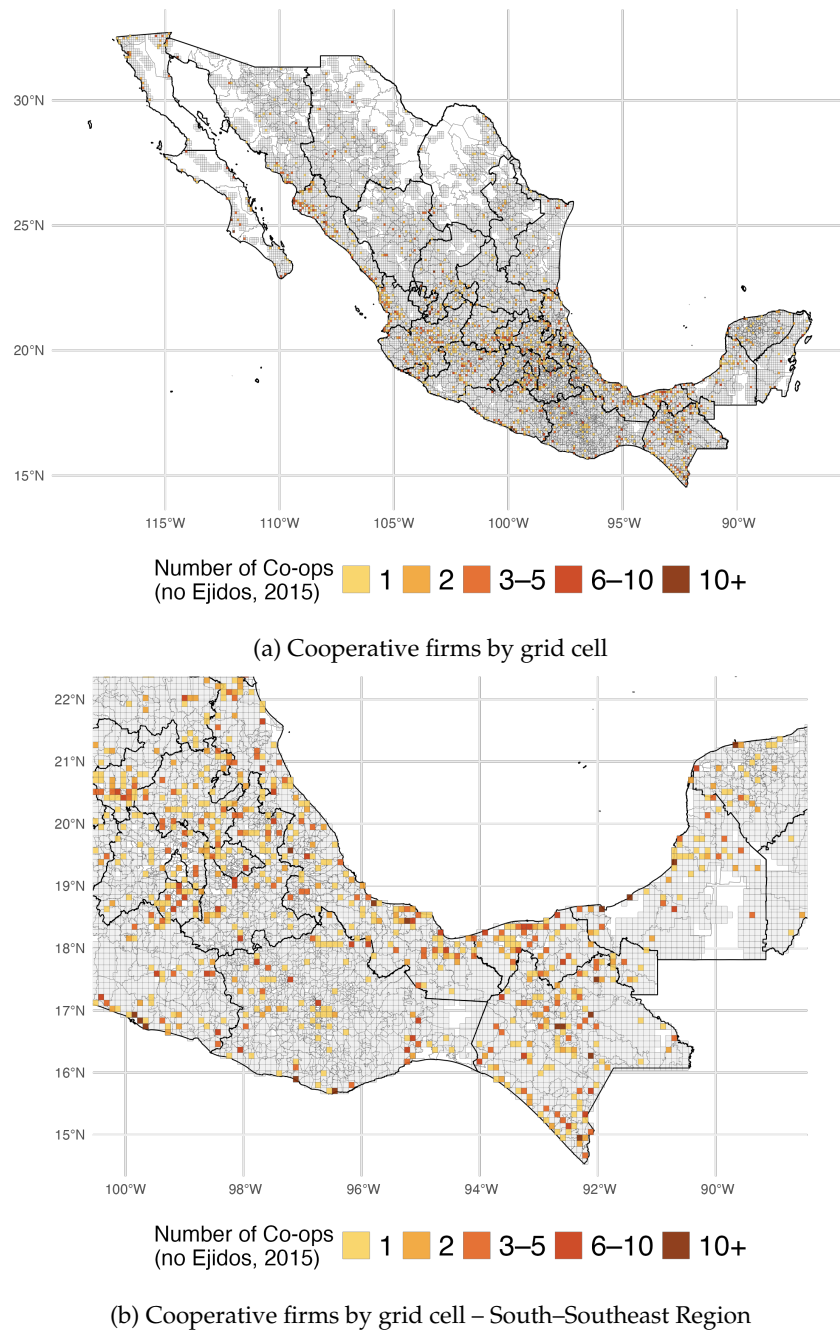


FIGURE 1 Spatial distribution of cooperative firms in Mexico, 2015

Notes: Based on FIDESUR's Directory of Cooperatives and Social Firms. The maps depict the spatial distribution of cooperative firms across Mexico, excluding *ejidos*, using a 10 × 10 km grid. Thin gray lines indicate municipal boundaries, while bold black lines represent state borders. White cells denote unpopulated areas, gray cells indicate areas with no cooperative firms, and colored cells represent the number of cooperative firms per grid cell.

(Supplemented Liability Cooperative Society), *Sociedad de Solidaridad Social* (Social Solidarity Society), and *Sociedades Mutualistas* (Mutual Societies). Other forms emphasizing collective well-being or mutual aid are also covered, such as *Comunidades*, *Ejidos*, *Asociaciones Rurales de Interés Colectivo* (ARIC), *Uniones de Sociedades de Producción Rural*, *Cajas de Ahorro de Trabajadores*, *Microindustrias en Solidaridad*, *SCPP* (*Sociedad Cooperativa de*

consumption, production, and savings-and-loan cooperatives.

We use the geographic coordinates reported in the DENUE and FIDESUR's Directory of Cooperatives and Social Firms to map the distribution of cooperatives across Mexico and track their presence between 2015 and 2023. Figure 1 on the preceding page illustrates the spatial distribution in 2015, excluding *ejidos*. The analysis is conducted on a uniform grid of 10×10 km cells covering the national territory. White cells correspond to unpopulated areas, gray cells to populated areas without cooperatives, and colored cells to cooperative presence, with darker shades indicating higher densities. Municipal boundaries are shown in thin gray lines and state borders in bold black. Out of more than 12,000 land cells in the grid, approximately 16% contained at least one cooperative between 2015 and 2023.

Local Economic Development. To measure local economic development, we combine the spatial distribution of cooperatives with remotely sensed nighttime lights. A large literature in economics shows that satellite-based luminosity provides a useful proxy for local economic activity, particularly where official statistics are infrequent or unavailable (Henderson et al., 2011, 2012; Donaldson and Storeygard, 2016; Pinkovskiy and Sala-I-Martin, 2016; Pinkovskiy, 2017; Michalopoulos and Papaioannou, 2018). Following best practices (Gibson et al., 2021), we use annual VIIRS data from Elvidge et al. (2021) and aggregate it to a uniform 10×10 km grid covering the Mexican territory. We then combine these data with gridded population estimates from Lebakula et al. (2024) to construct nightlight intensity per capita between 2015 and 2023. This measure captures both the scale of local activity and its relevance relative to population size.

Nighttime lights are not without limitations. As shown by Keola et al. (2015), luminosity may understate value added in sectors such as agriculture and forestry, where production does not generate substantial nighttime light. This concern is particularly relevant for our setting, since cooperatives often operate in these sectors. Nevertheless, we validate that our measure tracks key indicators of local development at a fine spatial scale. In Appendix Figure A.1, we show that nightlight intensity per capita is strongly correlated with municipal GDP per capita (Rossi-Hansberg and Zhang, 2025), with household income per capita (López-Calva et al., 2022), and negatively with food poverty rates (López-Calva et al., 2022). These patterns support the interpretation of nightlight intensity per capita as a credible proxy for local economic development in Mexico.

Additional Data. Since the spatial distribution of economic activity reflects both locational fundamentals ("first nature") and access to markets or infrastructure ("second nature") (Henderson et al., 2018), we complement our cooperative and nightlight measures with additional geographic, infrastructure, and socio-economic data.

First, to capture broader agglomeration forces, we compute the number of *non-cooperative* establishments in each grid cell and year using DENUE, subtracting cooperatives to avoid double counting. This variable reflects the density of surrounding economic activity. We further disaggregate establishments by firm size—micro, small, medium, and large—following the official Mexican classification.⁹

Second, we incorporate socio-economic baselines from the 2010 National Population and Housing Census. INEGI reports the location of more than 32,000 localities nationwide, which we link to our 10 km grid. Each grid cell is matched to its nearest 2010 locality, and we restrict the sample to cells within the 75th percentile of the (log) distance to the nearest locality. This trimming reduces the risk of including grid cells with missing socio-economic information due to DENUE's coverage rules, while ensuring that almost all populated areas remain represented. From this source, we extract indicators such as population density, education, and housing quality, among others.

Productores Pesqueros), *Uniones de Crédito*, *Sociedades Financieras Comunitarias*, and *SOFOM ENR*.

⁹See *Estratificación de empresas micro, pequeñas y medianas*.

Third, we merge georeferenced locational fundamentals from INEGI, including elevation, slope, and long-run climate normals (average temperature, precipitation, and humidity for 1902–2011). We also incorporate land use and vegetation rasters to measure proximity to water bodies, coastal areas, agricultural land, and forested regions.¹⁰

Finally, we add annual data on infrastructure and public goods from INEGI's National Road Network (*Red Nacional de Caminos*, RNC) for 2015–2023.¹¹ This dataset provides georeferenced information on roads (highways, paved and unpaved roads, trails), as well as the location of schools, hospitals, ports, airports, and government service buildings. These variables serve two roles in the analysis: as controls for the determinants of cooperative location, and as outcomes of interest when studying the potential role of public goods provision as a mechanism.

Final dataset. We combine all sources into a balanced panel of 10×10 km grid cells for the period 2015–2023, containing our measures of cooperative presence and local economic development (nightlights).

In constructing the panel, we exclude isolated grid cells located beyond the 75th percentile of the distance to the nearest 2010 locality, as well as cells with no resident population in all years.

Finally, in most specifications, we further restrict the sample by excluding grid cells that fall within an urban AGEB (*Área Geoestadística Básica*), the basic statistical unit used by INEGI to delineate city blocks in urban areas. Because these units correspond to densely populated, highly formalized settings, we focus instead on non-urban areas where cooperative firms are more prevalent and where their impact on local development is more plausibly identified.

The resulting dataset covers approximately 12,000 grid cells observed over nine years, providing a consistent spatial panel to analyze the relationship between cooperative activity and local development.

3.2 | Descriptive statistics on cooperative firms

In this section, we exploit establishment-level information from the DENUE–FIDESUR directory to characterize cooperative firms along three dimensions: their geographical distribution, sectoral composition, and size structure.

Geographical distribution. Even under the most restrictive definition, cooperative firms are present across the national territory, as shown in Figure 1 on page 9. Their distribution, however, is highly uneven. Most grid cells with cooperative activity contain only a single establishment, producing a markedly skewed spatial distribution. The second panel zooms into the South–Southeast region, where cooperatives are more numerous. The regional focus underscores the considerable heterogeneity in cooperative density both across states and within municipalities, highlighting the localized concentration of cooperative activity.

Sectoral composition. Cooperatives operate in nearly all NAICS two-digit sectors. Figure 2 on the following page displays, for each sector, the *pooled share* of cooperatives—i.e., the ratio of cooperative establishments to all establishments in that sector, pooled across our analysis years. In most sectors, cooperatives account for less than 1% of establishments. Three sectors stand out: agriculture, livestock, and fishing (NAICS 11), where cooperatives represent roughly 18% of establishments; mining (NAICS 21), with about 2.5%; and transportation (NAICS 48), with about 3%. Thus, while cooperatives are present throughout the economy, their relative importance is concentrated in primary activities and transportation.

Size composition. Most cooperative firms are classified as micro or small enterprises. Using INEGI's official size classification, we categorize firms by employment and sector

¹⁰See the INEGI webpage for [climate data, 1902–2011](#) and [land use and vegetation maps](#).

¹¹See the INEGI webpage for [National Road Network data](#).

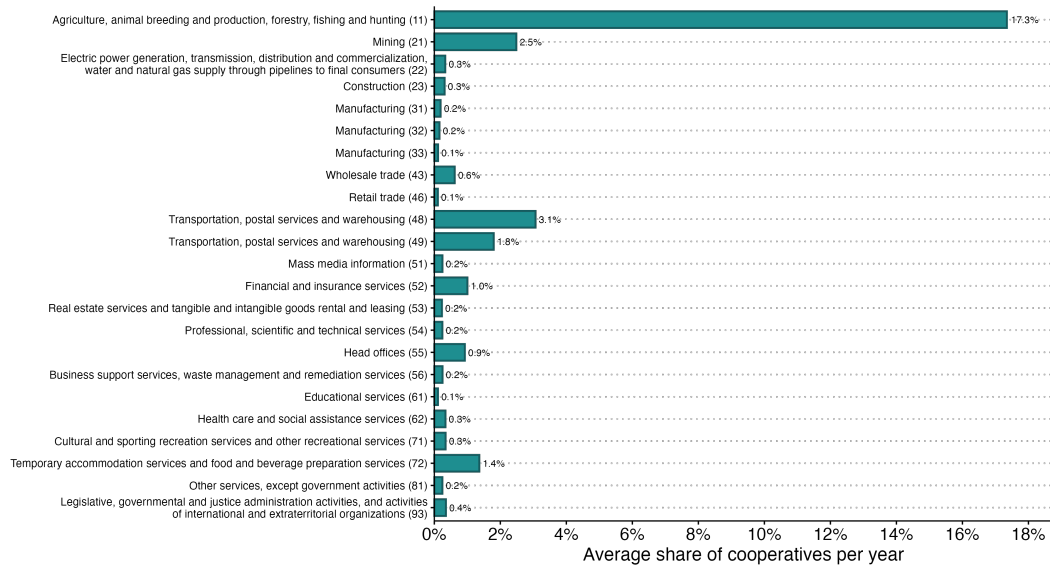


FIGURE 2 Cooperative share by NAICS two-digit sector (pooled across years)

Notes: Based on FIDESUR's Directory of Cooperatives and Social Firms matched to DENU. For each NAICS two-digit sector, the bar shows the pooled share of cooperatives: total cooperative establishments divided by total establishments in that sector, summed across years in our sample. Sectors are labeled by name and NAICS code.

(Appendix Figure 2). Across all sectors, as well as within agribusiness, the majority of cooperatives employ 10 or fewer workers (micro) or between 11 and 50 workers (small). This size distribution is consistent with the idea that cooperative enterprises remain relatively small to facilitate member coordination and collective governance.

Survival statistics. Finally, we use the panel structure of DENU to examine firm survival. We construct firm-level entry and exit spells by tracking establishments across years and define an event as exit before the final panel year (2023). We then estimate survival functions using Kaplan–Meier (KM) methods.

Panel (a) of Figure 3 on page 31 compares cooperative and non-cooperative firms. At entry, all establishments have a survival probability of one, but attrition occurs rapidly. By 2016, cooperative firms already display a higher survival rate than non-cooperatives, and this advantage persists throughout the sample. After nine years, roughly one third of establishments remain active, with the survival curve for cooperatives consistently above that of non-cooperatives. A log-rank test confirms that the difference is statistically significant.

Panel (b) adds an important geographical dimension by stratifying firms according to whether they are located in localities with indigenous presence, as classified by the National Institute of Indigenous Languages (INALI). Two patterns stand out. First, across both indigenous and non-indigenous localities, cooperatives survive longer than comparable non-cooperatives. Second, survival probabilities are generally higher in indigenous localities, with cooperatives located near indigenous communities showing the most persistent trajectories. It is important to stress that our data do not distinguish between indigenous and non-indigenous cooperatives; instead, we capture whether a cooperative is located in a geography with indigenous presence.

These descriptive associations resonate with anthropological accounts that emphasize an *indigenous sense of community* and long-standing practices of collective work—such as *tequio*, *mayordomía*, and *faena*—which may help sustain cooperative enterprises (de la Fuente,

1944). Consistent with cross-cultural evidence on variation in cooperative behavior (Henrich et al., 2001), our results suggest that the institutional environment of indigenous localities is associated with greater durability of cooperative firms.

4 | EMPIRICAL FRAMEWORK

4.1 | Estimation Strategy

We examine whether cooperative firms foster local economic development using a balanced panel of 10×10 km grid cells covering Mexico from 2015 to 2023. Each cell-year observation contains information on cooperative firm presence, nightlight intensity per capita (our outcome), and a rich set of time-varying covariates. This fine-grained structure allows us to exploit both temporal and spatial variation in cooperative activity.

Our baseline specification is:

$$y_{i(m)t} = \alpha_{i(m)} + \alpha_t + \beta x_{i(m)t} + \gamma' w_{i(m)t} + \varepsilon_{i(m)t} \quad (1)$$

where $y_{i(m)t}$ denotes nightlight intensity per capita in cell i within municipality m at year t , and $x_{i(m)t}$ is the number of cooperatives in that cell (excluding *ejidos*). The control vector $w_{i(m)t}$ includes the number of non-cooperative economic units, as well as first-nature, second-nature, and socio-demographic predictors selected via the double-LASSO procedure (Belloni et al., 2014). We include cell (or municipality) fixed effects $\alpha_{i(m)}$ and year effects α_t , cluster standard errors at the cell level, and weight by year-cell population.

Equation (1) provides the backbone for three complementary strategies, exploiting different sources of time and spatial variation:

(i) OLS with two-way fixed effects (TWFE). We first estimate equation (1) directly. We use within-cell variation over time to relate changes in cooperative presence to changes in nightlights, conditional on time and location effects and selected controls. While sensitive to potential unobserved shocks, this approach provides the broadest benchmark estimate by exploiting all available variation in the panel.

(ii) Border Design (BD). Second, we narrow the comparison to treated cells and their immediate untreated neighbors. For each cell hosting a cooperative, we construct a buffer of surrounding cells and compare outcomes within this local neighborhood. This spatial design, akin to a geographic regression discontinuity (Keele and Titiunik, 2015), relies on continuity: adjacent cells within the same buffer are assumed to share geography and background trends, so differences in cooperative presence can be more credibly attributed to cooperative activity rather than unobserved shocks at broader regional scales.

(iii) Difference-in-Differences (DiD). Third, we study the timing of cooperative expansions. We compare cells that receive their first cooperative to those that do not, before and after entry. To address issues of staggered and potentially heterogeneous treatment effects (de Chaisemartin and D'Haultfœuille, 2023; Roth et al., 2023), we use the robust estimator of Callaway and Sant'Anna (2021). Identification requires conditional parallel trends: in the absence of treatment, cells with and without new cooperatives would have followed similar trajectories. Control groups are drawn both across time (never-treated or not-yet treated cells) and across space (neighboring untreated cells from the border sample).

Identification concerns. While these three approaches rely on different sources of variation, they do not fully eliminate endogeneity concerns. Reverse causality (cooperatives choosing faster-growing, or potentially more undeveloped areas), unobserved local shocks at the 10 km scale, and measurement error may still bias β . Because no single design rules these out entirely, we move to a shift-share instrumental variables (SSIV) strategy, which

provides our main identification framework.

4.2 | Main Identification Strategy: Shift-Share IV (SSIV)

We implement a shift-share design in the *many shocks* framework (Borusyak et al., 2022, 2025), leveraging numerous sectoral shocks while explicitly allowing exposure weights to be endogenous. Identification therefore comes *from the shifts*: as-good-as-random variation in many sectoral shocks is translated into cell-level treatment variation through fixed, pre-period exposures.

Specification. We estimate the long-differences equation between 2015 and 2023:

$$\Delta y_{i(m)} = \alpha_m + \beta \Delta x_{i(m)} + \gamma' \Delta \mathbf{w}_{i(m)} + \varepsilon_{i(m)}, \quad (2)$$

where Δ is 2023–2015, $y_{i(m)}$ is nightlights per capita, $\Delta x_{i(m)}$ the change in cooperative presence, $\Delta \mathbf{w}_{i(m)}$ long-difference controls, and α_m municipality-specific trends. Long differences avoid period-by-period construction of shocks, mitigate bias from serially correlated or lagged shocks, and focus on a single, cumulative change.

Instrument and exposures. Decomposing $\Delta x_{i(m)} = \sum_k \Delta x_{i(m)k}$ by sector k , the SSIV takes the form

$$z_{i(m)} = \sum_k s_{i(m)k} g_{km}, \quad (3)$$

where $s_{i(m)k}$ are exposure weights and g_{km} are shocks, defined below.

