

The Local (Informal) Multiplier of Industrial Jobs*

Francesco Amodio[†]

Elia Benveniste[‡]

Hoang Pham[§]

Marco Sanfilippo[¶]

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Abstract

When the number of industrial jobs increases, employment at small informal firms also rises. We demonstrate this in the context of Ethiopia from 1999 to 2013. We use the term “industrial” jobs to capture work in manufacturing formal firms with 10 or more employees, as recorded in the annual census of medium and large manufacturers. Using survey data on micro and small manufacturing enterprises and a Bartik-type identification strategy, we find that each additional industrial job creates approximately 0.1 jobs and leads to higher wages at small informal firms in the same location. Most of these jobs are in the food and beverage sector. The size of this local multiplier varies widely across industries, reaching up to 3.83 for jobs in furniture making. Industrial jobs also increase informal employment in the services sector. Overall, the evidence suggests income effects and both substitution and complementarity between small and large firms.

Keywords: industrial development, local multiplier, informality, Ethiopia.

JEL Codes: L25, L60, O14, O17, O55, R11.

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[†]Department of Economics and ISID, McGill University and IZA, francesco.amodio@mcgill.ca.

[‡]Department of Economics and Business, Universitat Pompeu Fabra, elia.benveniste@upf.edu.

[§]Department of Economics, Oregon State University, hoang.pham@oregonstate.edu.

[¶]Department of Economics and Statistics “Cognetti de Martiis,” University of Torino and Collegio Carlo Alberto, marco.sanfilippo@unito.it.

1 Introduction

Industrialization and the expansion of a modern industrial sector have historically been key drivers of sustained economic growth and poverty reduction. Industrial jobs have the potential to generate stable employment at scale by productively absorbing low-skilled labor. Yet in many low- and middle-income countries today, this process appears to have stalled. Since the 1980s, many poor countries have experienced simultaneous deagrarianization and deindustrialization (Rodrik, 2016). In many African countries, even as GDP per capita rises and large manufacturing firms achieve productivity gains, they contribute little to employment growth, with most new manufacturing jobs emerging in small, informal firms rather than in formal, higher-productivity enterprises (Diao, McMillan and Rodrik, 2019; McMillan and Zeufack, 2022; Diao et al., 2021; Kruse et al., 2023). The most recent evidence highlights a sharp dichotomy: large firms exhibit strong productivity performance but generate few jobs, while small firms absorb labor without corresponding productivity gains.

This paper challenges this dichotomous view. We document a strong and robust relationship between the number of jobs at large manufacturing firms and employment at smaller firms in the same location. We use the term “industrial” jobs to capture work in manufacturing formal firms with 10 or more employees. The conceptual framework behind our analysis builds on Moretti (2010, 2011). Consider a permanent increase in the demand for industrial labor in a location z . If labor is not perfectly mobile across locations, the wages of all workers in location z will increase. As a result, local income and expenditure increase, driving up the demand for locally produced goods and services and employment at those firms that supply them. The size of these effects depends on consumer preferences, the type of industrial jobs, and the offsetting general equilibrium effects of increasing production costs and (particularly housing) prices.

We focus on Ethiopia and combine data from the annual census of medium and large manufacturers with survey data on micro and small (mostly informal) manufacturing enterprises from 2002 to 2013. We implement a Bartik-type identification strategy to estimate the effect of industrial jobs on small firms’ outcomes and calculate the associated “local multiplier.” We find that a 10% increase in industrial employment in a given location increases employment at the average small informal firm by approximately 0.03 workers and wages by 1.36%. This corresponds to a local multiplier of 0.09, meaning that, in the average location, each additional industrial job brings about 0.09 jobs at small informal firms. These results stand up to a battery of robustness checks. The size of this local multiplier is widely heterogeneous across industries, with evidence pointing to the presence of income effects as well as both substitution and complementarity patterns between small and large firms. In particular, each industrial job in furniture making comes with almost 4 more informal

jobs in the same sector and about 2 more informal jobs in food, apparel, and other sectors.

In an extension of our analysis, we use individual-level data and also explore the effect of industrial jobs on the services sector. We find some evidence that local industrial jobs increase the demand for certain types of service activities that are related to manufacturing because of production linkages (e.g. trade, wholesales, or transport) or through income effects (e.g. recreational activities). While public sector employment also increases, this analysis shows that industrial jobs increase informal service employment more than formal service employment.