Exposure weights.

$$s_{i(m)k} \equiv x_{i(m)k}^{2013} \geq 0,$$

where $x_{i(m)k}^{2013}$ denotes the pre-period count of legally registered cooperatives in sector k and municipality m (2013 DENU). The intuition for using endogenous exposure shares builds on well-documented patterns of agglomeration and “demonstration effects” in cooperative development (Conte, 1986; Arando et al., 2012; Conte and Jones, 2015). New cooperatives are more likely to emerge where potential members can observe nearby successful examples, reducing informational and organizational barriers. Classic cases include cooperative clusters in Emilia–Romagna (Italy) and the Basque Country (Spain), where past density provided both know-how and proof of feasibility. In our setting, baseline cooperative presence captures this diffusion channel, while identification comes from interacting these endogenous exposures with plausibly exogenous demand shocks.

Because total exposures $S_{i(m)} = \sum_k s_{i(m)k}$ vary across cells (an incomplete-shares case), we control for $S_{i(m)}$ in both stages so that identification comes from the shocks g_{km} rather than from exposure mass (Borusyak et al., 2022, 2025).

Nearby-outside, nationally-demeaned shocks. For sector k and municipality m , let $\mathcal{N}^{(3)}(m)$ be the set of third-degree neighboring municipalities. From DENU microdata, we compute growth in *non-cooperative, medium/large* establishments, $g_{km't}$,¹² and define the

¹²Formally, growth is defined as $g_{k,m',t} = \frac{n_{k,m',t} - n_{k,m',t-1}}{\max\{n_{k,m',t-1}, 1\}}$, where $n_{k,m',t}$ is the number of non-cooperative, medium and large establishments in sector k and municipality m' at time t .

shock as

$$g_{km} \equiv \frac{1}{T} \sum_{t=2015}^{2023} \left(\bar{g}_{k, \mathcal{N}^{(3)}(m), t} - \bar{g}_{kt} \right),$$

where $\bar{g}_{k, \mathcal{N}^{(3)}(m), t}$ is the mean growth rate in $\mathcal{N}^{(3)}(m)$ and $\bar{g}_{kt}$ the national sector mean.¹³

By construction: (i) the own municipality is excluded; (ii) cooperatives and micro/small units are excluded (to sharpen demand signals and avoid mechanical correlation with treatment); and (iii) national sector trends are netted out. This *nearby-outside, nationally-demeaned* design captures spatially proximate demand shocks while removing the aggregation channel that invalidates Bartik instruments when exposures are endogenous.

Bridging the gap. At one extreme, the ideal shocks would be randomized sectoral demand shifts (e.g., random subsidies) or exogenous foreign shocks, such as trade-induced shifts used by Autor et al. (2013). At the other extreme, Bartik-style instruments (Bartik, 1991) rely on national industry growth, which embeds endogenous local supply shocks unless exposure shares are exogenous (Borusyak et al., 2025). Our design lies between these poles: it exploits local demand variation from nearby-but-not-adjacent municipalities, purges national means, and excludes cooperatives and micro/small firms. The result is a set of geographically heterogeneous shocks that are plausibly as-good-as-random and compatible with the “many exogenous shocks” framework, even when exposures are endogenous.

An intuitive example. Consider the coffee sector. To study exogenous shocks to cooperative presence in coffee, a national growth rate in coffee employment would be invalid: it reflects aggregated supply and demand factors and embeds the Bartik aggregation problem. Using own-municipality coffee growth would be worse, since it is mechanically endogenous to cooperative activity. Our shocks instead use the growth of non-cooperative, medium/large coffee firms in neighboring municipalities, net of national coffee growth. These shocks plausibly capture demand-side fluctuations—such as export opportunities or consumer taste shifts—that predict cooperative expansion through lagged exposure but affect outcomes only via cooperative entry. This mirrors the formal assumptions in Appendix B.1: exposure endogeneity is allowed, while orthogonality is required only for the shocks.

Estimation and inference. Following the concerns raised by Adão et al. (2019), we implement Borusyak et al. (2022) shock-level IV: residualize outcomes and treatments by controls and α_m , aggregate to (k, m) with exposure weights, and instrument $\bar{x}_{km}$ with g_{km} . Inference uses exposure-robust standard errors clustered by municipality and sector.

4.2.1 | SSIV validation

We next assess the credibility of the design by testing the two conditions required for consistency under Proposition : (i) that the shocks are *relevant* predictors of treatment, and (ii) that they are *plausibly exogenous* with respect to baseline outcomes and covariates. We also document the “many-shocks” requirement by reporting the effective number of shocks.

Relevance. The first condition requires that the constructed shocks predict changes in cooperative presence, i.e. that $(g_{km}, \Delta x_{i(m)}) \neq 0$. To test this, we regress the change in cooperative presence between 2015 and 2023 on the shocks defined in Section 4.2, using the shock-level specification implied by the aggregation theorem of Borusyak et al. (2022). Observations are weighted by baseline (2013) cooperative counts and we control for the

¹³ Appendix Figure B.1 shows the national mean sectoral growth rates of non-cooperative medium and large firms, by 4-digit NAICS code between 2015 and 2023.

total baseline number of cooperatives (to address incomplete shares). Standard errors are clustered by municipality and sector.

Figure 4 on page 32 shows a clear positive relationship: a one standard-deviation increase in shocks predicts a 0.09 standard-deviation increase in cooperative entry. This confirms that the instrument satisfies the *relevance* condition.

Many-shocks requirement. Assumption (iv) of Proposition requires that no single shock dominates the instrument. Following [Borusyak et al. \(2025\)](#), Table 1 reports summary statistics and effective numbers of shocks. With 146 effective shocks at the sector $\times$ municipality level and 30.4 at the municipality level, our design draws on a large set of quasi-random shocks comparable in richness to [Autor et al. \(2013\)](#). Concentration becomes an issue only when aggregating across sectors alone (effective shocks = 10.6), reinforcing the importance of our granular construction. These diagnostics support the many-shocks condition underlying identification.

TABLE 1 Descriptive statistics for shocks and importance weights

Variation source	Summary Statistics			Counts & Weights			
	Mean	SD	IQR	Observations	Effective no. of shocks	95th pct. weight	Max weight
Sector $\times$ Municipalities	0.001	0.031	0.028	3,462	146.0	0.1%	4.9%
Sector	0.000	0.013	0.012	193	10.6	2.2%	26.5%
Municipalities	0.001	0.023	0.023	1,042	30.4	0.4%	14.4%

Notes: The effective number of shocks equals the inverse Herfindahl index over normalized importance weights: $1 / \sum_k w_k^2$, where w_k are the average exposure weights for each shock normalized to sum to one. The 95th percentile and maximum report the upper tail of the normalized weight distribution, indicating potential concentration of influence by a few shocks.

Plausible exogeneity. Conditions (A1) and (A2) in Appendix B.1 require that the demand component of the shocks, net of national trends, and any remaining proxy noise are orthogonal to baseline unobservables. To probe this, we conduct covariate balance tests: regressions of $g_{k,m}$ on baseline characteristics (including 2015 nightlight intensity, infrastructure, demographics, and geography), aggregated to the shock level. We implement exposure-robust inference, clustering by municipality and sector, and report FDR-adjusted q -values ([Anderson, 2008](#)).

Table 2 on the following page shows that few covariates display moderate correlations, and none remain significant after FDR correction. As a joint test, we compute the omnibus statistic of [Kerwin et al. \(2024\)](#). Conventional OLS yields an F-statistic of 0.558 ($p=0.987$). To avoid over-rejection, we also implement randomization inference by permuting shocks within municipality–sector strata: the RI p -value is 0.550, indicating that any imbalance could plausibly arise by chance (Appendix Figure B.3).

Finally, baseline economic development—proxied by 2015 log nightlights—is uncorrelated with the shocks, providing a pre-trend test consistent with the assumption that shocks are orthogonal to initial outcomes. Together, these diagnostics provide empirical support for the orthogonality assumptions (A1–A2), showing the plausibility of exogeneity in our shocks underpinning our identification strategy.

5 | RESULTS

5.1 | OLS/TWFE

Cooperative presence is positively associated with local economic development. Table 3 on page 18 reports population-weighted OLS estimates of the association between the number of cooperative firms and log nighttime lights per capita across finely disaggregated 10×10

TABLE 2 Plausible Exogeneity: Balance tests with baseline covariates

Variable	Estimate (z-score)	Std. Error	FDR q-value
NLPC (2015)	-0.001	0.003	[0.716]
Roads: principal (2015)	-0.016	0.008	[0.268]
Roads: local (2015)	-0.045	0.038	[0.376]
Roads: secondary (2015)	-0.029	0.040	[0.575]
Transport & mobility infra. (2015)	-0.008	0.037	[0.777]
Distance to locality (km) (2015)	-0.016	0.031	[0.636]
Distance to large agglom. (2015)	0.004	0.022	[0.777]
Log population (2015)	-0.023	0.019	[0.376]
Lang Index	-0.115	0.055	[0.268]
Precipitation	-0.124	0.058	[0.268]
Temperature	0.086	0.049	[0.283]
Elevation	-0.112	0.065	[0.283]
Slope	-0.112	0.066	[0.283]
Land use: water	0.154	0.079	[0.268]
Land use: no vegetation	-0.001	0.026	[0.819]
Land use: settlements	-0.016	0.023	[0.588]
Land use: forest	-0.139	0.049	[0.147]
Land use: humid agriculture	0.005	0.009	[0.619]
Land use: rainfed agriculture	0.015	0.015	[0.443]
Land use: irrigated agriculture	0.039	0.046	[0.496]
Land use: shrubland	0.012	0.012	[0.443]
Land use: grassland	0.007	0.018	[0.698]
Land use: jungle	-0.015	0.010	[0.295]
Pop. 15–64 (% , 2010)	-0.039	0.019	[0.268]
Pop. 65+ (% , 2010)	-0.040	0.022	[0.283]
Foreign-born (% , 2010)	-0.032	0.020	[0.283]
No primary school (% , 2010)	-0.046	0.023	[0.268]
No secondary school (% , 2010)	0.041	0.021	[0.268]
Indigenous hh (% , 2010)	0.053	0.029	[0.283]
Labor force (% , 2010)	-0.011	0.012	[0.443]
Without social security (% , 2010)	0.044	0.015	[0.147]
Catholic (% , 2010)	-0.041	0.028	[0.323]
No religion (% , 2010)	0.079	0.033	[0.268]
Sex ratio (2010)	-0.004	0.007	[0.625]
Avg. people per hh (2010)	0.018	0.019	[0.443]
Schooling years (avg., 2010)	-0.046	0.020	[0.268]
Employed (% , 2010)	0.050	0.023	[0.268]
Unemployed (% , 2010)	-0.007	0.005	[0.344]

Notes: Entries are standardized coefficients from pairwise regressions of the municipality–sector shock $g_{k,m}$ on baseline covariates. Standard errors are clustered at municipality and sector levels, with weights equal to exposure mass. q-values report [Anderson \(2008\)](#) FDR adjusted p-values.

km grid cells during 2015–2023. This high-resolution setup allows us to exploit within-unit variation at a very localized level, though the estimates should still be interpreted as correlations rather than causal effects.

Columns (1)–(2) report specifications that control only for longitude and latitude, with column (2) restricting the sample to rural grid cells. Column (3) adds year and municipality fixed effects, while column (4) introduces high-dimensional grid-cell and municipality-by-year fixed effects. Columns (5)–(6) further control for establishment size and the presence of ejidos. Notably, the inclusion of grid-cell fixed effects alone accounts for more than 93% of the total variation in log nighttime lights per capita.

TABLE 3 OLS: Nighttime Lights per Capita and Cooperative Presence

	Nighttime lights per capita (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No. of Cooperatives (not ejidos)	0.0181 (0.0047)	0.0177 (0.0065)	0.0075 (0.0033)	0.0054 (0.0025)	0.0060 (0.0024)	0.0060 (0.0024)	0.0063 (0.0024)	
1[Co-op] (dynamic, not ejidos)								0.0649 (0.0203)
Lon & Lat	✓	✓	✓					
Only rural cells		✓	✓	✓	✓	✓	✓	✓
Units size controls					✓	✓	✓	✓
D-LASSO							✓	✓
No. of Ejidos						✓	✓	✓
Year FE			✓					
Municipality FE			✓					
Raster FE				✓	✓	✓	✓	✓
Municipality × Year FE				✓	✓	✓	✓	✓
Observations	122,517	120,591	120,591	120,591	120,591	120,591	120,591	120,591
Grid cells	13,613	13,399	13,399	13,399	13,399	13,399	13,399	13,399
Adjusted R ²	0.0048	0.0038	0.2967	0.9393	0.9394	0.9394	0.9394	0.9394

Notes: The table reports population-weighted OLS associations between log nightlight intensity per capita (NLPC) and the number of cooperative firms across 10×10 km grid cells, 2015–2023. The main regressor is the number of cooperatives excluding *ejidos*; in column (8) it is replaced by a dynamic indicator equal to one from the first year a cooperative appears in the cell onward. Columns (1)–(2) include longitude and latitude; column (2) restricts the sample to non-urban (rural) cells. Column (3) adds year and municipality fixed effects. Columns (4)–(8) include raster fixed effects and municipality $\times$ year fixed effects. Columns (5)–(8) control for the establishment-size composition (counts of small, medium, and large non-cooperative units) and absorb fixed effects for total establishment counts. Columns (6)–(8) additionally control for the number of *ejidos*. Columns (7)–(8) further augment the specification with controls selected via a double-LASSO procedure from geographic, infrastructure, and socioeconomic predictors. The time-invariant control is the distance to the nearest high-agglomeration grid cell (pooled across years), while the time-varying controls include (log) principal roads, (log) local roads, (log) secondary roads, and the number of transport and mobility infrastructure points at the grid-cell level. Standard errors are clustered at the raster level.

Column (7) presents our most demanding specification, where the association is estimated controlling for raster and municipality-by-year fixed effects, establishment-size composition, ejido counts, and time-varying controls selected via double-LASSO. The results indicate that the addition of one cooperative firm within a grid cell is associated with a 0.63% increase in nightlight density.

Finally, column (8) replaces the continuous measure with a dynamic indicator of cooperative entry, yielding similar estimates. This reinforces the pattern that areas with more cooperative activity tend to experience higher levels of local development as captured by nighttime light intensity.

Overall, the findings highlight a robust positive association between cooperative activity and local development, which persists across increasingly demanding specifications.

5.2 | Border Design

While the OLS/TWFE estimates show a positive association between cooperative presence and our proxy for local economic development, a concern remains that these estimates compare grid cells that may differ in unobserved ways unrelated to cooperative activity. In particular, untreated cells located far from cooperatives may not provide an appropriate counterfactual for those that host cooperative firms.

From this point onwards, we restrict the analysis to the sample of *rural grid cells*. This restriction ensures that our comparisons are not confounded by structural differences between urban and rural areas, and provides a more homogeneous setting in which to evaluate local spillovers of cooperative activity.

To address the counterfactual concern, we turn to a *border design* (BD) strategy that leverages spatial discontinuities in cooperative presence. The idea is to compare grid cells that lie on either side of the “border” of cooperative presence: cells hosting at least one cooperative (treated) and their immediately adjacent non-cooperative neighbors (domain controls). This design ensures that comparisons are drawn across finely matched spatial units that are geographically proximate, and thus more likely to share similar unobserved characteristics.

Panel (a) of Figure 5 on page 33 illustrates the identification strategy. Colored cells indicate grid cells hosting at least one cooperative in 2015, with intensity bins reflecting the number of cooperatives. The black polygons delineate “domains” (or “buffers”), i.e., sets of neighboring cells grouped around an anchor treated cell. Control cells are drawn from the same domains, providing local counterfactuals. The identifying assumption is one of *spatial continuity*: absent cooperative presence, treated and domain-control cells would have followed parallel trends in local economic development.

Formally, we estimate regressions of nightlight density on cooperative presence restricting the sample to treated and domain-control cells. The first specification exploits within-cell variation in cooperative presence and nightlight density, conditioning on cell and municipality-by-year fixed effects. The second specification adds domain-by-year fixed effects, thereby comparing changes in cooperative activity and outcomes only among cells that belong to the same domain in the same year. This ensures that comparisons are not only spatially local but also contemporaneous within each cluster.

Panel (b) of Figure 5 on page 33 reports the results. Both specifications yield positive and statistically significant effects, consistent with the OLS/TWFE estimates but now under a more credible identification strategy. The magnitude of the estimated effects remains stable when moving from the baseline border design to the specification with buffer-by-year fixed effects: one extra cooperative firm is associated with a 0.72% increase in nightlight density. Provided that unobserved characteristics vary smoothly within domains and there is no selection into treatment across the border, the BD coefficients can be interpreted as causal effects of cooperative presence on local development.

5.3 | DiD/Event study

While our BD estimates provide evidence of a positive association between cooperative presence and local development, they rely on a continuity assumption that may be violated if unobserved spatial characteristics differ sharply across borders. Moreover, the BD design captures effects along the *intensive margin* (changes in the number of cooperatives), whereas we are also interested in the *extensive margin*—the effect of cooperative entry into previously untreated cells.

To investigate this, we exploit the panel structure of our data and implement a Difference-

in-Differences (DiD) design. The key identifying assumption is that of *parallel trends*: in the absence of cooperative entry, grid cells that eventually receive their first cooperative would have experienced similar trends (though not necessarily levels) in local development as those that remain untreated. Column (8) of Table 3 on page 18 already suggested that cooperative entry is positively associated with nightlight density. However, that specification does not provide a test of the parallel trends assumption and, because of staggered treatment adoption, risks making inappropriate comparisons across already-treated, not-yet-treated, and never-treated cells (Goodman-Bacon, 2021; de Chaisemartin and D’Haultfœuille, 2023; Roth et al., 2023).

Appendix Figure C.1 shows the timing of cooperative entry. While the majority of cells remain untreated throughout the period, a substantial number experience new entries between 2015 and 2023, generating the variation needed to identify dynamic effects.

We therefore estimate an event-study design using the Callaway and Sant’Anna (2021) estimator, which is robust to treatment effect heterogeneity and staggered adoption. This estimator recovers cohort-specific effects and averages them into dynamic treatment effects, while restricting comparisons to treated units and not-yet-treated controls, thus avoiding forbidden comparisons. To sharpen identification, we drop the 2015 cohort (which is always treated) and exclude never-treated cells, relying exclusively on not-yet-treated cells as the control group to make the parallel trends assumption more credible.

Figure 6 on page 34 reports the event-study estimates. Panel (a) presents results for the full sample. The pre-treatment coefficients are close to zero and statistically indistinguishable from it, lending support to the parallel trends assumption. After cooperative entry, we observe statistically significant and increasing effects: cooperative presence is associated with sustained growth in nightlight density.

Panel (b) replicates the analysis using the BD subsample of treated cells and their neighboring controls, thereby strengthening spatial comparability. In this more restrictive design, the estimates are somewhat more precise, the pre-treatment dynamics remain flat, and the post-entry effects are of comparable magnitude: two to four years after the arrival of at least one cooperative firm, nightlight density is higher by approximately 6.4% to 8.2%.

Taken together, the DiD event-study results corroborate the OLS/TWFE and BD findings: cooperative entry is followed by persistent increases in local economic development, as proxied by nightlight density.

5.4 | SSIV Results

Our three strategies—OLS/TWFE, the border design, and difference-in-differences—all pointed to a positive relationship between cooperative presence and local development. Yet, as discussed earlier, the causal interpretation of these estimates depends on assumptions that may not hold if cooperatives endogenously select into more dynamic cells. To address this concern, we turn to the shift-share IV (SSIV) design, which, as outlined in Section 4.2, leverages plausibly exogenous sectoral shocks from nearby municipalities to instrument for local cooperative growth.

The SSIV estimator identifies β in (2) by exploiting as-good-as-random variation in shocks g_{knt} , interacted with predetermined cooperative exposures $s_{ik,2013}$. Unlike Bartik-style instruments, this approach does not rely on exposure exogeneity: our identification comes entirely from the shocks, which are constructed to be orthogonal to local unobservables by (i) excluding own municipalities, (ii) excluding cooperatives and micro/small units, and (iii) demeaning national sector-year trends. The validity of the design rests on the conditions laid out in Proposition : relevance, many-shocks, and orthogonality of shocks. Section 4.2.1 provided empirical support for these conditions.

TABLE 4 Shift-Share IV: Effect of Δ Co-ops on Δ Nighttime Lights per Capita

	Δ Nighttime lights per capita (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Co-ops	0.0155 (0.0073)	0.0266 (0.0114)	0.0285 (0.0114)	0.0286 (0.0114)	0.0275 (0.0124)	
Δ Co-ops (Micro and Small)						0.0245 (0.0075)
Shock level	✓	✓	✓	✓	✓	✓
Lon & Lat	✓	✓	✓	✓	✓	✓
Municipal FE	✓	✓	✓	✓	✓	✓
Incomplete shares (S_i)		✓	✓	✓	✓	✓
Units size controls (Δ)			✓	✓	✓	✓
No. of Ejidos (Δ)				✓	✓	✓
Roads/Transport (Δ)					✓	✓
Observations	3,462	3,462	3,462	3,462	3,462	3,462
F-test (1st stage)	104.2	50.52	82.89	83.15	83.11	40.60

Notes: The table reports shift-share IV (SSIV) estimates of the effect of changes in cooperative presence on changes in (log) nighttime lights per capita at the grid-cell level between 2015 and 2023. The endogenous regressor is the change in the number of cooperatives, and the instrument is constructed as $z_i = \sum_k s_{ik,2013} \tilde{g}_{k,m}$, where $s_{ik,2013}$ are baseline (2013) cooperative shares at the 4-digit sector level and $\tilde{g}_{k,m}$ are sectoral shocks computed as third-degree neighboring municipality growth net of national sector-by-year averages. All specifications are estimated in first differences, weighted by total exposure (s_n), and estimated at the level of sectoral shocks (Borusyak et al., 2022). All specifications residualize for longitud, latitude, and municipal fixed effects at the grid cell level before aggregating at the shock level. Column (1) includes only the shift-share instrument. Column (2) adds the incomplete-share term $S_i = \sum_k s_{ik,2013}$ to isolate variation arising from shifts rather than levels. Column (3) further controls for changes in the size distribution of non-cooperative establishments (small, medium, and large). Column (4) additionally controls for changes in the number of extitejidos. Columns (5) and (6) augments the specification with changes in infrastructure measures (principal roads, local roads, secondary roads, and transport/mobility points). Standard errors are two-way clustered at the municipality and 4-digit sector level. Reported F-statistics correspond to the first stage on Δ Co-ops.

Table 4 on the previous page reports the SSIV estimates. Column (1) presents the baseline specification, where changes in cooperative presence are instrumented solely with the shift–share term. Column (2) introduces the incomplete-share correction S_i , ensuring that identification comes from shifts rather than exposure levels. Column (3) adds controls for the changing size distribution of non-cooperative establishments, Column (4) controls for changes in the number of *ejidos*, and Column (5) adds controls for infrastructure changes (roads and transport facilities). All specifications are estimated at the shock level with exposure-robust inference.

Across specifications, the effect of cooperative presence on local development is consistently positive and statistically significant. In our most demanding specification (Column 5), the coefficient implies that one additional cooperative raises nighttime light intensity per capita by roughly 2.9%. The stability of the point estimates across specifications underscores that the results are not driven by incomplete-share bias, changes in non-cooperative firm size composition, or infrastructure confounders.

Taken together, the SSIV results provide a causal interpretation of the relationship documented in the OLS, border design, and DiD estimates. The identifying variation comes from sectoral demand shocks in neighboring municipalities—plausibly exogenous shifts that affect local development only through their impact on cooperative expansion. The validation exercises in Section 4.2.1 support the underlying assumptions: the shocks are strongly predictive of cooperative growth (relevance), numerous and not overly concentrated (many-shocks), and uncorrelated with baseline covariates or pre-trends (plausible exogeneity). Under these conditions, the SSIV estimates can be interpreted as causal effects of cooperative entry on local development.

5.5 | Robustness

Our findings demonstrate remarkable consistency across four distinct identification strategies, each relying on different sources of variation and identifying assumptions. Moreover, the results are coherent across both the extensive margin (cooperative entry) and the intensive margin (changes in the number of cooperatives), with effect magnitudes that align when accounting for the different scales of variation. This convergence of results across methodologically diverse approaches provides strong evidence for the robustness of our central finding that cooperative presence fosters local economic development.

To further validate our main SSIV estimates, we now test their robustness to a range of additional potential concerns.

Weak instruments. A first concern is that the shift–share instrument may be weak, raising the risk of biased estimates. Across all specifications, however, the instrument performs well. The effective first-stage F-statistics (Olea and Pflueger, 2013) reported in the bottom rows of Table 4 on the preceding page consistently exceed conventional thresholds, indicating strong instrument relevance. Moreover, since the model is just-identified, the scope for weak instrument bias is limited (Angrist and Kolesár, 2024).

Medium and Large Cooperatives. Although medium and large cooperatives are relatively few, we test whether our results are sensitive to their exclusion. Column (6) in Table 4 on the previous page, reports estimates based only on micro and small cooperatives. The results are very similar to those obtained when including all cooperative sizes, indicating that our findings are not only driven by medium or large cooperative firms.

Alternative local development measures. Another relevant concern is that nightlight density might not fully capture local development, or that it is not as easily benchmarked as other standard measures.

To address this concern, we use local development measures at the locality level, a

geographic non-administrative unit measured by INEGI, in the 2010 and 2020 Census. As explained in Section 3.1, we match each grid cell with the closest locality and assign the socio-economic characteristics from 2010 and 2020. We control for whether we match the same locality and for the distance to the locality.

We then adapt Equation (2) on page 14 to evaluate how changes in cooperatives between 2015 and 2020 affect changes in local development measures between 2010 and 2020. The results are presented in Table 5.

The estimates show that increases in cooperative presence lead to significant improvements across multiple dimensions of local development. Specifically, we find that cooperative growth is associated with increases in mean years of schooling and household asset indices, while reducing persons per room (indicating less crowding) and unemployment rates. We also observe changes in migration patterns, with increases in the share of residents living in the same state and decreases in the share from other states, suggesting that cooperative development may reduce out-migration pressures.

Most coefficients are statistically significant after correcting for multiple testing using FDR q-values (Anderson, 2008). These results complement our nightlight-based findings and provide additional evidence that cooperative development generates broad-based improvements in local socio-economic conditions.

TABLE 5 SSIV: Effect of Δ Co-ops on Δ Local Development measures

	Mean years of schooling (Δ SD) (1)	Avg. number of children per woman (Δ SD) (2)	Persons per room (Δ SD) (3)	Share without health insurance (Δ SD) (4)	Household asset index (Δ SD) (5)	Unemployment rate (Δ SD) (6)	Share living in same state (Δ SD) (7)	Share from another state (Δ SD) (8)
Δ Co-ops	0.0488 (0.0187)	-0.0259 (0.0226)	-0.0433 (0.0121)	0.0055 (0.0266)	0.0261 (0.0062)	-0.0260 (0.0041)	0.0215 (0.0079)	-0.0340 (0.0182)
FDR q-value	[0.010]	[0.093]	[0.001]	[0.265]	[0.001]	[0.001]	[0.009]	[0.033]
Observations	3,462	3,462	3,462	3,462	3,462	3,462	3,462	3,462
F-test (1st stage)	83.30	83.30	83.30	83.30	83.30	83.30	83.30	83.30

Notes: The table reports shift-share IV (SSIV) estimates of the effect of changes in cooperative presence on changes on local development indicators at the locality level matched at the grid-cell level between 2010 and 2020. The endogenous regressor is the change in the number of cooperatives between 2015 and 2020, and the instrument is constructed as $z_t = \sum_k s_{1k,2013} \bar{g}_{k,m}$, where $s_{1k,2013}$ are baseline (2013) cooperative shares at the 4-digit sector level and $\bar{g}_{k,m}$ are sectoral shocks computed as third-degree neighboring municipality growth net of national sector-by-year averages. All specifications are estimated in first differences, weighted by total exposure (s_{it}), and estimated at the level of sectoral shocks (Borusyak et al., 2022). All specifications residualize for longitude, latitude, and municipal fixed effects at the grid cell level before aggregating at the shock level. All specification control for the incomplete-share term $S_t = \sum_k s_{1k,2013}$ to isolate variation arising from shifts rather than levels; for changes in the size distribution of non-cooperative establishments (small, medium, and large); for changes in the number of ejidos; for changes in infrastructure measures (principal roads, local roads, secondary roads, and transport/mobility points). Standard errors are two-way clustered at the municipality and 4-digit sector level. Reported F-statistics correspond to the first stage on Δ Co-ops.

Sector influence. An important consideration is whether our results are disproportionately driven by a handful of industries. This issue is particularly salient given i) we include different types of cooperatives (consumption, production, and savings-and-loan), and ii) the diagnostics in Table 1 on page 16, which show that exposure weights are highly concentrated, with some sectors accounting for nearly one quarter of the total.

To probe this, we first conduct a leave-one-industry-out exercise. As shown in Appendix Figure C.2, excluding each sector in turn yields stable SSIV estimates: only *Fishing* (NAICS 1141) generates a negative coefficient, though it is statistically indistinguishable from both the baseline and zero. This sector's apparent influence likely reflects its large leverage in the instrument, as it alone represents about 26.5% of the total weights (Appendix Figure C.3).

To address this directly, we re-estimate the SSIV specification while capping the fishing sector's exposure weights at different thresholds: the 99th, 95th, 90th, and 75th percentiles of its distribution, as well as the Tukey upper whisker. This procedure down-weights extreme observations, limiting the disproportionate leverage of fishing.

Appendix Figure C.4 shows that across all caps the estimates remain positive, close to the baseline, and statistically overlapping. Thus, the main SSIV result is not driven by extreme values within the fishing sector: even after heavily curbing its influence, the cooperative

effect on local development remains stable. Finally, to further verify that the main results are not driven by the fishing sector, we replicate the event-study analysis excluding all cooperatives in fishing. Appendix Figure C.5 shows that the dynamic effects remain positive and of similar magnitude, confirming that our findings are robust to the exclusion of this sector.

Sensitivity to the exclusion restriction. A central challenge for our identification strategy is that the instrument must affect local development solely through cooperative presence. In our context, this requires that plausibly exogenous shocks—once weighted by lagged cooperative exposure shares—influence nightlight density only via changes in cooperatives, and not through other time-varying channels.

While Table 2 on page 17 showed that shocks are orthogonal to baseline covariates, one might still worry that sectoral growth in nearby medium and large non-cooperative firms could indirectly spur the creation of other firms or otherwise shape local development. To address this, Appendix Table C.1 reports balance tests on time-varying outcomes and covariates.

The results provide no evidence that shocks directly predict changes in (log) nightlight density between 2015 and 2023. Nor are shocks systematically correlated with changes in the total number of establishments, by size (large, medium, small, or micro), or with infrastructure variables such as roads and transport facilities. Consistent with this, Table 4 on page 21 also reports specifications that include these controls directly, with estimates remaining positive and statistically significant.

We further probe the exclusion restriction using a zero first stage test (van Kippersluis and Rietveld, 2018). The idea is straightforward: if shocks operate only through cooperatives, then in subsamples where exposure weights s_n are near zero, the first stage (instrument on cooperatives) should vanish, and so should the reduced form (instrument on nightlight density).

We implement this test by progressively restricting the sample to the bottom 5–35% of the exposure distribution and re-estimating both the first stage (π) and reduced form (γ). Appendix Figure C.6 confirms the expected pattern: in subsamples with limited exposure, both coefficients converge to zero, with confidence intervals overlapping the null.

Taken together, the balance tests and zero first stage test provide complementary evidence in support of the exclusion restriction. Overall, the shocks appear to operate exclusively through cooperative presence, rather than through alternative channels of local development.

OLS–IV Decomposition. A key issue with our empirical strategy is that the direction of bias in OLS estimates is *a priori* ambiguous, making it unclear what our SSIV estimates capture. If more productive cooperatives self-select into dynamic areas (*positive selection*), OLS will be upward biased, while if they locate in poorer or declining areas (*negative selection*), OLS will be downward biased. Classical measurement error—for example, overcounting of cooperatives in the registry—would instead attenuate coefficients toward zero. Because these forces pull in opposite directions, it is not evident whether OLS should lie above or below IV. To probe this, we apply the decomposition framework of Ishimaru (2024).

This approach partitions the OLS–IV gap into three components: (i) *covariate weight differences*, reflecting that OLS and IV emphasize different subpopulations; (ii) *treatment-level weight differences*, capturing differences in the range of treatment intensity emphasized when effects are nonlinear; and (iii) the *marginal effect difference*, which captures residual discrepancies due to endogeneity bias or unobserved treatment heterogeneity. The decomposition helps identify whether the OLS–IV gap reflects weighting differences or genuine endogeneity.

Appendix Figure C.7 shows that covariate and treatment-level differences account for

only a negligible share of the gap. Instead, nearly all of it (about 96%) is explained by the marginal effect difference. This indicates that the divergence between OLS and IV cannot be attributed to weighting artifacts, but is consistent with endogeneity in OLS, even if the exact source—selection, measurement error, or unobservables—cannot be fully separated.

5.6 | Heterogeneity

We next explore whether the effects of cooperatives on local development vary with baseline characteristics of grid cells, providing suggestive evidence on the contexts where cooperatives may matter more.

TABLE 6 SSIV: Heterogeneous Effects of Δ Co-ops on Δ Nighttime Lights per Capita

	Δ Nighttime lights per capita (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Coops (baseline, $Z = 0$)	0.0294 (0.0142)	0.0276 (0.0091)	0.0469 (0.0102)	0.0373 (0.0109)	0.0219 (0.0071)	0.0499 (0.0245)
Δ Coops $\times$ Low population ($\leq$ mean)	0.4243 (0.3501)					
Δ Coops $\times$ Low human capital ($\leq$ mean)		0.0278 (0.0240)				
Δ Coops $\times$ High sector diversity (low HHI)			0.0658 (0.0246)			
Δ Coops $\times$ Low tertiary sector share ($\leq$ mean)				0.1337 (0.1517)		
Δ Coops $\times$ High indigenous share ($\geq$ mean)					0.1248 (0.0322)	
Δ Coops $\times$ High Catholic share ($\geq$ mean)						0.1633 (0.0791)
Observations	3,462	3,462	3,462	3,462	3,462	3,462
F-test (1st stage), Δ Coops (baseline, $Z = 0$)	41.71	48.39	40.22	37.89	49.12	58.50
F-test (1st stage), Δ Coops $\times$...	9.079	126.1	206.5	11.10	114.4	151.7

Notes: Notes: The table reports shift-share IV (SSIV) estimates of the effect of changes in cooperative presence on changes in (log) nighttime lights per capita at the grid-cell level between 2015 and 2023. The endogenous regressor is the change in the number of cooperatives, instrumented with $z_i = \sum_k s_{ik,2013} \bar{g}_{k,m}$, where $s_{ik,2013}$ are baseline (2013) cooperative shares at the 4-digit sector level and $\bar{g}_{k,m}$ are sectoral shocks computed as third-degree neighboring municipality growth net of national sector-by-year averages. For the heterogeneity analysis, both the endogenous regressor and the instrument are interacted with baseline indicators (population size, human capital, sectoral diversity, indigenous share, and Catholic share), and the baseline indicators are included directly as controls. All specifications are estimated in first differences, weighted by total exposure (s_n), and estimated at the level of sectoral shocks (Borusyak et al., 2022). All specifications residualize for longitude, latitude, and municipal fixed effects at the grid cell level before aggregating at the shock level. All specification control for the incomplete-share term $S_i = \sum_k s_{ik,2013}$ to isolate variation arising from shifts rather than levels; for changes in the size distribution of non-cooperative establishments (small, medium, and large); for changes in the number of *ejidos*; for changes in infrastructure measures (principal roads, local roads, secondary roads, and transport/mobility points). Standard errors are two-way clustered at the municipality and 4-digit sector level. Reported F-statistics correspond to the first stage on Δ Co-ops.

Specifically, we extend our SSIV specification by interacting the change in cooperative presence and its instrument—sectoral shocks in economic unit growth—with indicators for baseline population size, human capital, sectoral diversity, and the prevalence of indigenous or Catholic populations. Each regression also includes the baseline indicator itself as a direct control, so the interaction terms capture differential effects of cooperative entry across these dimensions.

Table 6 reports the results. Across specifications, the baseline effect of cooperatives remains positive and statistically significant. By contrast, interactions with low population,

low human capital, or low tertiary sector share yield weaker and noisier estimates.

The results suggest stronger effects in areas with higher sectoral diversity (Column (3)), consistent with the idea that cooperative activity may spur development in contexts with greater economic complementarities. We also find indicative evidence of stronger effects in places with larger shares of indigenous or Catholic populations (Columns (5)–(6)). This pattern resonates with anecdotal accounts of religious orders supporting cooperatives, as well as with the cooperative traditions in some indigenous communities, echoing recent evidence on complementarities between cultural factors and policy interventions (Bau et al., 2025).

6 | MECHANISMS

We now turn to potential mechanisms that may explain why cooperative firms foster local development. Importantly, this is a *bundle treatment*: cooperatives can influence development through multiple microeconomic channels. They may facilitate access to capital, enable risk pooling, raise firm productivity, increase labor income and consumption, or act as economic and social buffers in the face of shocks, among other possibilities.

In the absence of detailed firm-level data that would allow us to systematically compare cooperatives and non-cooperatives across these dimensions, it is difficult to isolate the dominant channel. Instead, we leverage data at the grid-cell and municipal level to provide suggestive evidence on the aggregate pathways through which cooperatives contribute to local development.

| Sectoral structure.

One potential channel through which cooperatives affect local development is by reshaping the sectoral composition of the economy.

Cooperatives could foster diversification by entering complementary activities, or reinforce concentration if they cluster within a few industries. Because sectoral diversity and the balance across primary, secondary, and tertiary activities are often linked to resilience and growth, examining these dynamics helps clarify how cooperatives contribute to development.

We construct measures of sectoral structure at the grid-cell level between 2013 and 2023 using DENU microdata. At the 4-digit sector level, we compute the Herfindahl–Hirschman Index (HHI), a measure of concentration. We also classify establishments into broad sectors (primary, secondary, and tertiary) using 2-digit SCIAN codes, and calculate their respective shares of total establishments. In all cases, cooperatives are excluded from these measures to avoid mechanical correlations.

We then take changes between 2015 and 2023—in line with our main outcome on night-light density—and regress each of these indicators on instrumented changes in cooperative presence. This allows us to assess whether cooperatives are associated with shifts in local economic structure, such as increased diversification or changes in the relative weight of primary, secondary, and tertiary activities.