This paper contributes to several strands of literature. First, we contribute to the literature on industrialization and early deindustrialization in Africa. There is a concern that many developing countries might be prematurely deindustrializing or skipping the industrialization phase of development altogether. This could be problematic because industrialization is widely regarded as a crucial step in the development process: the manufacturing sector is technologically dynamic, it can absorb unskilled labor, and it is tradable, meaning that it does not face the constraint of a low-income domestic market (Rodrik, 2016). Although the employment share in manufacturing has increased in Ethiopia over the last 30 years, much of this growth has occurred in small informal firms rather than in larger, more productive formal firms (Diao et al., 2021). Yet, there is a lack of evidence on the indirect effects of “good” jobs in manufacturing and their potential spillovers on small manufacturing firms through input-output linkages or shifts in demand (McMillan and Zeufack, 2022).

Second, our paper contributes to the literature on job multipliers, which has mostly focused on estimating local job multipliers in developed economies: for example, see Moretti (2010) and Van Dijk (2017) for estimates of local job multipliers in the US, Moretti and Thulin (2013) in Sweden and Faggio and Overman (2014) in England. One notable exception is Toews and Vezina (2022) who assess the job creation effects of gas discovery-driven FDI bonanzas in Mozambique. Combining household surveys and firm censuses, they estimate that each new FDI job creates additional 4.4 jobs locally, most of them being informal.

Third, we contribute to the literature on informality in low-income countries. Following the work of Ulyssea (2018), Donovan, Lu and Schoellman (2023) and Amodio, Medina and Morlacco (2022), we challenge the *dual* view that conceptualizes formal and informal labor markets as distinct and separate from each other. Instead, we show the two are interlinked: an increase in demand for formal industrial labor in a location causes an increase in demand for informal labor in the manufacturing and services sectors.

The remainder of the paper is organized as follows. Section 2 provides a brief overview of Ethiopia’s industrial development. Section 3 introduces the data we use and their summary statis-

tics. Section 4 introduces the identification strategy, and Section 5 presents the results. Section 6 concludes.

2 Industrial Development in Ethiopia

Since Ethiopia launched its Agricultural Development-Led Industrialization (ADLI) strategy in 1995, the country has made industrialization and structural transformation central to its development agenda. Since 2000, policy design has been guided by successive five-year plans, with private sector development at their core. Specific provisions to foster industrialization were included in the Growth and Transformation Plans I and II (2010–2020), as well as in the Ethiopian Industrial Development Strategic Plan. Over the last two decades, the industrial sector has grown steadily, but has fallen short of the ambitious targets set in national development plans, particularly in terms of employment generation and structural change.

Ethiopia’s industrial policy has rested on three main pillars ([Oqubay, 2019](#)). The first has been direct support to labor-intensive industries, especially those linked to agriculture, such as food processing, leather goods, textiles and apparel, and basic construction materials like cement and steel. These sectors were prioritized for fiscal incentives, especially if they exported or operated outside Addis Ababa. Evidence suggests these policies had positive effects on firm-level productivity ([Gebrewolde and Rockey, 2023](#)).

The second pillar focused on attracting Foreign Direct Investment (FDI), with the aim of leveraging global capital, managerial know-how, and technology transfer. The Growth and Transformation Plans prioritized FDI as a lever for productivity gains and integration into global value chains. Recent empirical evidence finds positive effects of FDI on both firm performance ([Abebe, McMillan and Serafinelli, 2022](#)) and aggregate productivity through heightened competition ([Asturias, Sanfilippo and Sundaram, 2023](#)).

The third and most recent policy instrument has been the establishment of industrial parks modeled on East Asian experiences. These parks were intended to attract export-oriented, light manufacturing firms and generate large-scale employment. While promising in design, their overall impact remains uncertain, partly due to the shock of the COVID-19 pandemic and evolving global supply chains (e.g. [Hardy et al., 2024](#)).

A fourth, often underemphasized but critical, component of Ethiopia’s industrial strategy has been investment in infrastructure, especially through the Road Sector Development Programme (RSDP). Launched in 1997, the RSDP expanded the country’s road network from 26,550 km to

over 113,000 km by 2016, dramatically improving domestic connectivity. These investments lowered internal trade costs, expanded consumer and firm market access, and reshaped competition across local markets (Perra, Sanfilippo and Sundaram, 2024). The evidence suggests that better connectivity raised productivity, capital intensity, and wages among formal firms, while informal firms—typically smaller and more credit-constrained—saw little productivity improvement and even declines in investment and capital intensity.