Table 7 on the following page presents the results. We find that increases in cooperative presence are associated with a rise in the Herfindahl–Hirschman Index. Since the HHI measures concentration, a higher value indicates less diversification, suggesting that cooperative growth tends to reinforce activity in a narrower set of industries within a locality.

Turning to sectoral shares, we observe a positive effect on primary activities, little change in secondary activities, and a decline in tertiary activities. Overall, cooperative presence

TABLE 7 SSIV: Effect of Δ Co-ops on Changes in Sectoral Structure (2015–2023)

	Δ HHI (SCIAN-4)	Δ Share primary	Δ Share secondary	Δ Share tertiary
	(1)	(2)	(3)	(4)
Δ Co-ops	0.0192 (0.0091)	0.0357 (0.0103)	-0.0034 (0.0039)	-0.0157 (0.0044)
FDR q-value	[0.025]	[0.002]	[0.108]	[0.002]
Observations	3,462	3,462	3,462	3,462
F-test (1st stage)	83.11	83.11	83.11	83.11

Notes: Each column reports a shift-share IV (SSIV) estimate of the effect of changes in cooperative presence on changes in sectoral composition between 2015 and 2023. Outcomes are: the Herfindahl–Hirschman Index (SCIAN-4) and the shares of primary, secondary, and tertiary establishments (SCIAN-2). The endogenous regressor is the change in the number of cooperatives; the instrument is $z_i = \sum_k s_{ik,2013} \tilde{g}_{k,m}$, where $s_{ik,2013}$ are baseline (2013) cooperative counts by 4-digit sector and $\tilde{g}_{k,m}$ are sectoral shocks from third-degree neighboring municipalities net of national sector-by-year means. All specifications are estimated in first differences, weighted by total exposure (s_{it}), and estimated at the level of sectoral shocks (Borusyak et al., 2022). All specifications residualize for longitud, latitude, and municipal fixed effects at the grid cell level before aggregating at the shock level. All specification control for the incomplete-share term $S_i = \sum_k s_{ik,2013}$ to isolate variation arising from shifts rather than levels; for changes in the size distribution of non-cooperative establishments (small, medium, and large); for changes in the number of *ejidos*; for changes in infrastructure measures (principal roads, local roads, secondary roads, and transport/mobility points). Standard errors are two-way clustered at the municipality and 4-digit sector level. Reported F-statistics correspond to the first stage on Δ Co-ops.

appears to shift local economies toward primary activities and away from services, while also concentrating the distribution of establishments across sectors. These results suggest a potential mechanism through which cooperatives shape local economic structure.

| Infrastructure, Public Goods, and Market Access.

A natural possibility is that cooperative firms foster local development by improving access to markets and public goods. Better connected areas, with more roads or transport facilities, could enhance the diffusion of goods and services, reduce costs, and integrate local economies into broader markets. If cooperatives were able to mobilize or attract such investments, one would expect to see systematic changes in the provision of infrastructure where they expand.

To test this, we estimate the effect of changes in cooperative presence on grid-cell level measures of infrastructure and market access between 2015 and 2023. Specifically, we examine log changes in the length of main roads, local streets, and secondary roads, as well as changes in the number of transport and mobility facilities. The results, reported in Appendix Table D.1, show no systematic relationship between cooperative growth and improvements in infrastructure provision. The estimated coefficients are small in magnitude and statistically indistinguishable from zero, consistent with the simple correlations shown in Appendix Table C.1.

This null finding suggests that while cooperatives appear to shape other aspects of local economic development, they do not by themselves generate additional infrastructure or public goods provision. Instead, their positive effects may require complementary top-down investments in market access, such as those provided by state or municipal governments. In this sense, cooperatives might contribute to local development through other channels, but infrastructure provision seems to lie outside their direct scope of influence. g market access and the positive effects of cooperative firms

| Agricultural productivity.

If cooperative firms foster specialization into primary activities, then one potential mechanism for their effect on local development is through productivity gains in the agricultural sector. Since most cooperatives in our setting operate in agriculture and livestock production, the productivity channel is a natural test case. However, we cannot directly observe intra-firm dynamics or farm-level productivity. Instead, we rely on municipal-level agricultural data to proxy for sectoral productivity.

Specifically, we use annual Agricultural and Livestock Production Statistics (SIAP) from 2015 to 2023, which provide detailed information on surface cultivated, harvested output, rural producer prices, and the value of production by crop and municipality. From these data, we construct a set of specialization-weighted indicators at the municipality level: (i) total cultivated surface, (ii) yield per hectare (tons/ha), (iii) production value per hectare (in real 2020 pesos), (iv) median rural price (pesos/ton, real 2020), and (v) crop diversity measured by the Shannon index of cultivated area shares. We then take first differences (2023 minus 2015, in logs where appropriate) to capture medium-run changes in agricultural productivity.

TABLE 8 SSIV (Municipality-Level): Effect of Δ Co-ops on Δ Agricultural Productivity (2015–2023)

	Δ Cultivated surface (log, hectares) (1)	Δ Yield per hectare (log) (2)	Δ Production value per hectare (log) (3)	Δ Median Price per hectare (log) (4)	Δ Crop diversity (Shannon index) (5)
Δ Co-ops	0.001 (0.005)	0.010 (0.002)	0.011 (0.004)	0.0008 (0.003)	0.012 (0.003)
FDR q-value	[0.495]	[0.001]	[0.003]	[0.495]	[0.001]
Observations	4,497	4,497	4,497	4,497	4,497
F-test (1st stage)	56.0	56.0	56.0	56.0	56.0

Notes: The table reports shift-share IV (SSIV) estimates at the municipality level. Outcomes are changes (log differences, 2023 minus 2015) in specialization-weighted agricultural indicators at municipality m : cultivated surface (hectares), yield (tons/ha), value per hectare (pesos/ha, real 2020), rural price (pesos/ton, real 2020), and Shannon diversity. The endogenous regressor is Δ Co-ops at the municipality level (2015–2023). The instrument is constructed as $z_m = \sum_k s_{mk,2013} \tilde{g}_{k,m}$, where $s_{mk,2013}$ are baseline (2013) cooperative exposure shares at 4-digit sector k , and $\tilde{g}_{k,m}$ are sectoral shocks computed from third-degree neighboring municipalities' growth net of national sector-by-year averages. Estimation follows a two-stage least squares at the shock level after aggregating municipality data with exposure weights $s_{mk,2013}$ (reported as s_n). All specifications control for longitude, latitude, log(area), and log(population) via residualization in the aggregation step, and include fixed effects for agglomeration class and state (cve_ent). Controls include the incomplete-share term $S_m = \sum_k s_{mk,2013}$, changes in the size distribution of non-cooperative establishments (small/medium/large), changes in the number of ejidos, and changes in infrastructure (principal roads, local roads, secondary roads, and transport/mobility points). Standard errors are two-way clustered at the municipality and 4-digit sector level. Reported F-statistics correspond to the first stage on Δ Co-ops.

To assess whether cooperatives affect these outcomes, we regress the change in each agricultural productivity measure on the change in cooperative presence at the municipality level. As in our baseline analysis, identification relies the same SSIV strategy used at the grid cell level.¹⁴ Estimation is conducted at the shock level, with residualization for longitude, latitude, area, and population, and fixed effects for agglomeration class and state.

Table 8 reports the results. We find statistically meaningful effects of cooperative presence on agricultural productivity: municipalities with larger increases in cooperatives between 2015 and 2023 experienced higher yields, higher production value per hectare, and greater

¹⁴The instrument is constructed at the municipality level as

$$z_m = \sum_k s_{mk,2013} \tilde{g}_{k,m},$$

where $s_{mk,2013}$ are baseline (2013) cooperative shares at the 4-digit sector level and $\tilde{g}_{k,m}$ are sectoral shocks defined as growth in neighboring municipalities, net of national sector-by-year trends.

crop diversity. For instance, an extra cooperative firm between 2015 and 2023 leads to a 1% increase in yields per hectare. The effects on cultivated surface and rural prices are close to zero. These findings suggest that cooperatives do not expand the scale of agriculture but rather contribute to gains in productivity and diversification within existing cultivated land.

| Redistribution: Income and poverty.

Finally, we test whether, consistent with the social economy narrative, cooperative firms act as a source of local redistribution.

As with agricultural productivity, the lowest level of disaggregation for income and poverty indicators is the municipality. We therefore aggregate cooperative firms at the municipal level in 2020 and estimate cross-sectional SSIV regressions of income and poverty outcomes in levels on the number of cooperative firms, using the same shift-share instrument as before.

Income data come from INEGI's 2020 income module, while poverty and deprivation indicators are from CONEVAL. We focus on mean household income per capita (log), as well as multiple poverty dimensions: multidimensional poverty, income poverty, and extreme poverty (both multidimensional and income-based), alongside indicators of deprivation (at least one, and three or more deprivations).

TABLE 9 SSIV (Municipality-Level): Effect of Co-ops on Income and Poverty (2020)

	Mean HH income pc (log) (1)	Multidim. Poverty(pp) (2)	Extreme Multidim. Poverty (pp) (3)	Income Poverty (pp) (4)	Extreme Income Poverty (pp) (5)	At least 1 deprivation (pp) (6)	3+ deprivations (pp) (7)
# Co-ops (2020)	0.002 (0.0004)	-0.0010 (0.001)	-0.0007 (0.0002)	-0.0010 (0.001)	-0.0009 (0.0008)	-0.0005 (0.0005)	-0.001 (0.0002)
FDR q-value	[0.001]	[0.280]	[0.004]	[0.280]	[0.280]	[0.280]	[0.001]
Observations	4,697	4,697	4,697	4,697	4,697	4,697	4,697
F-test (1st stage)	44.2	44.2	44.2	44.2	44.2	44.2	44.2

Notes: The table reports shift-share IV (SSIV) estimates at the municipality level. Outcomes are levels in 2020 in income and poverty indicators at municipality m . The endogenous regressor is the number of Co-ops at the municipality level by 2020. The instrument is constructed as $z_m = \sum_k s_{mk,2013} \bar{g}_{k,m}$, where $s_{mk,2013}$ are baseline (2013) cooperative exposure shares at 4-digit sector k , and $\bar{g}_{k,m}$ are sectoral shocks computed from third-degree neighboring municipalities' growth net of national sector-by-year averages. Estimation follows a two-stage least squares at the shock level after aggregating municipality data with exposure weights $s_{mk,2013}$ (reported as s_n). All specifications control for longitude, latitude, log(area), and log(population) via residualization in the aggregation step, and include fixed effects for agglomeration class and state. Controls include the incomplete-share term $S_m = \sum_k s_{mk,2013}$, counts in the size distribution of non-cooperative establishments (small/medium/large), counts in the number of ejidos, and counts in infrastructure (principal roads, local roads, secondary roads, and transport/mobility points). Standard errors are two-way clustered at the municipality and 4-digit sector level. Reported F-statistics correspond to the first stage on Δ Co-ops.

Table 9 shows that municipalities with more cooperative firms in 2020 report significantly higher mean household income per capita: each additional cooperative firm increases average income per capita by roughly 0.2%. This result is consistent with our earlier findings at the grid-cell level, where cooperative presence raised local development indicators. We also find that cooperative firms reduce poverty, particularly extreme poverty and multidimensional deprivation. These effects suggest that cooperatives not only raise average income but also improve outcomes at the bottom of the distribution.

Taken together, the results are consistent with the idea that cooperatives redistribute locally, whether through higher wages, profit sharing, or other post-market mechanisms of redistribution, contributing to both higher mean income and reductions in poverty. A potential link between these improvements and broader local economic activity is that with higher disposable income, households may increase local consumption, thereby further stimulating the local economy.

7 | CONCLUSION

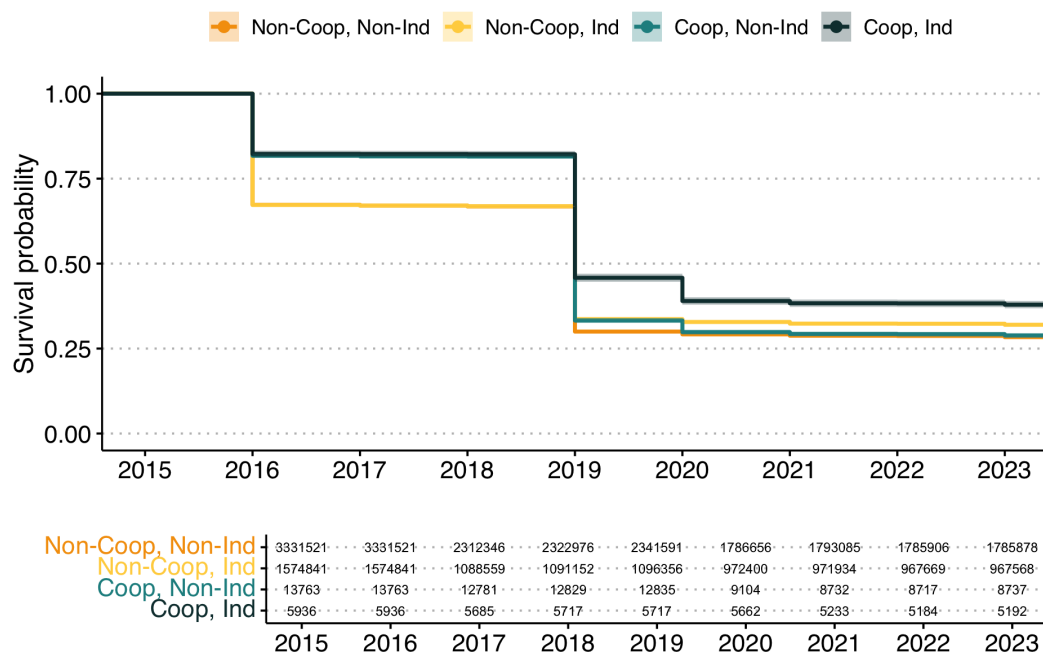
This paper studies whether and how cooperative firms foster local economic development, focusing on the case of Mexico. Using newly assembled georeferenced and multiple quasi-experimental strategies, we find consistent evidence that cooperative presence and growth increase local economic activity, improve human capital and living standards, and reduce poverty. These effects are particularly pronounced in Indigenous communities, where cooperatives exhibit longer survival spells and stronger impacts. While the mechanisms are multifaceted, our results point to two broad pathways: productivity gains in agriculture, where cooperatives help raise yields and crop diversity, and redistributive effects that increase household income and reduce deprivation.

These findings suggest that cooperatives can serve as valuable, locally embedded institutions for promoting inclusive development. By aligning with traditions of collective organization, cooperatives may complement broader place-based policies and provide cost-effective alternatives in resource-constrained settings. However, their impacts are not uniform. The magnitude of development gains might vary with the economic structure of local markets, the institutional environment, and prevailing social norms. This heterogeneity underscores the importance of tailoring cooperative promotion to contexts where complementarities are strongest, rather than treating them as a one-size-fits-all policy tool.

At the same time, important questions remain. Our aggregate approach highlights broad pathways but cannot disentangle firm-level mechanisms such as productivity, employment, profit distribution, or access to credit and capital. Future research that links cooperative-level outcomes to local development effects will be crucial for understanding when and why cooperatives succeed. Bridging the gap between firm-level theory and economy-wide evidence would clarify which mechanisms dominate, deepen our understanding of cooperative dynamics, and provide clearer guidance for designing effective, context-sensitive development policies.



(a) Cooperative vs. non-cooperative firms



(b) By cooperative status and indigenous locality

FIGURE 3 Kaplan-Meier survival estimates for firms, 2015–2023

Notes: Based on the DENU panel of establishments. Panel (a) plots KM survival functions for cooperative and non-cooperative firms. Panel (b) stratifies by cooperative status and whether the entry locality is classified as indigenous (INALI). Survival is defined as continued presence in DENU up to 2023; exit is disappearance from the panel before the final year. The marked drop in 2019 reflects an update of official establishment records following the Economic Census, which introduced adjustments in firm reporting and registration.

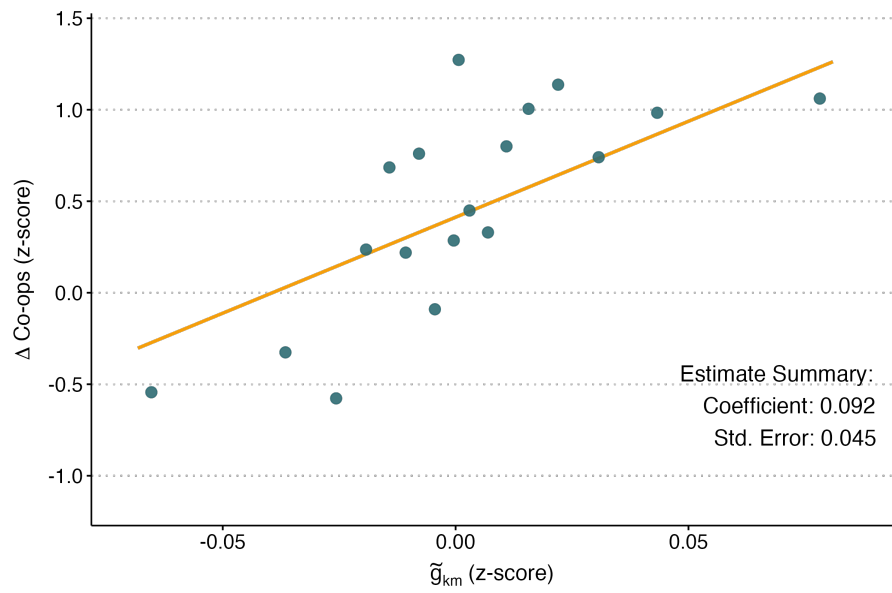
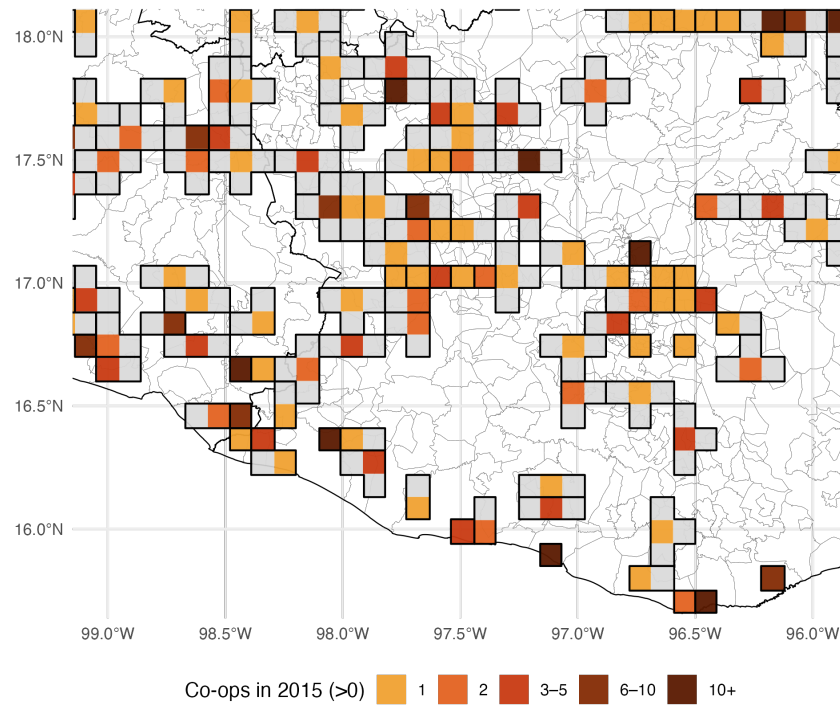
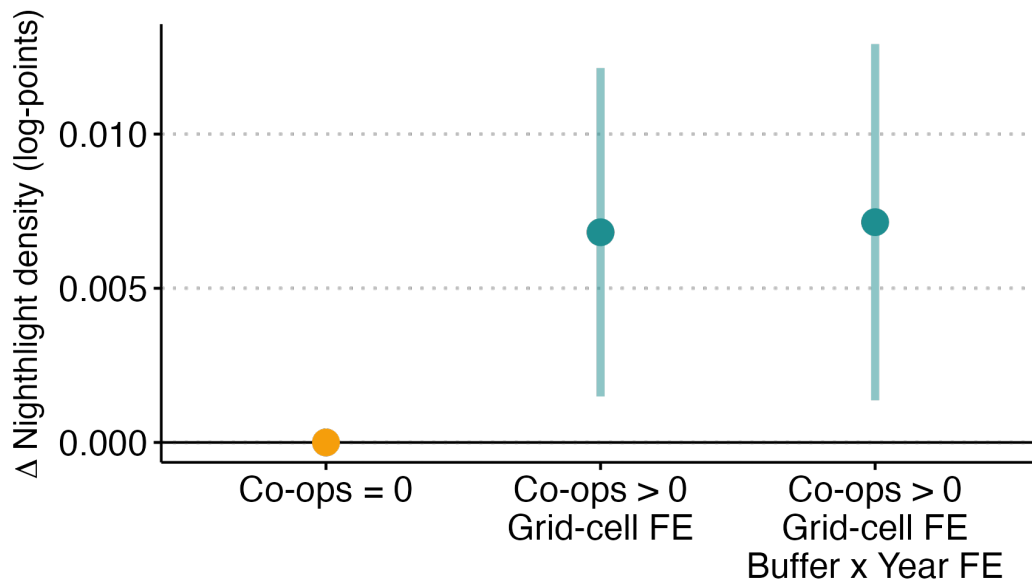


FIGURE 4 First-stage relationship between shocks and changes in cooperative presence.

Notes: The figure plots the correlation between exposure-weighted shocks $\tilde{g}_{k,m}$ (standardized) and changes in cooperatives (standardized) between 2015 and 2023. Dots correspond to binned averages, and the orange line represents the fitted regression line. Estimates are weighted by 2013 cooperative counts (exposure weights) and control for the incomplete sum of shares.



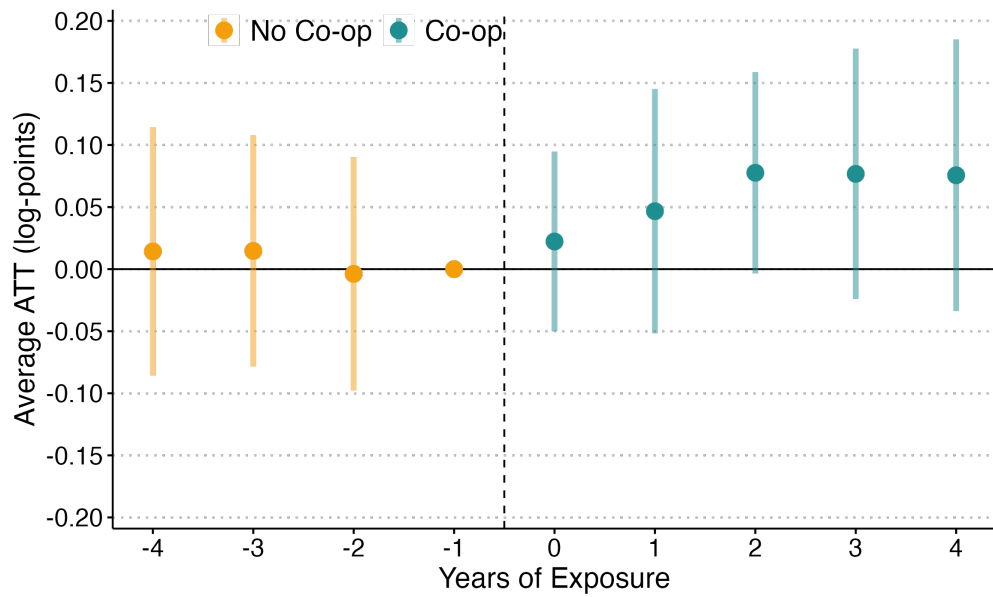
(a) Border design identification strategy illustration



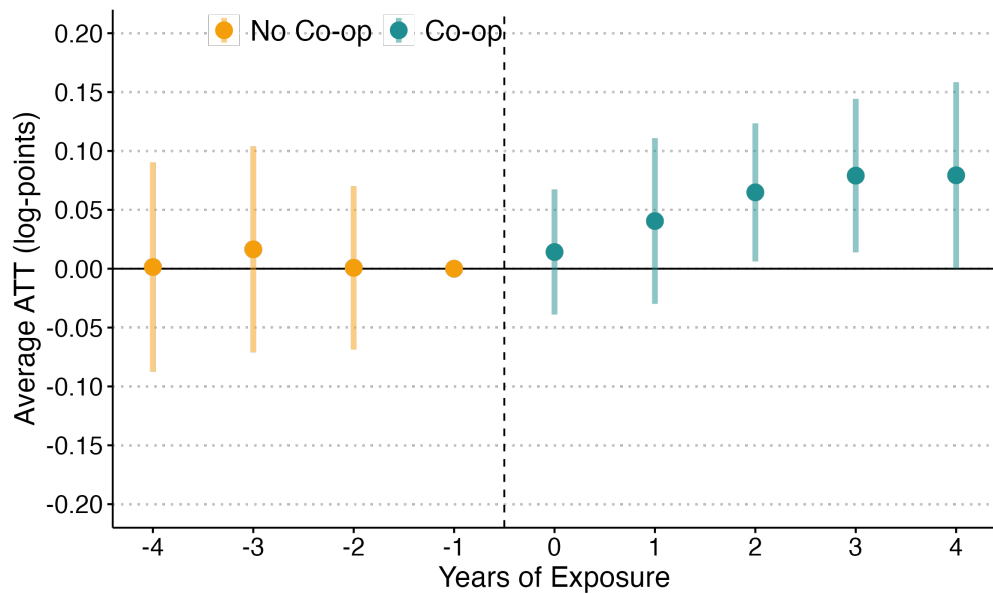
(b) Border design estimates of cooperative presence on nightlight density

FIGURE 5 Border design strategy and results.

Notes: Panel (a) shows treated cells (colored) that host at least one cooperative in 2015. Colors indicate the number of cooperatives, while grey cells denote domain controls, i.e., neighboring untreated cells. Thick black boundaries mark the domains constructed around anchor treated cells. Panel (b) reports point estimates with 95% confidence intervals. Both specifications mirror the baseline regression reported in column (7) of Table 3, which controls for raster and municipality-by-year fixed effects, establishment-size composition, ejido counts, and double-LASSO selected controls. The only difference is that the sample is restricted to treated and domain-control cells. The second specification further includes buffer-by-year fixed effects, ensuring that comparisons are drawn only among cells within the same buffer and year.



(a) Complete sample



(b) Border design subsample

FIGURE 6 Event-study estimates of cooperative entry on nightlight density

Notes: Each panel reports dynamic treatment effects from the [Callaway and Sant'Anna \(2021\)](#) estimator, averaging across treated cohorts and exploiting the staggered timing of first cooperative entry. Effects are reported relative to the year prior to cooperative entry ($t = -1$) under the universal base period, with 95% confidence intervals. Panel (a) uses the complete sample of rural grid cells. Panel (b) restricts to the border-design subsample of treated cells and their domain-control neighbors; in the residualization step it absorbs domain (buffer) fixed effects in addition to the controls listed below. In both panels, the dependent variable is first residualized by regressing log nightlight density per capita on establishment-size composition (counts of small, medium, and large non-cooperative units), ejido counts, and the double-LASSO-selected geographic, infrastructure, and socio-economic predictors (the same covariate set used in Column (8) of Table 3 on page 18). We set `balance.e = 4` so that only cohorts observed from the baseline ($e = 0$) through at least four subsequent periods ($e = 1, \dots, 4$) are retained, ensuring a consistent set of cohorts across event times. Estimates are population-weighted, use not-yet-treated cells as the comparison group (never-treated are excluded), and omit 2015-entry cohorts which are always treated.

| Acknowledgements

We are especially grateful to Guillermo Alves, Adriana Camacho, Francesco Caselli, Peter Hull, Federico Juncosa, Antonio León, Karen Macours, Eduardo Montero, María Montoya-Aguirre, Alex Rivadeneira, and the seminar participants at the *Rural World in Latin America and the Caribbean Workshop* at CAF, *Workshop on Social Economy for Young Economist* at Bologna University, and Banco de México for their insightful feedback. We also thank the Banco de Desarrollo de América Latina y el Caribe (CAF) for funding this project through its call *The rural world in Latin America and the Caribbean*. Raúl Cepeda Suárez provided excellent research assistance for an earlier version of this project. All errors remain our own.

REFERENCES

- Abramitzky, R. (2008) The limits of equality: Insights from the israeli kibbutz. *The Quarterly Journal of Economics*, **123**, 1111–1159. URL: <https://dx.doi.org/10.1162/qjec.2008.123.3.1111>.
- (2011) Lessons from the kibbutz on the equality-incentives trade-off. *Journal of Economic Perspectives*, **25**, 185–208.
- Adão, R., Kolesár, M. and Morales, E. (2019) Shift-share designs: Theory and inference. *The Quarterly Journal of Economics*, **134**, 1949–2010. URL: <https://dx.doi.org/10.1093/qje/qjz025>.
- Alves, G., Blanchard, P., Burdín, G., Chávez, M. and Dean, A. (2022) Like principal, like agent? managerial preferences in employee-owned firms. *Journal of Institutional Economics*, **18**, 877–899. URL: <https://www.cambridge.org/core/journals/journal-of-institutional-economics/article/like-principal-like-agent-managerial-preferences-in-employeeowned-firms/2CAA1C375E7DDF64739ACF3AE9439062>.
- Alves, G., Burdín, G. and Dean, A. (2016) Workplace democracy and job flows. *Journal of Comparative Economics*, **44**, 258–271.
- Anderson, M. L. (2008) Multiple inference and gender differences in the effects of early intervention: A reevaluation of the abecedarian, perry preschool, and early training projects. *Journal of the American Statistical Association*, **103**, 1481–1495. URL: <https://www.tandfonline.com/doi/full/10.1198/016214508000000841>.
- Angrist, J. and Kolesár, M. (2024) One instrument to rule them all: The bias and coverage of just-id iv. *Journal of Econometrics*, **240**, 105398.
- Arando, S., Gago, M., Podivinsky, J. M. and Stewart, G. (2012) Do labour-managed firms benefit from agglomeration? *Journal of Economic Behavior & Organization*, **84**, 193–200. URL: <https://www.sciencedirect.com/science/article/abs/pii/S0167268112001527>.
- Asher, S., Campion, A., Gollin, D. and Novosad, P. (2024) The long-run development impacts of agricultural productivity gains: Evidence from irrigation canals in india. Working Paper.
- Asher, S. and Novosad, P. (2020) Rural roads and local economic development. *American Economic Review*, **110**, 797–823.
- Ashraf, N., Bau, N., Nunn, N. and Voena, A. (2020) Bride price and female education. <https://doi.org/10.1086/704572>, **128**, 591–641. URL: <https://www.journals.uchicago.edu/doi/10.1086/704572>.
- Autor, D. H., Dorn, D. and Hanson, G. H. (2013) The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, **103**, 2121–68. URL: <http://dx.doi.org/10.1257/aer.103.6.2121>.
- Autor, D. H. and Duggan, M. G. (2003) The rise in the disability rolls and the decline in unemployment. *The Quarterly Journal of Economics*, **118**, 157–206. URL: <https://dx.doi.org/10.1162/00335530360535171>.
- Banerjee, A., Gertler, P. and Ghatak, M. (2002) Empowerment and efficiency: Tenancy reform in west bengal. *Journal of Political Economy*, **110**, 239–280. URL: <https://www.journals.uchicago.edu/doi/10.1086/338744>.
- Bartik, T. J. (1991) *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, MI: W. E. Upjohn Institute for Employment Research.
- Bau, N., Lowes, S. and Montero, E. (2025) Culture, policy, and economic development. URL: <https://www.nber.org/papers/w33947>.
- Bautista Páez, D. (2022) Orígenes del cooperativismo en méxico. notas para historiar la otra economía. *Religación*, **7**, e210904.

- Belloni, A., Chernozhukov, V. and Hansen, C. (2014) Inference on treatment effects after selection among high-dimensional controls. *The Review of Economic Studies*, **81**, 608–650. URL: <https://dx.doi.org/10.1093/restud/rdt044>.
- Besley, T. and Burgess, R. (2000) Land reform, poverty reduction, and growth: Evidence from india. *The Quarterly Journal of Economics*, **115**, 389–430. URL: <https://dx.doi.org/10.1162/003355300554809>.
- Blasi, J., Conte, M. and Kruse, D. (1996) Employee stock ownership and corporate performance among public companies. *ILR Review*, **50**, 60–79. URL: <https://www.jstor.org/stable/2524389>.
- Bonin, J. P. (1977) Work incentives and uncertainty on a collective farm. *Journal of Comparative Economics*, **1**, 77–97.
- Bonin, J. P., Jones, D. C. and Putterman, L. (1993) Theoretical and empirical studies of producer cooperatives: Will ever the twain meet? *Journal of Economic Literature*, **31**, 1290–1320.
- Borusyak, K. and Hull, P. (2023) Nonrandom exposure to exogenous shocks. *Econometrica*, **91**, 2155–2185. URL: <https://onlinelibrary.wiley.com/doi/full/10.3982/ECTA19367><https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA19367><https://onlinelibrary.wiley.com/doi/10.3982/ECTA19367>.
- Borusyak, K., Hull, P. and Jaravel, X. (2022) Quasi-experimental shift-share research designs. *The Review of Economic Studies*, **89**, 181–213. URL: <https://dx.doi.org/10.1093/restud/rdab030>.
- (2025) A practical guide to shift-share instruments. *Journal of Economic Perspectives*, **39**, 181–204. URL: <https://pubs.aeaweb.org/doi/10.1257/jep.20231370>.
- Brzustowski, T. and Caselli, F. (2024) Economic growth in a cooperative economy. *Journal of the European Economic Association*. URL: <https://dx.doi.org/10.1093/jeea/jvae050>.
- Burdín, G. (2016) Equality under threat by the talented: Evidence from worker-managed firms. *The Economic Journal*, **126**, 1372–1403. URL: <https://dx.doi.org/10.1111/eoj.12272>.
- Burdín, G. and Dean, A. (2009) New evidence on wages and employment in worker cooperatives compared with capitalist firms. *Journal of Comparative Economics*, **37**, 517–533.
- (2012) Revisiting the objectives of worker-managed firms: An empirical assessment. *Economic Systems*, **36**, 158–171.
- Callaway, B. and Sant’Anna, P. H. (2021) Difference-in-differences with multiple time periods. *Journal of Econometrics*, **225**, 200–230. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0304407620303948>.
- Card, D. (2009) Immigration and inequality. *American Economic Review*, **99**, 1–21.
- Casaburi, L. and Macchiavello, R. (2015) Loyalty, exit, and enforcement: Evidence from a kenya dairy cooperative. *American Economic Review*, **105**, 286–90.
- Caselli, G., Costa, M. and Delbono, F. (2022) What do cooperative firms maximize, if at all? evidence from emilia-romagna in the pre-covid decade. *Annals of Public and Cooperative Economics*, **93**, 821–847. URL: <https://doi/pdf/10.1111/apce.12354><https://onlinelibrary.wiley.com/doi/abs/10.1111/apce.12354><https://onlinelibrary.wiley.com/doi/10.1111/apce.12354>.
- de Chaisemartin, C. and D’Haultfoeulle, X. (2023) Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: a survey. *The Econometrics Journal*, **26**, C1–C30. URL: <https://dx.doi.org/10.1093/ectj/utac017>.

- Clemente, J., Diaz-Foncia, M., Marcuello, C. and Sanso-Navarro, M. (2012) The wage gap between cooperative and capitalist firms: Evidence from Spain. *Annals of Public and Cooperative Economics*, **83**, 337–356. URL: <https://onlinelibrary.wiley.com/doi/full/10.1111/j.1467-8292.2012.00466.x><https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-8292.2012.00466.x><https://onlinelibrary.wiley.com/doi/10.1111/j.1467-8292.2012.00466.x>.
- Coccorese, P. and Shaffer, S. (2021) Cooperative banks and local economic growth. *Regional Studies*, **55**, 307–321. URL: https://scholar.google.com/scholar_url?url=https://www.tandfonline.com/doi/pdf/10.1080/00343404.2020.1802003%3Fcasa_token%3Dylx8ee2c91MAAAA:zQAYYATNanu0exyZe0t75x89pot2NvaNn5LWQY8BqHiEkt8Wr13svENmd7lyyItbMbV4aYiwWkgLsg&hl=es&sa=T&oi=ucasa&ct=ucasa&ei=x9aoaLf5B4rO6rQPrPTx2QM&scisig=AAZF9b-EL9xz1lrN_XUxOVAHUZ-.
- CONEVAL (2019a) La pobreza en la población indígena de México, 2008 - 2018. URL: https://www.coneval.org.mx/Medicion/MP/Documents/Pobreza_Poblacion_indigena_2008-2018.pdf.
- (2019b) Pobreza rural en México. URL: https://www.coneval.org.mx/Medicion/MP/Documents/PATP/Pobreza_rural.pdf.
- Conte, M. A. (1986) Entry of worker cooperatives in capitalist economies. *Journal of Comparative Economics*, **10**, 41–47. URL: <https://www.sciencedirect.com/science/article/abs/pii/0147596786901174>.
- Conte, M. A. and Jones, D. C. (2015) On the entry of employee-owned firms: Theory and evidence from U.S. manufacturing industries, 1870–1960. *Advances in the Economic Analysis of Participatory and Labor-Managed Firms*, **16**, 1–31. URL: <https://www.emerald.com/books/edited-volume/14521/chapter/85509558/On-the-Entry-of-Employee-Owned-Firms-Theory-and>.
- Coraggio, J. L. (2015) *La economía social y solidaria: El trabajo antes que el capital*. Buenos Aires: CLACSO. URL: <http://biblioteca.clacso.edu.ar/clacso/gt/20160210123227/EconomiaSocial.pdf>.
- Costa, M. and Delbono, F. (2023) Regional resilience and the role of cooperative firms. *Social Enterprise Journal*, **19**, 435–458. URL: <https://dx.doi.org/10.1108/SEJ-07-2022-0064>.
- Costa, M., Delbono, F. and Linguiti, F. (2023) Cooperative movement and widespread prosperity across Italian regions. *Annals of Public and Cooperative Economics*, **94**, 475–494. URL: <https://doi/pdf/10.1111/apce.12387><https://onlinelibrary.wiley.com/doi/abs/10.1111/apce.12387><https://onlinelibrary.wiley.com/doi/10.1111/apce.12387>.
- Craig, B. and Pencavel, J. (1992) The behavior of worker cooperatives: The plywood companies of the Pacific Northwest. *The American Economic Review*, **82**, 1083–1105. URL: <http://www.jstor.org/stable/2117468>.
- Deutsche Welle (2020) Tosepan titataniske, ejemplo de cooperativismo indígena. Video report. URL: <https://www.dw.com/es/tosepan-titataniske-ejemplo-de-cooperativismo-ind%C3%ADgena/video-54253218>. Accessed: 2025-08-22.
- Dinkelman, T. (2011) The effects of rural electrification on employment: New evidence from South Africa. *American Economic Review*, **101**, 3078–3108.
- Domar, E. D. (1966) The Soviet collective farm as a producer cooperative. *The American Economic Review*, **56**, 734–757. URL: <http://www.jstor.org/stable/1813525>.
- Donaldson, D. (2018) Railroads of the Raj: Estimating the impact of transportation infrastructure. *American Economic Review*, **108**, 899–934.
- Donaldson, D. and Storeygard, A. (2016) The view from above: Applications of satellite data in economics. URL: <https://dx.doi.org/10.1257/jep.30.4.171>[doi=10.1257/jep.30.4.171](https://doi.org/10.1257/jep.30.4.171).