These heterogeneous effects underscore the structural divide between formal and informal firms in Ethiopia’s manufacturing sector. While industrial policy has succeeded in stimulating firm-level productivity growth and attracting foreign investment, it has been less effective in generating broad-based, stable employment. The majority of new jobs in manufacturing have emerged in small, informal firms rather than in productive, formal enterprises. As a result, despite substantial public investment and strategic planning, Ethiopia’s industrial transformation has delivered only partial success: productivity is rising, but without inclusive employment growth or robust backward linkages to the broader economy (McMillan and Zeufack, 2022; Diao et al., 2021; Perra, Sanfilippo and Sundaram, 2024).

3 Data and Descriptives

3.1 Large and Small Firm-Level Data

We combine two sources of micro-data that together cover the entire manufacturing sector in Ethiopia. The first is the Large and Medium Manufacturing industry Survey (LMMS), an annual census of firms published by the Central Statistical Agency (CSA). The survey covers all firms with at least 10 persons engaged and that use electricity in their production process. Firms are required to respond to this census every year; therefore, this source includes the universe of large and medium firms in the manufacturing sector. The census records provide information on the characteristics of each establishment, as well as detailed information on the size and composition of the workforce and on the location of each firm. Firms also provide details on sales values and quantity produced for the domestic and international market for each product, as well as information on raw materials, both domestic and imported, employed at the firm level for the production processes, and their share in total firm expenditure. Manufacturing industries are defined at the 4-digit level according to the ISIC Rev. 3 classification.

The second dataset is the Survey of Small-scale Manufacturing Industries (SSIS). We combine all existing waves of the SSIS, covering the years 2002, 2004, 2007, 2010, 2013. This is a survey that

covers small (with less than 10 persons engaged, including any working owner) and mainly informal firms operating in the manufacturing sector. The sample is single-stage stratified, considering six main industries (textiles and garments, metal work, wood work, leather and leather products, other manufacturing sectors and the grain mills industry), sampled in similar proportions across regions.

Figure 1 illustrates the evolution of industrial employment from the LMMS as well as employment at small formal and informal firms from the SSIS over time. Appendix Table A.1 reports figures for the years in which the SSIS and the LMMS were run simultaneously. On average small firms represent the majority of all manufacturing establishments. As shown in Figure 1, they account for over half of total employment. But, small firms are much less important in terms of production, capital stock, and total wage bill. Also, and consistent with the evidence in the literature from similar contexts, the vast majority of small firms' sales are local (Startz, 2024; Bassi et al., 2022, 2023; Vitali, 2023). The two most recent waves of the SSIS survey ask firms whether they sell domestically and/or abroad and, in the former case, if their market is mostly local or national. More than 99% of the firms sell within Ethiopia. Out of them, slightly more than 91% state that their market is local, and the rest also sell elsewhere in the country.

3.2 Individual-Level Data

To gain insight on the services sector, we use data at the individual level. We obtain them from the Ethiopian National Labour Force (NLF) survey. This is a representative survey of both urban and rural areas administered by the Central Statistical Agency (CSA), with the objective of monitoring the economic and social conditions of the economically active population. The NLF surveys are representative at the national level and use regions, the first administrative units, as the main sample domains. They cover all urban and rural areas of the country except the non-sedentary areas in the Somali region. The sampling frame to select enumerator areas is provided by the population census (the 1994 census for the 1999 and 2005 NLF waves and the 2007 census for the 2013 wave). All of the relevant information on the sampling procedures, coverage and full descriptive statistics are available in the survey reports published by the CSA (2004, 2006, 2014). The information provided in the survey includes, among others, the demographic characteristics of the individuals, their education and working conditions. The NLF includes information on whether respondents report a previous residence different from the current, thus allowing the identification of internal migrants, as well as on the formal or informal nature of an individual's current job. We use all existing waves of the NLF, covering the years 1999, 2005 and 2013.

3.3 Descriptives

Appendix Table A.2 shows the summary statistics of the variables we use in the empirical analysis. Panel A focuses on the small firm-level sample. The average firm counts 3 employees. About 80% of the firms in the sample are informal, and distributed across 20 2-digit sectors and 42 zones. Appendix Table A.3 shows how the full sample is distributed across sectors and survey years, both overall and then separately focusing on formal and informal firms. About half of the small firms are in the food and beverage manufacturing sector, followed by furniture (16%), fabricated metal products (12.5%) and apparel (11.25%).

Our geographical unit of analysis is the zone, the second-level administrative subdivision of Ethiopia. To maintain consistency over time and across data sources, we use the GeoLevel2 boundaries defined by IPUMS, which divide the country into 50 zones. Zone codes in the SSIS and NFL surveys always match a code in the IPUMS definition. Some zone codes in the LMMS do not map to any of the codes in IPUMS. When this is the case, we use town names to assign the firm to a zone. Appendix Figure A.1 shows the map of Ethiopia with zone boundaries and information about which one of them are covered by each source of firm-level and individual-level data.