- Dragusanu, R., Giovannucci, D. and Nunn, N. (2014) The economics of fair trade. *Journal of Economic Perspectives*, **28**, 217–36. URL: <http://dx.doi.org/10.1257/jep.28.3.217>.
- Dragusanu, R., Montero, E. and Nunn, N. (2022) The effects of fair trade certification: Evidence from coffee producers in costa rica. *Journal of the European Economic Association*, **20**, 1743–1790. URL: <https://dx.doi.org/10.1093/jeea/jvac026>.
- Duranton, G. and Venables, A. J. (2021) Place-based policies: Principles and developing country applications. *Handbook of Regional Science: Second and Extended Edition: With 238 Figures and 78 Tables*, 1009–1030. URL: https://link.springer.com/referenceworkentry/10.1007/978-3-662-60723-7_142.
- El Financiero (2023) Esta cafetalera de indígenas chiapanecos factura 30 mdp al año. Online article. URL: <https://www.elfinanciero.com.mx/empresas/indigenas-chiapanecos-exportan-cafe-a-eu-y-espana/>. Accessed: 2025-08-22.
- El País México (2025) Cómo un plan para sortear costos se convirtió en la mayor cooperativa indígena de México. *El País*. URL: <https://elpais.com/mexico/2025-04-23/como-un-plan-para-sortear-costos-se-convirtio-en-la-mayor-cooperativa-indigena-de-mexico.html>. Accessed: 2025-08-22.
- Elvidge, C. D., Zhizhin, M., Ghosh, T., Hsu, F.-C. and Taneja, J. (2021) Annual time series of global viirs nighttime lights derived from monthly averages: 2012 to 2019. *Remote Sensing*, **13**, 922. URL: <https://www.mdpi.com/2072-4292/13/5/922>.
- Eum, H. (2017) *Cooperatives and Employment: Second Global Report. Contribution of cooperatives to decent work in the changing world of work*. Brussels: CI-COPA. URL: https://www.cicopa.coop/wp-content/uploads/2017/11/Second_Global_Report_Coop_Employment_EN_Digital.pdf. Carried out with the financial support of the International Cooperative Alliance.
- Fakhfakh, F., Perotin, V. and Gago, M. (2012) Productivity, capital, and labor in labor-managed and conventional firms: An investigation on french data. *ILR Review*, **65**, 847–879. URL: <https://journals.sagepub.com/doi/abs/10.1177/001979391206500404>.
- de la Fuente, J. (1944) Cooperacion indigena y cooperativismo moderno. *El Trimestre Económico*, **10**, 749–765. URL: <http://www.jstor.org/stable/20854585>.
- Gertler, P. J., Gonzalez-Navarro, M., Gračner, T. and Rothenberg, A. D. (2024) Road maintenance and local economic development: Evidence from indonesia's highways. *Journal of Urban Economics*, **143**, 103687. URL: <https://www.sciencedirect.com/science/article/pii/S0094119024000573>.
- Gibson, J., Olivia, S., Boe-Gibson, G. and Li, C. (2021) Which night lights data should we use in economics, and where? *Journal of Development Economics*, **149**, 102602.
- Goodman-Bacon, A. (2021) Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, **225**, 254–277. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0304407621001445>.
- Henderson, J. V., Squires, T., Storeygard, A. and Weil, D. (2018) The global distribution of economic activity: Nature, history, and the role of trade. *The Quarterly Journal of Economics*, **133**, 357–406. URL: <https://dx.doi.org/10.1093/qje/qjx030>.
- Henderson, J. V., Storeygard, A. and Weil, D. N. (2012) Measuring economic growth from outer space. *American Economic Review*, **102**, 994–1028. URL: <https://pubs.aeaweb.org/doi/10.1257/aer.102.2.994>.
- Henderson, V., Storeygard, A. and Weil, D. N. (2011) A bright idea for measuring economic growth. *American Economic Review*, **101**, 194–99.
- Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H. and McElreath, R. (2001) In search of homo economicus: Behavioral experiments in 15 small-scale societies. *American Economic Review*, **91**, 73–78.

- Herrera, M. E. R. and Rojas, D. A. M. (2020) Educando para la solidaridad: La experiencia de la unión de cooperativas tosepan titataniske. *Textual*, 45–73.
- Holmstrom, B. (1982) Moral hazard in teams. *The Bell Journal of Economics*, **13**, 324.
- Illades, C. (1996) *Hacia la República del Trabajo. La organización artesanal en la Ciudad de México, 1853–1876*. UAM–COLMEX.
- Instituto Nacional de Estadística y Geografía (México) (2022) *Estudio de caso de la economía social de México, 2013 y 2018*. México: INEGI. Cuentas nacionales - México - Metodología. Economía - México.
- International Cooperative Alliance and Euricse (2023) World cooperative monitor 2023: Exploring the cooperative economy. *Tech. rep.*, International Cooperative Alliance and Euricse. URL: https://monitor.coop/sites/default/files/2024-01/wcm_2023_3101.pdf. Accessed: 2025-08-22.
- International Labour Organization (2014) Cooperatives and the sustainable development goals: A contribution to the post-2015 development debate. URL: https://www.ilo.org/global/topics/cooperatives/publications/WCMS_306072/lang-en/index.htm.
- Ishimaru, S. (2024) Empirical decomposition of the iv-ols gap with heterogeneous and nonlinear effects. *The Review of Economics and Statistics*, **106**, 505–520. URL: https://dx.doi.org/10.1162/rest_a_01169.
- Jones, D. C. (2018) The economics of Participation and Employee Ownership (PEO): an assessment. *Journal of Participation and Employee Ownership*, **1**, 4–37.
- Kandel, E. and Lazear, E. P. (1992) Peer pressure and partnerships. *Journal of Political Economy*, **100**, 801–817. URL: <https://www.journals.uchicago.edu/doi/10.1086/261840>.
- Keele, L. and Titiunik, R. (2015) Geographic boundaries as regression discontinuities. *Political Analysis*, **23**, 127–155.
- Keola, S., Andersson, M. and Hall, O. (2015) Monitoring economic development from space: Using nighttime light and land cover data to measure economic growth. *World Development*, **66**, 322–334.
- Kerwin, J., Rostom, N. and Sterck, O. (2024) Striking the right balance: Why standard balance tests over-reject the null, and how to fix it. URL: <https://papers.ssrn.com/abstract=4926535>.
- van Kippersluis, H. and Rietveld, C. A. (2018) Beyond plausibly exogenous. *The Econometrics Journal*, **21**, 316–331. URL: <https://dx.doi.org/10.1111/ectj.12113>.
- Kline, P. and Moretti, E. (2014) People, places, and public policy: Some simple welfare economics of local economic development programs. *Annual Review of Economics*, **6**, 629–662. URL: <https://www.annualreviews.org/content/journals/10.1146/annurev-economics-080213-041024>.
- Kremer, M. (1997) Why are worker cooperatives so rare? *Tech. rep.*, National Bureau of Economic Research.
- Kruse, D. L., Freeman, R. B. and Blasi, J. R. (eds.) (2010) *Shared Capitalism at Work: Employee Ownership, Profit and Gain Sharing, and Broad-Based Stock Options*. Chicago, IL: University of Chicago Press. URL: <https://www.nber.org/books-and-chapters/shared-capitalism-work-employee-ownership-profit-and-gain-sharing-and-broad-based-stock-options>.
- Lebakula, V., Epting, J., Moehl, J., Stipek, C., Adams, D., Reith, A., Kaufman, J., Gonzales, J., Reynolds, B., Basford, S., Martin, A., Buck, W., Faxon, A., Cunningham, A., Roy, A., Barbose, Z., Massaro, J., Walters, S., Woody, C. and Urban, M. (2024) Landscan silver edition. Data set. URL: <https://doi.org/10.48690/1531770>.

- Leñero, V. (2015) *Los periodistas*. Ciudad de México: Seix Barral. Publicado el 31 de marzo de 2015.
- Lowes, S. and Montero, E. (2021) Concessions, violence, and indirect rule: Evidence from the congo free state. *The Quarterly Journal of Economics*, **136**, 2047–2091. URL: <https://dx.doi.org/10.1093/qje/qjab021>.
- López-Calva, L. F., Ortiz-Juarez, E. and Rodríguez-Castelán, C. (2022) Within-country poverty convergence: evidence from mexico. *Empirical Economics*, **62**, 2547–2586. URL: <https://link.springer.com/10.1007/s00181-021-02109-0>.
- Ma, W. and Abdulai, A. (2017) The economic impacts of agricultural cooperatives on smallholder farmers in rural china. *Agribusiness*, **33**, 537–551. URL: <https://doi/pdf/10.1002/agr.21522https://onlinelibrary.wiley.com/doi/abs/10.1002/agr.21522https://onlinelibrary.wiley.com/doi/10.1002/agr.21522>.
- Magne, N. (2017) Wage inequality in workers' cooperatives and conventional firms. *The European Journal of Comparative Economics*, **14**, 303–329. URL: <https://ejce.liuc.it/articles/ejce-14201702.pdf>.
- McGuirk, E. F. and Nunn, N. (2024) Development mismatch? evidence from agricultural projects in pastoral africa. URL: <https://www.nber.org/papers/w33191>.
- Michalopoulos, S. and Papaioannou, E. (2018) Spatial patterns of development: A meso approach. *Annual Review of Economics*, **10**, 383–410.
- Montero, E. (2022) Cooperative property rights and development: Evidence from land reform in el salvador. *Journal of Political Economy*, **130**, 48–93. URL: <https://www.journals.uchicago.edu/doi/10.1086/717042>.
- Moscona, J. and Seck, A. A. (2024) Age set versus kin: Culture and financial ties in east africa. *American Economic Review*, **114**, 2748–91.
- Neumark, D. and Simpson, H. (2015) Place-based policies. *Handbook of Regional and Urban Economics*, **5**, 1197–1287.
- Nunn, N. (2019) Rethinking economic development. *Canadian Journal of Economics/Revue canadienne d'économie*, **52**, 1349–1373. URL: <https://onlinelibrary.wiley.com/doi/full/10.1111/caje.12406https://onlinelibrary.wiley.com/doi/abs/10.1111/caje.12406https://onlinelibrary.wiley.com/doi/10.1111/caje.12406>.
- Olea, J. L. M. and Pflueger, C. (2013) A robust test for weak instruments. *Journal of Business Economic Statistics*, **31**, 358–369. URL: <https://www.tandfonline.com/doi/abs/10.1080/00401706.2013.806694>.
- Pencavel, J. (2013) *Worker cooperatives and democratic governance*. Edward Elgar Publishing.
- Pencavel, J. and Craig, B. (1994) The empirical performance of orthodox models of the firm: Conventional firms and worker cooperatives. *Journal of Political Economy*, **102**, 718–744. URL: <https://www.journals.uchicago.edu/doi/10.1086/261952>.
- Pencavel, J., Pistaferri, L. and Schivardi, F. (2006) Wages, employment, and capital in capitalist and worker-owned firms. *ILR Review*, **60**, 23–44. URL: <https://www.jstor.org/stable/25067573>.
- Pinkovskiy, M. and Sala-I-Martin, X. (2016) Lights, camera ... income! illuminating the national accounts-household surveys debate. *The Quarterly Journal of Economics*, **131**, 579–631. URL: <https://academic.oup.com/qje/article/131/2/579/2607043>.
- Pinkovskiy, M. L. (2017) Growth discontinuities at borders. *Journal of Economic Growth*, **22**, 145–192. URL: <https://link.springer.com/article/10.1007/s10887-016-9139-2>.
- Placencia Alarcón, L. A. (2022) *El Cooperativismo en México: Análisis económico-tributario*. Ciudad de México: Procuraduría de la Defensa del Contribuyente (Prodecon). Dirección de Cultura Contributiva.

- Putterman, L. (1980) Voluntary collectivization: A model of producers' institutional choice. *Journal of Comparative Economics*, **4**, 125–157.
- Rojas Coria, R. (1952) *Tratado de Cooperativismo Mexicano*. Fondo de Cultura Económica.
- Rossi-Hansberg, E. and Zhang, J. (2025) Local gdp estimates around the world.
- Roth, J., Sant'Anna, P. H., Bilinski, A. and Poe, J. (2023) What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*, **235**, 2218–2244. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0304407623001318>.
- Sen, A. K. (1966) Labour allocation in a cooperative enterprise. *Review of Economic Studies*, **33**, 361–371. URL: <https://dx.doi.org/10.2307/2974432>.
- Sukhtankar, S. (2016) Does firm ownership structure matter? evidence from sugar mills in india. *Journal of Development Economics*, **122**, 46–62.
- Terzo, G., Notarstefano, G. and Maggio, U. D. (2024) Strengthening local economies through social capital: The role of cooperative firms in driving economic growth in italy. *Annals of Public and Cooperative Economics*, **95**, 863–882. URL: [/doi/pdf/10.1111/apce.12463](https://doi/pdf/10.1111/apce.12463)<https://onlinelibrary.wiley.com/doi/abs/10.1111/apce.12463><https://onlinelibrary.wiley.com/doi/10.1111/apce.12463>.
- United Nations General Assembly (2023) Promoting the social and solidarity economy for sustainable development. URL: <https://documents.un.org/en/A/RES/77/281>. Resolution A/RES/77/281, adopted 18 April 2023.
- Utting, P. (2015) *Social and Solidarity Economy: Beyond the Fringe*. London: Zed Books.
- Ward, B. (1958) The firm in illyria: Market syndicalism. *The American Economic Review*, **48**, 566–589. URL: <https://www.jstor.org/stable/1808268>.
- World Bank (2024) *Poverty, Prosperity, and Planet Report 2024: Pathways Out of the Polycrisis*. Washington, DC: World Bank.

A | DATA AND DESCRIPTIVE STATISTICS

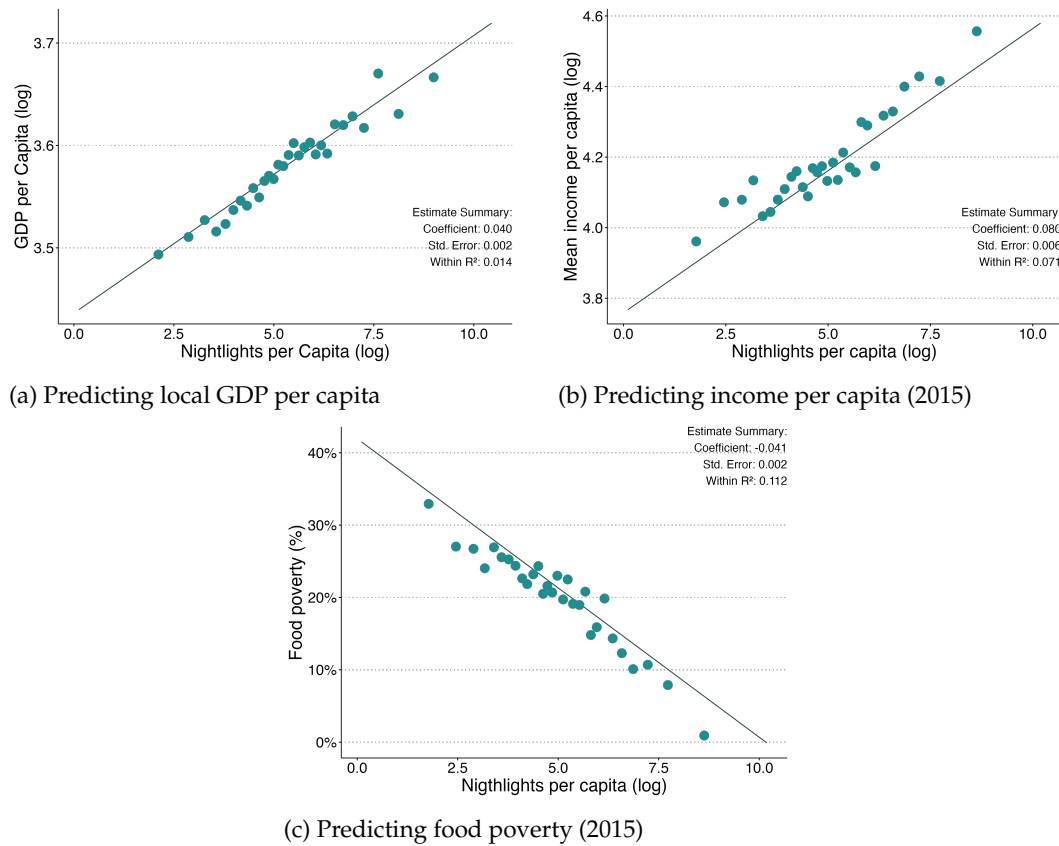


FIGURE A.1 Nightlight intensity per capita and economic development in Mexico

Notes: Each panel presents the binscatter between nightlight intensity per capita and key economic indicators at the municipal level in Mexico. Panel (a) compares nightlight intensity with local GDP per capita from Rossi-Hansberg and Zhang (2025) for 2015 to 2021, using municipal and year fixed effects. Panel (b) examines its correlation with mean household income per capita from López-Calva et al. (2022) for the year 2015 and include state fixed effects. Panel (c) evaluates its predictive power for food poverty levels from López-Calva et al. (2022) for the year 2015 and include state fixed effects. All estimates are at the municipal level.

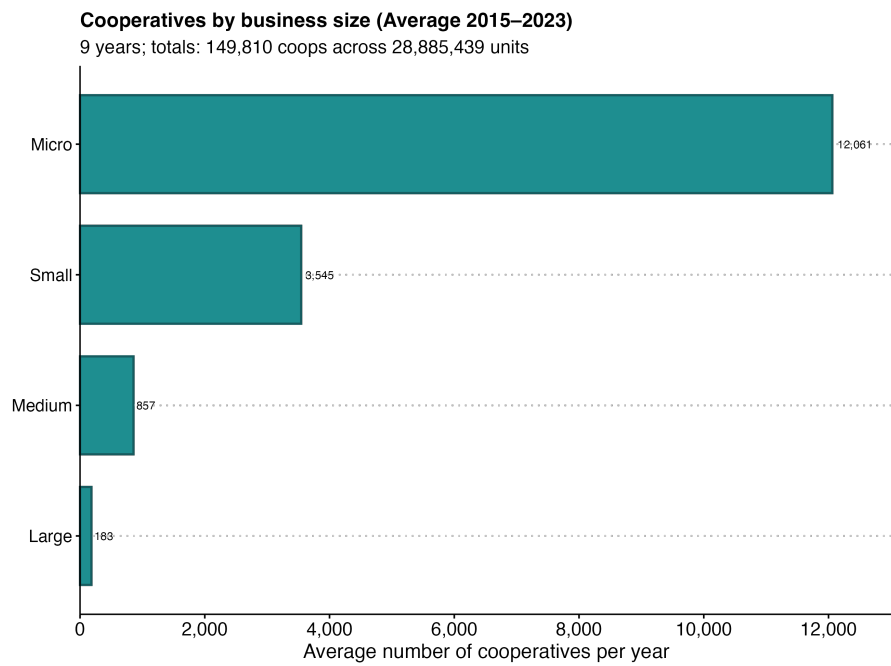


FIGURE A.2 Average annual number of cooperative establishments by firm size, 2015–2023

Notes: Based on FIDESUR's Directory of Cooperatives and Social Firms matched to DENUE. Bars report the *time-mean (per year)* count of cooperative establishments within each size category over the sample years. Firm size follows INEGI's official business-size classification (*business_size*), which is employment-based and sector-contingent. The subtitle in the plot reports the number of years and pooled totals used to compute the averages.

B | EMPIRICAL FRAMEWORK

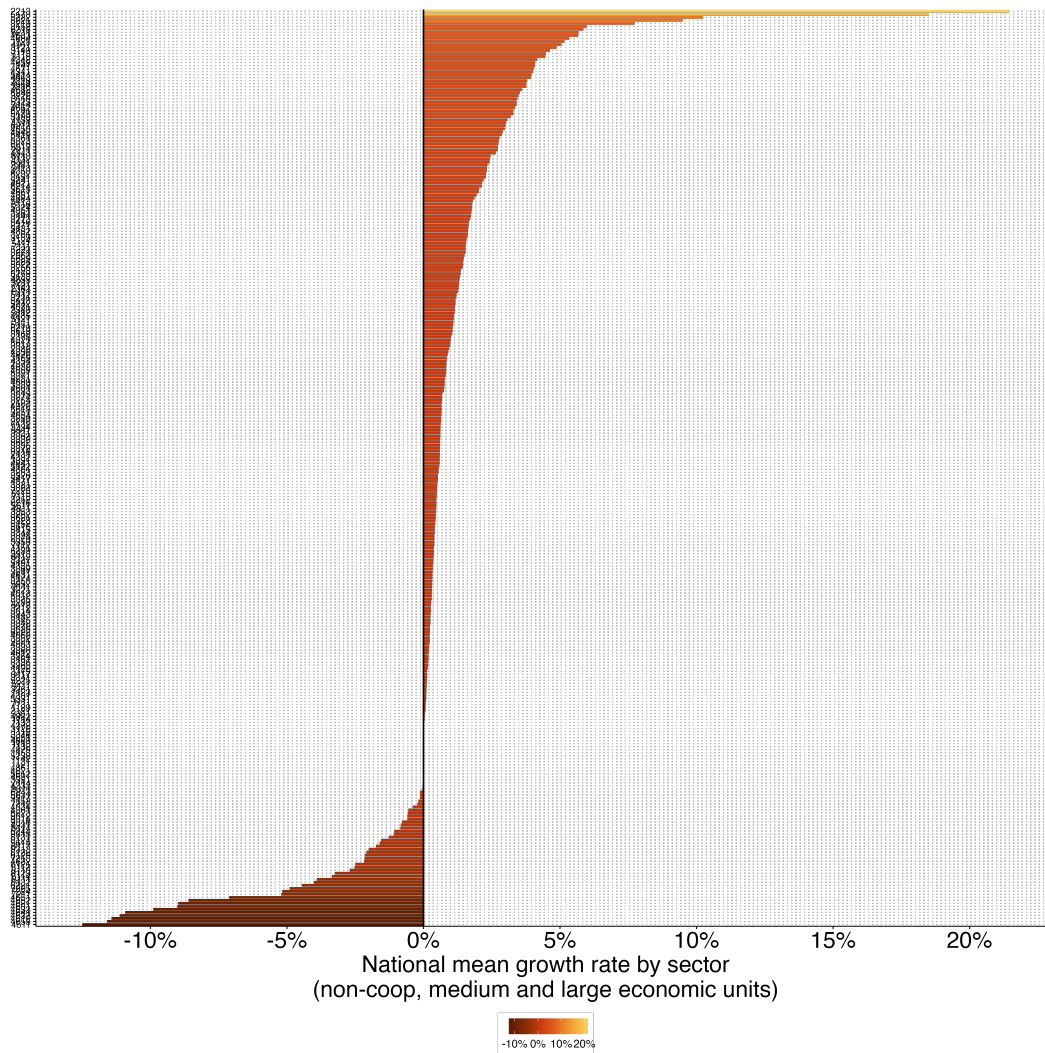


FIGURE B.1 Mean sectoral growth rates of non-cooperative medium and large firms, by 4-digit NAICS code (2015–2023)

Notes: Each bar reports the national mean growth rate of non-cooperative, medium and large establishments by 4-digit NAICS sector, calculated from DENUe microdata for 2015–2023. Growth rates are defined as the change in the number of establishments relative to the previous period. Sectors are ordered by average growth.

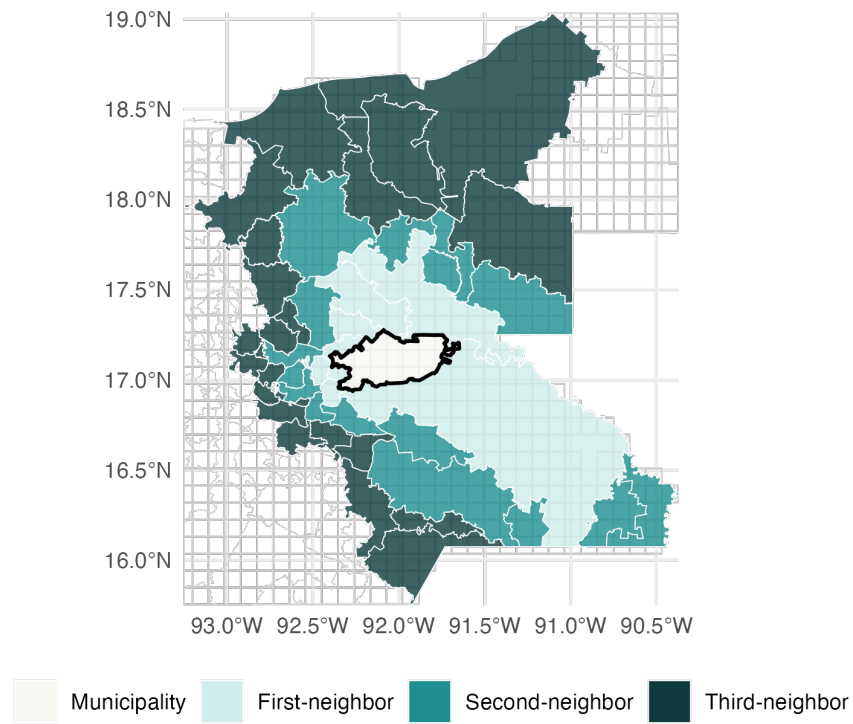


FIGURE B.2 Illustration of third-degree neighboring municipalities (example: Chilón, Chiapas)

Notes: The figure highlights the focal municipality (black outline; Chilón, Chiapas) and its first-, second-, and third-degree neighbors, overlaid on the 10×10 km raster used in the analysis. Neighbor rings are computed on municipal polygons using queen contiguity: ring 1 are contiguous neighbors, ring 2 are neighbors of ring 1 (excluding ring 1 and the focal unit), and ring 3 are neighbors of ring 2 (excluding rings 1–2 and the focal unit). In our shift construction, shocks for municipality m are measured from *third-degree* neighbors only (nearby but outside m), averaging their sectoral establishment growth and netting out national sector–year means. The map is for illustration; the procedure is applied to all municipalities in Mexico.

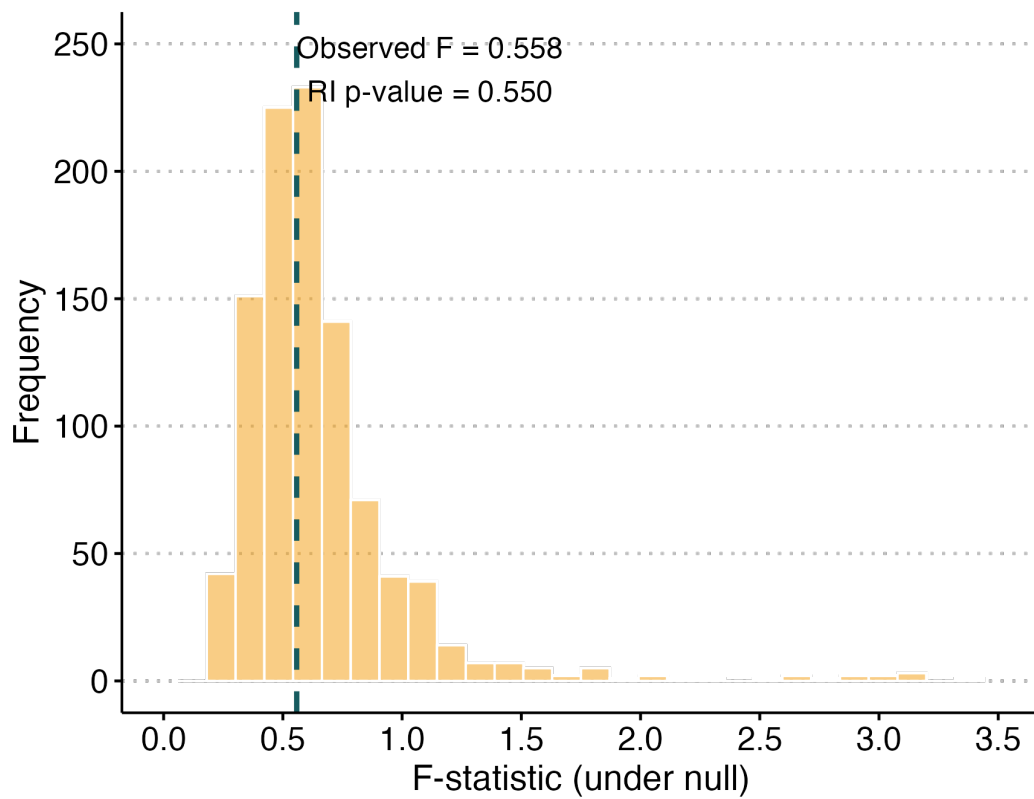


FIGURE B.3 Randomization Inference for Omnibus Balance F-test

Notes: This figure shows the distribution of F-statistics from 1,000 permutations of the shock variable $g_{k,m}$, randomly shuffled within municipality and five-digit sector strata. The red dashed line marks the observed F-statistic from the actual regression of shocks on predetermined covariates. The RI p-value corresponds to the proportion of permuted F-statistics that exceed the observed value, providing a design-consistent test of joint orthogonality, following [Kerwin et al. \(2024\)](#).

B.1 | Why our SSIV differs from Bartik (1991) and can be valid

This appendix formalizes why our shift-share IV (SSIV) differs from Bartik-style instruments and why it can be valid under a “many exogenous shifts” design (Borusyak et al., 2022, 2025). The core idea is that we aim to capture *latent exogenous sectoral demand shifts* using growth in *non-cooperative, medium/large* establishments in nearby-but-not-adjacent municipalities, after *netting out national sector-time means*. This construction is designed to isolate as-good-as-random, spatially heterogeneous demand movements while avoiding the aggregation channel that undermines the exogeneity of classical Bartik (1991) and Card (2009) instruments (see Borusyak et al., 2025, App. A.11–A.12).

B.1.1 | Setup and notation

Let i index 10×10 km cells, m municipalities, k four-digit sectors, and consider long differences between 2015 and 2023. The outcome is

$$\Delta y_i = \beta \Delta x_i + u_i, \quad \Delta x_i \equiv \sum_k \Delta x_{ik}, \quad (4)$$

where Δx_i is the change in cooperative presence in cell i and u_i collects all remaining shocks (including measurement error), after conditioning on controls and municipality trends in the main text.

Baseline exposures are

$$s_{ik} \equiv x_{ik}^{2013} \geq 0, \quad S_i \equiv \sum_k s_{ik},$$

i.e., *counts* of legally registered cooperatives by sector in 2013. Using counts generates “incomplete shares” (S_i varies across i), which we handle by controlling for S_i in first-stage and reduced-form equations (Borusyak et al., 2025).

Latent shocks and observed shocks.

Let δ_{krt} denote a *latent sectoral demand shock* for sector k in region r at time t . We partition the country into disjoint regions $\{r\}$ (e.g., municipality clusters); each municipality m belongs to $r(m)$. We assume that δ_{krt} is mean-independent of baseline exposures and potential outcomes after controls (defined below).

Our observed (constructed) shock for a pair (k, m) is the time-averaged, neighbor-based deviation from national sector means:

$$\begin{aligned} g_{km} &\equiv \frac{1}{T} \sum_{t=2015}^{2023} \left(\bar{g}_{k, \mathcal{N}^{(3)}(m), t} - \bar{g}_{kt} \right) \\ &= \underbrace{\frac{1}{T} \sum_t \left(\bar{\delta}_{k, \mathcal{N}^{(3)}(m), t} - \bar{\delta}_{kt} \right)}_{\text{latent demand component}} + \underbrace{\frac{1}{T} \sum_t \left(\bar{v}_{k, \mathcal{N}^{(3)}(m), t} - \bar{v}_{kt} \right)}_{\text{proxy noise}}, \end{aligned} \quad (5)$$

where $\bar{(\cdot)}$ denotes simple averages over the third-degree neighbor set $\mathcal{N}^{(3)}(m)$, $\bar{(\cdot)}$ denotes national sector means, and v_{kmt} collects non-demand components of sectoral growth (e.g., local labor supply, reclassification, measurement error) for *non-cooperative, medium/large* firms. Excluding own municipality, excluding cooperative and micro/small units, and netting out $\bar{g}_{kt}$ are the three design choices that distinguish our shocks from Bartik-style

national averages.

Instrument.

The SSIV is

$$z_i = \sum_k s_{ik} g_{k\,m(i)}. \quad (6)$$

Following [Borusyak et al. \(2022\)](#), the cell-level SSIV is numerically equivalent to a shock-level IV where outcomes, treatments, and controls are aggregated with exposure weights.

B.1.2 | Bartik vs. our shocks: the aggregation channel

Let E_{kmt} denote (endogenous) local employment growth in sector k and municipality m at time t . A Bartik shift uses national averages:

$$g_{kt}^{\text{Bartik}} = \sum_m \omega_{kmt} E_{kmt} = \bar{\delta}_{kt} + \sum_m \omega_{kmt} v_{kmt}, \quad (7)$$

with weights ω_{kmt} (e.g., employment shares). When industries are regionally concentrated or when local supply shocks v_{kmt} covary across places, the second term transmits local endogeneity into the national shift. As shown in [Borusyak et al. \(2025, App. A.11\)](#), the resulting confounder is an exposure-weighted average of local errors, so validity requires not only exogenous shifts but also *exogenous shares*.

By contrast, our g_{km} in (5) is *local and differenced from the national mean*, cutting the aggregation channel from (7): it loads on neighbor-region demand movements relative to national sector conditions and excludes own-municipality components that could be mechanically correlated with u_i .

B.1.3 | Exogeneity condition in the many-shocks design

Define exposure masses by shock cell: $S_{km} \equiv \sum_{i:m(i)=m} s_{ik}$. The exposure-weighted error associated with shock (k, m) is

$$\bar{u}_{km} \equiv \frac{1}{S_{km}} \sum_{i:m(i)=m} s_{ik} u_i. \quad (8)$$

As in [Borusyak et al. \(2022\)](#), the SSIV exclusion restriction is equivalent to

$$(g_{km}, \bar{u}_{km}) = 0 \quad \text{for all } (k, m) \text{ in importance,} \quad (9)$$

and identification leverages a Lindeberg-type “many small shocks” condition (importance weights not overly concentrated) so that small residual correlations average out.

Using the decomposition (5), condition (9) holds if both components are orthogonal to $\bar{u}_{km}$:

$$\text{(A1) Demand exogeneity: } \left(\bar{\delta}_{k, \mathcal{N}^{(3)}(m)} - \bar{\delta}_k, \bar{u}_{km} \right) = 0; \quad (10)$$

$$\text{(A2) Proxy-noise orthogonality: } \left(\bar{v}_{k, \mathcal{N}^{(3)}(m)} - \bar{v}_k, \bar{u}_{km} \right) = 0. \quad (11)$$

Why (10) is plausible in our design.

(i) *Spatial separation*: excluding own m and using third-degree neighbors makes neighbor demand shocks independent of u_i under limited interference/spillovers beyond second-degree borders. (ii) *National demeaning*: subtracting $\bar{\delta}_{kt}$ removes aggregate sector shocks that could correlate with common components of $\bar{u}_{km}$. (iii) *Long differences*: time-averaging over 2015–2023 weakens incidental serial correlation between shocks and persistent u_i .

Why (11) is more plausible than in Bartik.

Proxy noise in g_{km} arises from non-demand forces in *neighbors' non-cooperative, medium/large* sectors. We (a) exclude own m , avoiding mechanical correlation between g_{km} and $\bar{u}_{km}$; (b) exclude cooperative and micro/small units, reducing any channel where cooperative-specific or micro-firm supply factors directly move the instrument; and (c) net out the national sector mean, so only *local* deviations remain. Under weak spatial correlation of neighbors' supply shocks with $\bar{u}_{km}$ after controls (roads, distances, baseline NLPC, etc.), the covariance in (11) is near zero.¹⁵

B.1.4 | First stage and exclusion with incomplete shares

Write the first stage in long differences as

$$\Delta x_i = \sum_k s_{ik} \pi_{k\ m(i)} g_{k\ m(i)} + \xi_i, \quad \pi_{km} > 0, \quad (12)$$

where π_{km} maps shocks into cooperative expansions (capturing technological/market linkages). Because S_i varies across i , we follow [Borusyak et al. \(2025\)](#) and control for S_i so that identifying variation in (12) and (4) comes from *shifts* $\{g_{km}\}$ rather than exposure mass. The exclusion restriction is that g_{km} affects Δy_i only through Δx_i ; this is plausible because shocks are computed outside m , on non-cooperative medium/large firms, and net of national sector means.

B.1.5 | Comparison result and identification

Let the importance weight of shock (k, m) be $\omega_{km} \propto S_{km}$ (normalized to sum to one). Under Assumptions (10)–(11), incomplete-share control, and many-shocks (bounded $\sum_{km} \omega_{km}^2$), we obtain:

[propositionSSIV identification under nearby-outside shocks] Suppose (i) $\{g_{km}\}$ are constructed as in (5); (ii) (10) and (11) hold after conditioning on covariates used in the main text; (iii) the first stage (12) is relevant; and (iv) $\sum_{km} \omega_{km}^2 = o(1)$. Then the SSIV estimator using (6) is consistent for β in (4) with exposure-robust (shock-level) inference ([Borusyak et al., 2022](#)).

Sketch By shock-level equivalence, the SSIV estimand is

$$\beta^{SSIV} = \frac{\sum_{km} \omega_{km} (g_{km}, \bar{y}_{km})}{\sum_{km} \omega_{km} (g_{km}, \bar{x}_{km})} = \beta + \frac{\sum_{km} \omega_{km} (g_{km}, \bar{u}_{km})}{\sum_{km} \omega_{km} (g_{km}, \bar{x}_{km})}.$$

By (9), the numerator bias term is zero. Many-shocks ensures the sample analog converges to this population ratio with valid exposure-robust standard errors.

¹⁵In Bartik, proxy noise is a *national* average of local supply shocks and generically correlates with exposure-weighted local errors when industries are geographically concentrated; see [Borusyak et al. \(2025, App. A.11\)](#). Our neighbor-demeaned construction eliminates this national aggregation pathway.