Panel B of Appendix Table A.2 shows the summary statistics of industrial employment across zone \times year observations. This is obtained by calculating total employment across all large firms in the LMMS in each zone and year. We focus only on those zones with at least one industrial job. The average is about 3,800, with large variation across units. On average, about one fourth of these jobs are in food and beverage manufacturing, followed by textiles, non-metallic mineral products, rubber and plastic products, and chemicals and chemical products.

Appendix Figure A.2 shows the distribution of industrial employment across zones at different points in time, from 1996 to 2016. The growth of industrial employment is visible as the distribution shifts towards the right over time. Appendix Figure A.3 does so separately for industrial jobs in what will be key sectors in the empirical analysis due to their associated local multiplier.

4 Empirical Strategy

Does the size of the industrial sector matter for small firm-level outcomes in the same location? We implement the following regression specification

$$y_{iszt} = \beta \ln ind_{zt} + \alpha_s + \theta_z + \delta_t + u_{iszt} \quad (1)$$

where y_{iszt} is the outcome y of small firm i belonging to (2-digit) sector s and zone z , surveyed in year t . The main independent variable is $\ln ind_{zt}$, which is the (log of) total industrial employment in the same zone and year. α_s and θ_z are sector and zone fixed effects, which capture and net out all sector and zone-specific time-invariant determinants of y . δ_t stands for year fixed effects and allows for flexible time trends that are common to all firms in the sample. The term u_{iszt} captures any residual determinants of the outcome of interest. We allow such residuals to be correlated among all observations belonging to the same zone by clustering standard errors at that level. Each observation is weighted according to its original survey weight.

Estimating the parameters in equation (1) using OLS is likely to deliver biased and inconsistent estimates of β . This is because the size of the industrial sector is not as good as randomly assigned to locations, and likely correlated with small firms' characteristics. For instance, a positive productivity shock to all firms in a particular zone would drive up labor demand and employment simultaneously at both large and small firms, generating an upward bias in the estimate of β . The same would be true in the presence of reverse causality, meaning if the productivity of small firms in a location was among the determinants of large firms' localization and thus industrial employment in the same area. Note that the bias could also be negative. This is the case if, for instance, a positive productivity shock is differentially higher for larger firms, therefore inducing reallocation of employment from small to large firms.

To achieve identification, we implement a Bartik-type identification strategy that exploits variation across zones in their baseline industrial composition, combined with changes over time in national industrial employment trends. For each zone z and year t , we construct the following predicted measure of industrial employment:

$$\widehat{ind}_{zt} = \sum_j \frac{ind_{jz,1996-98}}{ind_{z,1996-98}} \times ind_{jt} \quad (2)$$

In this expression, the first term inside the summation is the share of industrial employment in zone z accounted for by industry j , averaged over the baseline period 1996–1998. The second term is the national level of employment in industry j in year t . The variable \widehat{ind}_{zt} thus captures the degree to which each zone is exposed to national changes in industrial employment, weighted by its initial composition. Following the language of [Borusyak, Hull and Jaravel \(2025\)](#), national employment levels ind_{jt} are common shifts, while baseline employment shares $\frac{ind_{jz,1996-98}}{ind_{z,1996-98}}$ are exposure shares that vary across units. Note that sum of exposure shares is always equal to one.

We use this predicted measure as an instrument for actual industrial employment in zone z and

year t , and estimate the following first-stage specification:

$$\ln ind_{zt} = \gamma \ln \widehat{ind}_{zt} + \phi_s + \rho_z + \lambda_t + v_{iszt} \quad (3)$$

where $\ln ind_{zt}$ is the actual log of industrial employment, and ϕ_s , ρ_z , and λ_t are fixed effects for small firm sector, zone, and year, respectively.

The validity of this identification strategy rests upon the following assumptions. First, the instrument needs to be relevant, i.e. trigger sufficient variation in the endogenous regressor of interest. This is the case if baseline employment shares effectively capture differential exposure to nationwide industry-level trends, and can be tested in light of the first-stage regression results. Second, the instrument needs to satisfy the exclusion restriction, meaning it has to be as good as randomly assigned and affect the outcomes of interest only through the variation it induces in the endogenous regressor. This is achieved in this context if the exposure shares $\frac{ind_{jz,1996-98}}{ind_{z,1996-98}}$ are exogenous (Goldsmith-Pinkham, Sorkin and Swift, 2020). That is, baseline shares must satisfy a parallel trends assumption: in the absence of national changes in industry-level employment, average changes in small firm outcomes would have been similar across zones regardless of the initial composition of their industrial sector. Note that the exposure shares are explicitly tailored to the nature of the treatment of interest—industrial employment—and vary meaningfully across zones. The inclusion of zone and sector fixed effects helps mitigate concerns about systematic differences. We will also empirically assess the plausibility of the parallel trends assumption by analyzing pre-trends in small firm outcomes across zones with varying baseline exposure.