B.1.6 | Why leave-one-out (LOO) is not the point here

LOO Bartik replaces $\bar{g}_{kt}$ by a national average that drops the unit of observation (Autor and Duggan, 2003). LOO mitigates mechanical correlation but, as stressed by Borusyak et al. (2025, App. A.12), does *not* generally solve endogeneity when shares are correlated with errors. Our strategy is different: we do not pool to a national shift at all; instead, we form *neighbor-demeaned, non-cooperative, medium/large* shocks g_{km} , which removes the national aggregation pathway and targets local demand variation that is plausibly orthogonal to $\bar{u}_{km}$.

B.1.7 | Testable implications and diagnostics

The above conditions imply: (i) strong first stage at the (k, m) level when weighting by S_{km} ; (ii) many-shocks diagnostics (high effective number of shocks; limited weight concentration); and (iii) balance of g_{km} with pre-treatment covariates using exposure-robust inference. Our empirical Section 4.2.1 reports exactly these diagnostics, consistent with Assumptions (10)–(11).

C | RESULTS

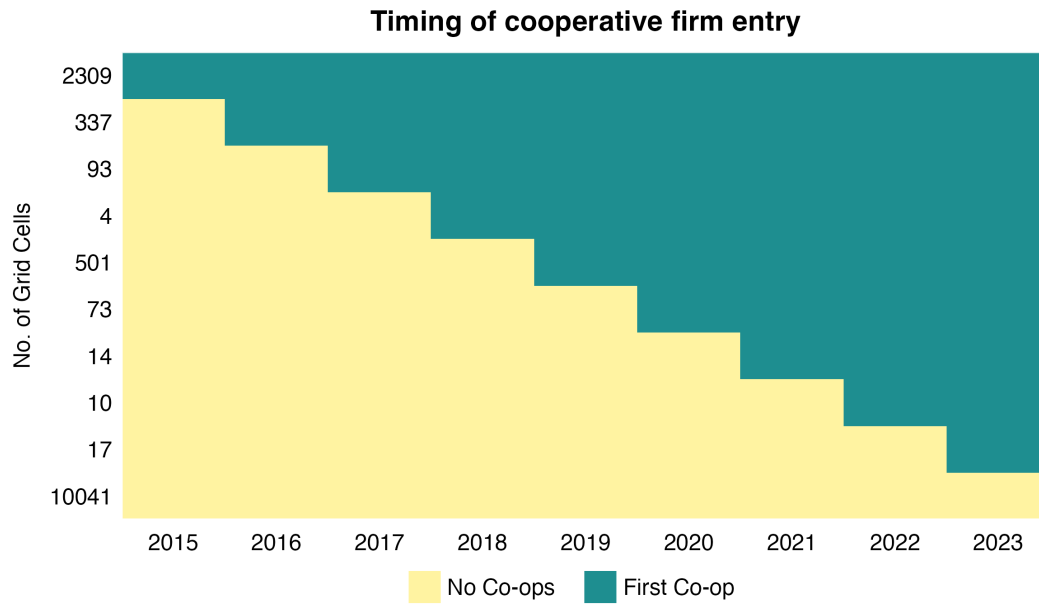


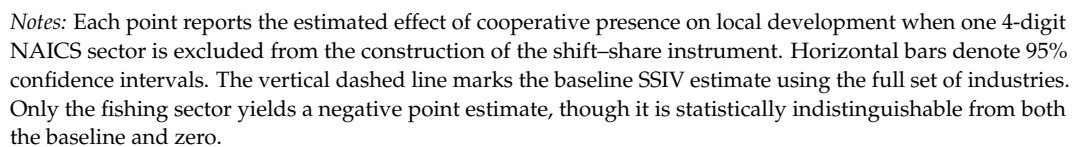
FIGURE C.1 Timing of cooperative firm entry across grid cells

Notes: The figure shows the staggered adoption of cooperatives across 10×10 km rural grid cells during 2015–2023. Yellow areas denote cells that have not yet received a cooperative, while teal areas denote cells that experience their first cooperative entry in the given year. The figure illustrates the distribution of treatment timing used in the Difference-in-Differences event-study design.

TABLE C.1 Balance tests: time-varying covariates

Variable	Estimate (z-score)	Std. Error	FDR q-value
Δ NLPC	0.006	0.005	[0.327]
Δ Total units (2015-2023)	-0.012	0.021	[0.619]
Δ Large units (2015-2023)	0.040	0.041	[0.443]
Δ Medium units (2015-2023)	0.004	0.024	[0.777]
Δ Small units (2015-2023)	0.022	0.013	[0.283]
Δ Micro units (2015-2023)	-0.014	0.021	[0.619]
Δ Roads: principal (2015-2023)	0.006	0.005	[0.376]
Δ Roads: local (2015-2023)	0.024	0.026	[0.443]
Δ Roads: secondary (2015-2023)	-0.015	0.028	[0.625]
Δ Transport & mobility infra. (2015-2023)	-0.015	0.039	[0.698]

Entries are standardized coefficients from pairwise regressions on the sector–municipality shock, with clustered SEs at municipality and sector levels and weights equal to exposure mass. q-values report BH–FDR adjusted p-values.



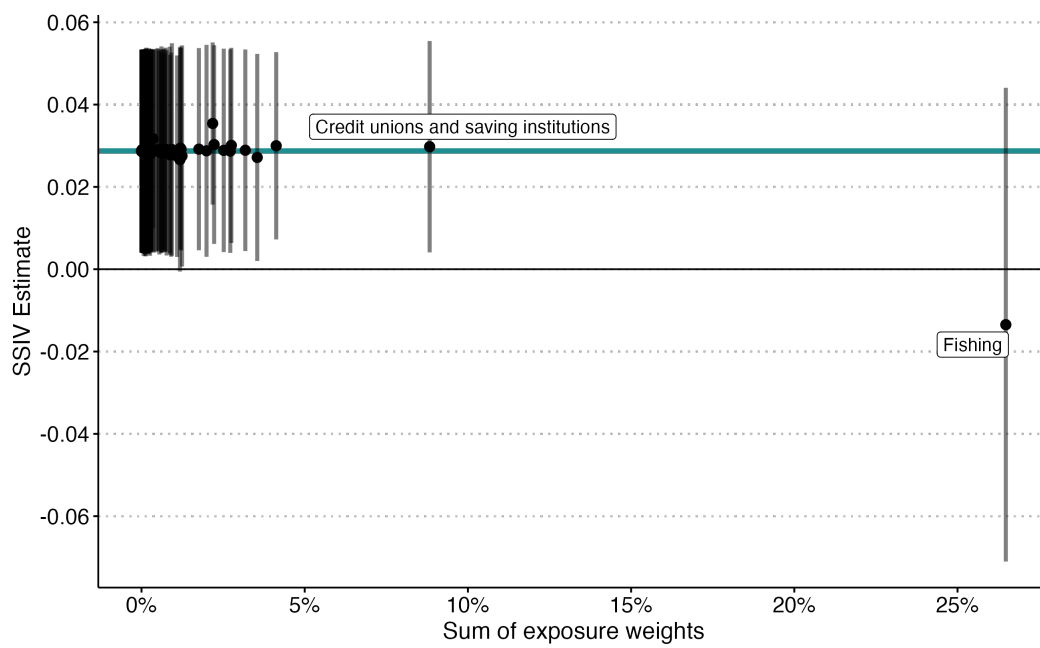


FIGURE C.3 Industry exposure weights and leave-one-out estimates.

Notes: The horizontal axis reports the share of baseline exposure weights s_n accounted for by each sector, expressed as a proportion of the total across industries. The vertical axis shows the corresponding leave-one-out SSIV estimate with 95% confidence intervals. The blue horizontal line represents the baseline SSIV estimate. Credit unions and fishing stand out as sectors with disproportionately large weights (26.5% and 23.0%, respectively), raising concerns that overall results may be sensitive to these industries' leverage.

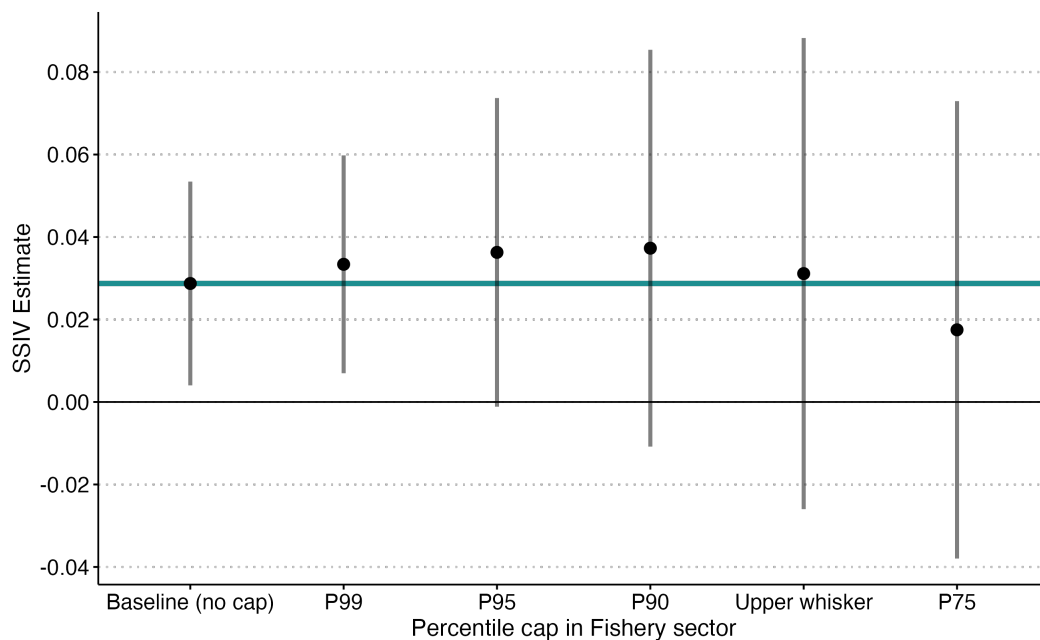


FIGURE C.4 Robustness to reweighting the fishing sector.

Notes: The figure reports SSIV estimates of the effect of cooperatives on local development under different caps on the exposure weights for the fishing sector (NAICS 1141). The vertical axis plots the estimated coefficient on cooperative presence, with 95% confidence intervals. The horizontal axis reports the capping rule applied: baseline (no cap), 99th, 95th, 90th, and 75th percentiles of the weight distribution, and the Tukey upper whisker. The horizontal blue line marks the baseline estimate. Results show that capping extreme values of the fishing sector does not materially change the estimated effect.

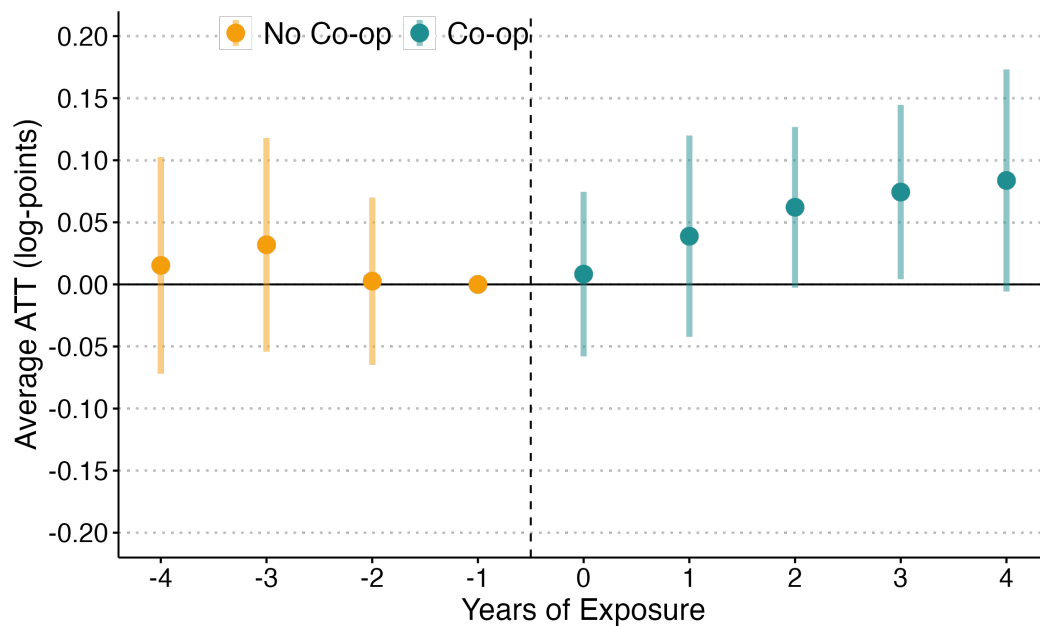


FIGURE C.5 Event-study estimates excluding fishing cooperatives.

Notes: The figure reports dynamic treatment effects from the [Callaway and Sant'Anna \(2021\)](#) estimator, restricting the treatment to the entry of non-fishery cooperatives. Estimates remain robust and closely track the baseline results in both magnitude and dynamics.

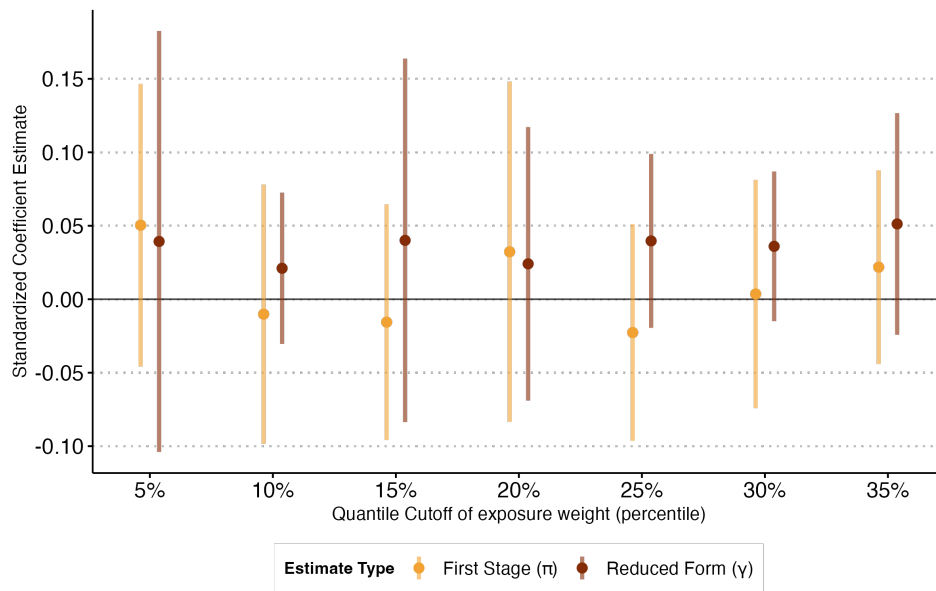
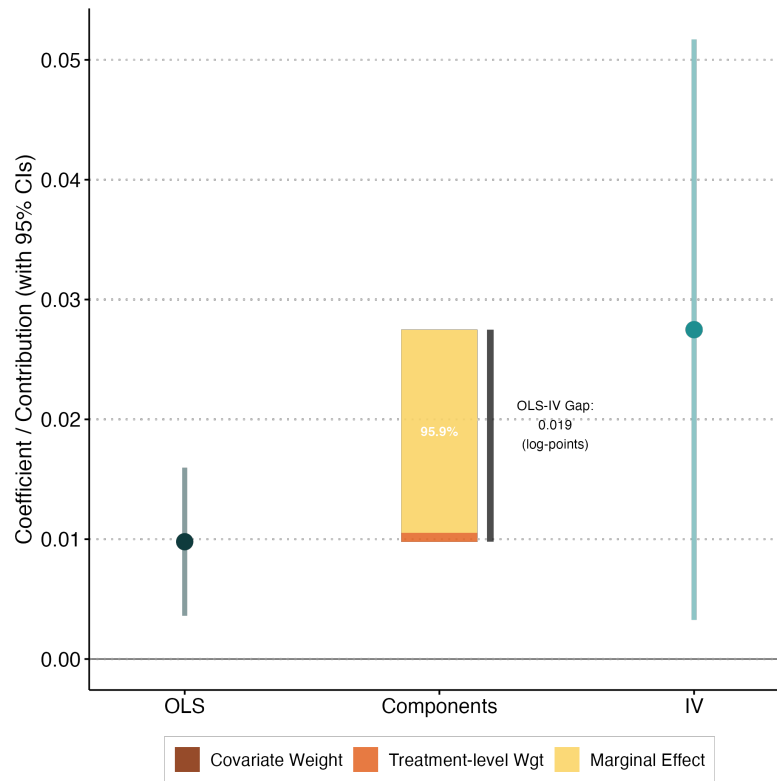


FIGURE C.6 Zero first stage test

Notes: The plot shows first stage (π) and reduced form (γ) estimates when restricting the sample to grid cells with low exposure weight s_n . Each point corresponds to a quantile cutoff (5%, 10%, 15%, 20%, 25%, 30%, 35%) of the exposure distribution. Confidence intervals at 95% level are displayed. In subsamples with very low exposure, both the first stage and reduced form coefficients converge to zero, consistent with the exclusion restriction.

FIGURE C.7 OLS–IV Decomposition of the Cooperative Effect



Notes: The figure displays the decomposition of the OLS–IV gap following [Ishimaru \(2024\)](#). The total gap is partitioned into three components: (i) covariate weight difference, (ii) treatment–level weight difference, and (iii) marginal effect difference. In our application, the decomposition shows that almost the entire gap is driven by the marginal effect difference, suggesting that endogeneity (or unobserved heterogeneity) is the primary factor behind the divergence between OLS and IV estimates.

D | MECHANISMS

TABLE D.1 SSIV: Effect of Δ Co-ops on Changes in Infrastructure and Public Goods (2015–2023)

	Main roads (km, Δ log) (1)	Local streets (km, Δ log) (2)	Secondary roads (km, Δ log) (3)	No. of Transport infrastructure (Δ) (4)
Δ Co-ops	0.0124 (0.0142)	0.0222 (0.0319)	-0.0213 (0.0334)	-0.0008 (0.0128)
FDR q-value	[0.025]	[0.002]	[0.108]	[0.002]
Observations	3,462	3,462	3,462	3,462
F-test (1st stage), Δ Co-ops	85.29	85.29	85.29	85.29

Notes: Each column reports a shift-share IV (SSIV) estimate of the effect of changes in cooperative presence on changes in infrastructure/public goods between 2015 and 2023. Outcomes are log changes in kilometers of main roads, local streets, and secondary roads, and changes in the count of transport/mobility facilities. The endogenous regressor is the change in the number of cooperatives; the instrument is $z_i = \sum_k s_{ik,2013} \tilde{g}_{k,m}$, where $s_{ik,2013}$ are baseline (2013) cooperative counts by 4-digit sector and $\tilde{g}_{k,m}$ are sectoral shocks from third-degree neighboring municipalities net of national sector-by-year means. All specifications are estimated in first differences, weighted by total exposure (s_n), and estimated at the level of sectoral shocks [Borusyak et al. \(2022\)](#). All specifications residualize for longitude, latitude, and municipal fixed effects at the grid cell level before aggregating at the shock level. All specification control for the incomplete-share term $S_i = \sum_k s_{ik,2013}$ to isolate variation arising from shifts rather than levels; for changes in the size distribution of non-cooperative establishments (small, medium, and large); for changes in the number of *ejidos*; for changes in infrastructure measures (principal roads, local roads, secondary roads, and transport/mobility points). Standard errors are two-way clustered at the municipality and 4-digit sector level. Reported F-statistics correspond to the first stage on Δ Co-ops.