Note that we can also support our empirical strategy with an alternative path to identification based on the exogeneity of the shifts ind_{jt} (Borusyak, Hull and Jaravel, 2022). This holds if changes in nationwide industrial employment are orthogonal to the evolution of small firms' outcomes. If this is the case, identification remains valid even if baseline exposure shares are endogenous, in the sense that small firms across zones with different sectoral composition at baseline may have systematically different unobservables. We explore the validity of this alternative path to identification in Appendix B.

The main focus of the empirical analysis will be on the impact that industrial jobs have on employment at small firms in the same location. This means that employment at the firm level will be the outcome y_{iszt} in equation (1). Upon obtaining $\hat{\beta}_{IV}$, we can calculate the local multiplier of industrial jobs akin to Moretti (2010). We multiply the average employment effect $\hat{\beta}_{IV}$ by the average number of small firms by zone over the period. This is an estimate of the total number of new jobs at small firms associated with doubling industrial jobs in the average location. To obtain the local multiplier, we divide this number by the average of industrial employment across

zones over the period, thus capturing how many jobs at small firms are created on average by one additional industrial job in the same location.

5 Results

5.1 Baseline

Table 1 provides the first set of results. We start by considering the number of workers as the outcome y_{iszt} in equation (1). The first column reports the OLS estimate of β , which is negligible in magnitude and not statistically different from zero at standard levels. Column 2 reports the reduced form regression results, meaning the OLS coefficient estimate that we obtain when regressing employment over the instrument $\ln \widehat{ind}_{zt}$ and the three sets of fixed effects. The estimated coefficient is positive and significant at the 5% level. Column 3 reports instead the 2SLS estimate of β that we obtain when using $\ln \widehat{ind}_{zt}$ as instrument for the log of actual industrial employment. The *F-statistic* associated with the first-stage regression is safely above 10, which indicates that the instrument is strong enough to generate meaningful variation in the endogenous variable of interest. The estimated β is equal to 0.27 and significant at the 5% level. This indicates that a 10% increase in industrial employment in a given zone increases employment at the average small firm by approximately 0.03 workers. Given that the number of small firms is on average about 0.4 times the number of industrial jobs, the associated local multiplier is 0.11.

The difference between the OLS estimate in column 1 and the IV estimate in column 3 indicates that the former is biased downwards. This would be the case if, for instance, the industrial sector expands over time (differentially more) in those zones where small firms' employment (differentially) decreases.

Next, we investigate whether the employment effect is concentrated among formal or informal firms. First, in column 5, we replace a dummy equal to one if the firm is informal as outcome in equation (1). We find no systematic relationship between the number of industrial jobs and the extent of informality among small firms included in the survey. In columns 5 and 6, we implement the same employment regression of column 3, this time separately for the sample of formal and informal firms. While two estimates are not statistically different from each other, only the one for informal firms is significantly different from zero at the 1% level. The point estimate is very similar to the one in column 3. Moreover, because informal firms are more prevalent than formal firms, the multiplier for informal jobs is about 4 times the one for formal jobs.

In columns 7 and 8, we replace the log of average wage as dependent variable in equation (1). This information is available for about 77% of formal and 60% of informal small firms. Also, the *F*-statistic associated with the first-stage regression is only about 7.6 in the informal sample. Keeping these limitations in mind, evidence suggests that the average wage at informal firms increases with the local number of industrial jobs. A 10% increase in the number of industrial jobs increases the wage paid at informal firms by 1.36%.

5.2 Robustness

The employment (and multiplier) results in Table 1 stand up to several robustness checks, which we summarize in Table 2. We begin by excluding the zone of the capital Addis Ababa from the sample, as it is clearly an outlier in terms of both numbers of industrial jobs and small firms. Columns 1 and 2 show that the estimated β is very similar to the one obtained from the full sample.

Next, we consider a refined version our instrument where we exclude the zone itself in computing nationwide industry-level employment ind_{st} . Columns 3 and 4 of Table 2 report the results that we obtain when using this alternative instrument. The first stage is somewhat weaker than at baseline, but the estimated employment effect is once again very comparable to the one in Table 1 in terms of both magnitude and significance.

We also provide suggestive evidence on the validity of the exclusion restriction. This requires that both baseline employment shares by sector within each zone and nationwide employment at the industry level are uncorrelated with the evolution of small firm-level outcomes. In particular, we would want to rule out the possibility that the instrument is correlated with pre-existing employment trends at small firms. To address this concern, we use the instrument value as computed in the following survey wave instead of the contemporaneous one. Columns 5 and 6 of Table 2 show that the first stage is very weak in this case, and that (not surprisingly) the second stage estimates are very imprecise. This assuage the concern that the instrument is correlated with pre-existing small firm-level trends. Appendix Table A.4 reports the results that we obtain when implementing these same robustness checks but looking at the (log of) average wage as outcome. These results corroborate the validity of the baseline ones reported in the last two columns of Table 1.

Finally, in Appendix B we follow the recommendations of recent shift-share econometric literature (Goldsmith-Pinkham, Sorkin and Swift, 2020; Borusyak, Hull and Jaravel, 2022) and regress industry- and zone-level outcomes of small firms in period t on the corresponding-level regressors or instruments from industrial firms in period $t + 1$. This allows to see if we can detect any placebo effect, which is not the case in our analysis.

5.3 Heterogeneity and Multipliers by Industry

In the last part of the analysis, we investigate the extent to which the employment effects and related multipliers vary by industry. From now on, we restrict the sample to informal small firms only, which is where the employment and wage effects are concentrated.

To begin, we split the sample of small firms by sector s , looking separately at food and beverage, apparel, furniture, and (to increase the power of the first stage) all other sectors together. Table 3 shows the corresponding results. The employment effects are large and significant for the food and apparel sector, and negligible for the others. The average employment effect is largest in magnitude for small firms in apparel, but because the average number of such firms is typically lower than the one of those in the food and beverage sector, the multiplier is about 3 times larger for the latter than for the former. About 67% of the new informal jobs created locally by industrial jobs are in the food and beverage sector, and 22% in apparel.

Finally, we disentangle industrial employment by industry. We consider a modified version of equation (1) where the main regressor is not the (log of) total industrial employment, but employment at large firms by industry. We also modify our instrument accordingly, which we derive by no longer adding over all sectors s in equation (2) but considering instead one sector at the time. That is, the second stage regression becomes

$$y_{iszt} = \beta^s \ln ind_{zt}^j + \alpha_s + \theta_z + \delta_t + u_{iszt} \quad (4)$$

with ind_{zt}^j being industrial employment in industry j , and the first-stage regression is

$$\ln ind_{zt}^j = \gamma^j \ln \widehat{ind}_{zt}^j + \phi_s + \rho_z + \lambda_t + v_{iszt} \quad (5)$$

with

$$\widehat{ind}_{zt}^j = \frac{ind_{jz,1996-98}}{ind_{z,1996-98}} \times ind_{jt} \quad (6)$$

Table 4 shows the corresponding results, each panel focusing on a different industry j and its impact on small informal firms across different sectors s . For instance, the top left estimate in Panel A shows the employment effect of industrial jobs in food manufacturing on employment at small informal food manufacturing enterprises (so that in this case $j = s$).¹

The point estimate of β and the associated multiplier are highly heterogeneous across (j, s) pairs.

¹Appendix Table A.5 shows the results that we obtain when considering all small informal firms together, without differentiating by sector. Table 4 then focuses on those four industries for which the estimated β reported in Table A.5 is largest.

For example, the results in Panel A show that one additional industrial job in food manufacturing does not systematically bring about any informal jobs at small firms in the same sector. Similarly, Panel B shows that one additional industrial job in apparel does not bring about any informal jobs at small firms in apparel. At the same time, however, each industrial job in food (apparel) comes with almost 1 more informal job in apparel (food). This is consistent with employment at small firms increasing because local income and expenditure increase with the number of industrial jobs. It also points towards some degree of substitution and competition between the product of large firms and the one of small informal firms.

For jobs in furniture making, the results in Panel D suggest instead some degree of complementarity between large and small firms. The multiplier is large across all sectors, but in particular for furniture making itself. Each industrial job in furniture comes with almost 4 more informal jobs in the same sector. This would be consistent with, for instance, large firms producing more standardized products that are then customized by the small informal firms. Indeed, [Bassi et al. \(2023\)](#) show that the vast majority of small firms doing carpentry in Uganda customize their products to the needs of individual consumers. Consistent with the virtuous income cycle that these complementarities may generate, the multiplier of furniture industrial jobs is high and significant across all sectors, with each job bringing about 2 more informal jobs in food, apparel, and other sectors.

5.4 Industrial Jobs and Service Jobs

Finally, we look at the effect of industrial jobs on employment in the services. We can do this by matching the information on the number of industrial jobs from the manufacturing census with individual-level data from the NLF surveys introduced in Section 3. We harmonized the codes of each zone across different datasets and matched the information for the three years for which the NLF surveys overlap with the industrial census (1999, 2005 and 2013). By doing this, we can replicate the empirical strategy employed with firm-level observations, using as a dependent variable a dummy equal to one if individual i is employed in a given sector. As in the previous analysis, we include zone and year fixed effects and cluster the standard errors at the zone level, and use sampling weights to ensure representativeness.

We look at the services sector while zooming into informal employment. The NLF surveys provide a fairly detailed definition of informal sector employment. Informal workers are identified using two criteria. First, the worker is not employed in one of the following sectors (considered formal by definition): government, government development organization, NGOs and members of

a cooperative. Second, the enterprise for which they work does not keep a book of accounts or does not have a license.²

Table 5 reports the 2SLS coefficient estimates from these individual-level regressions. The results point to positive, although not precisely estimated coefficients of the variable of interest when looking at the services sector as a whole. Targeting specific industries within services provides evidence of a positive effect of industrial jobs on informal service employment. This includes activities with production linkages to the manufacturing sector, such as retail, wholesale, and transportation. It also encompasses other types of services whose demand may increase due to income effects, such as recreational activities. Public administration jobs also increase due to linkages or income effects, and possibly because of higher revenues from taxation.

6 Conclusion

While the recent transformation experiences of countries like China and Vietnam serve as beacons of industrial success and poverty reduction, many poorer countries, including Ethiopia, continue to grapple with the challenges of deagrarianization and deindustrialization. In this context, our study utilizes micro firm-level data and a Bartik-type identification strategy to uncover a strong and robust relationship between industrial job creation and employment at smaller firms in Ethiopia. We find that each additional industrial job creates approximately 0.1 jobs and leads to higher wages at small informal firms in the same location. The size of this local multiplier varies widely across industries in ways that suggest income effects and both substitution and complementarity between small and large firms.

These findings challenge the established divide outlined in the literature between large, productive firms and smaller, informal enterprises. Additionally, our individual-level data analysis underscores the interconnectedness between industrial development and the services sector, suggesting that employment effects extend beyond manufacturing. Recognizing these connections, accurately measuring them, and understanding the mechanism behind them is essential for the design of impactful and inclusive industrial policies, and central to the objectives of our current and future research.

²The data show large discrepancies in the number and share of informal work between 1999 and the remaining years. Since 2005, the relevant questions were asked only to a part of the employed population, excluding individuals engaged in subsistence farming and those who worked in private households. Hence, excluding agriculture, 57.8% of employed individuals in the sample can be classified as informal.

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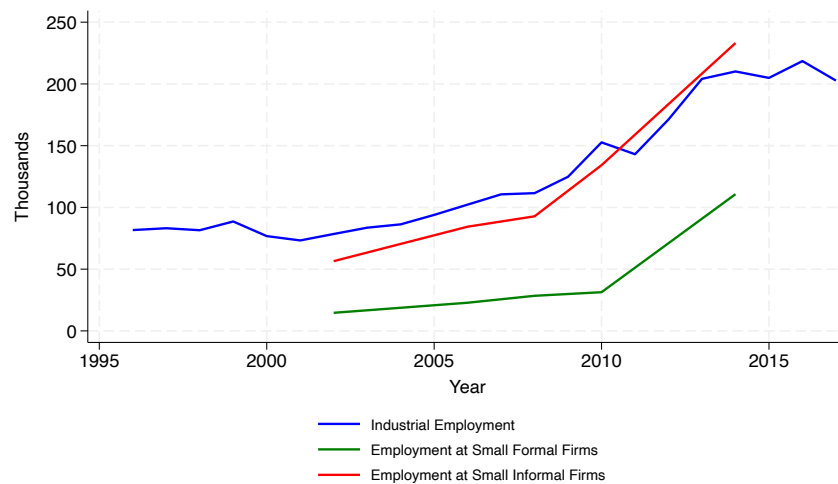
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Exhibits

Figure 1: Industrial Jobs and Employment at Small Firms Over Time



Notes. The figure plots the total number of industrial jobs, employment at small formal firms, and employment at small informal firms in Ethiopia over time.

Table 1: Industrial Jobs, Employment and Wages at Small Firms

	No. of Workers			Status Informal	No. of Workers		Log of Avg. Wage	
	OLS	RF	IV		Formal	Informal	Formal	Informal
Industrial Employment	-0.000 (0.040)		0.271** (0.115)	-0.033 (0.035)	0.192 (0.230)	0.279*** (0.097)	0.081 (0.105)	0.136** (0.062)
Industrial Employment (predicted)		0.037** (0.014)						
<i>F-statistic</i>			13.66	13.66	12.49	12.92	10.66	7.59
Implied Multiplier			0.108** (0.045)		0.015 (0.018)	0.088*** (0.031)		
Zone FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	31032	31032	31032	31032	6426	24601	4837	14728
R^2	0.108	0.109						

Notes. * p-value< 0.1; ** p-value<0.05; *** p-value<0.01. The unit of observation is a manufacturing small firm. The dependent variable is the number of workers at these firms except for column 4, where the dependent variable is a dummy equal to one if the firm is informal. In columns 5 and 6 the sample is restricted to formal and informal firms, respectively. The main independent variable is the log of the number of industrial jobs in the zone and year the small firm observation belongs to, or its predicted value that is used as instrument. The multiplier is derived considering the average number of small firms and the average of industrial employment in each zone. Standard errors are clustered at the zone level.

Table 2: Robustness Checks

	No. of Workers					
	Excluding Addis		Leave-Out Instrument		Instrument at $t + 1$	
	Formal	Informal	Formal	Informal	Formal	Informal
Industrial Employment	0.203 (0.241)	0.295*** (0.097)	0.203 (0.252)	0.301*** (0.106)	-0.302 (0.853)	-1.007 (1.650)
<i>F-statistic</i>	10.88	11.08	10.14	11.53	0.43	0.36
Zone FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	5161	19918	6426	24601	3546	15914

Notes. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. The unit of observation is a manufacturing small firm. The dependent variable is the number of workers at these firms. The main independent variable is the log of the number of industrial jobs in the zone and year the small firm observation belongs to. All columns present 2SLS estimates. Columns 1 and 2 exclude the Addis Abeba zone from the sample. In columns 3 and 4, industrial employment in the zone itself is excluded when calculating aggregate nationwide employment by industry in the calculation of the instrument. In columns 5 and 6, the instrument is predicted employment in the next wave of the small firm-level data. Standard errors are clustered at the zone level.

Table 3: Heterogeneity by Industry of Small Firm

	No. of Workers			
	Food	Apparel	Furniture	Others
Industrial Employment	0.328*** (0.109)	0.513*** (0.115)	0.002 (0.175)	0.054 (0.214)
<i>F-statistic</i>	10.35	57.93	10.07	11.83
Implied Multiplier	0.067*** (0.022)	0.022*** (0.005)	0.000 (0.008)	0.003 (0.010)
Zone FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	12392	3028	3628	5552

Notes. * p-value< 0.1; ** p-value<0.05; *** p-value<0.01. The unit of observation is a manufacturing small firm. The sample is restricted to informal firms. The dependent variable is the number of workers at these firms. The main independent variable is the log of the number of industrial jobs in the zone and year the small firm observation belongs to. All columns present 2SLS estimates. Each column restricts the sample based on the 2-digit sector the small firm belongs to. The multiplier is derived considering the average number of small firms and the average of industrial employment in each zone. Standard errors are clustered at the zone level.

Table 4: Heterogeneity by Industrial Job Category and Industry of Small Firm

	No. of Workers			
	Food	Apparel	Furniture	Others
<i>Panel A: 15 - Food products and beverages</i>				
Industrial Employment	0.029 (0.048)	0.575*** (0.209)	0.094 (0.097)	0.124** (0.058)
<i>F-statistic</i>	36.78	50.20	54.44	86.35
Implied Multiplier	0.041 (0.069)	0.821*** (0.299)	0.135 (0.139)	0.176** (0.083)
<i>Panel B: 18 - Apparel; dressing and dyeing of fur</i>				
Industrial Employment	0.102*** (0.011)	-0.003 (0.021)	-0.002 (0.022)	0.090*** (0.032)
<i>F-statistic</i>	15.55	178.16	178.23	83.64
Implied Multiplier	0.910*** (0.102)	-0.026 (0.189)	-0.020 (0.201)	0.801*** (0.286)
<i>Panel C: 28 - Fabricated metal products, etc.</i>				
Industrial Employment	0.068 (0.046)	0.096 (0.144)	0.057 (0.068)	0.123*** (0.042)
<i>F-statistic</i>	17.20	9.56	24.31	13.14
Implied Multiplier	0.542 (0.369)	0.770 (1.153)	0.454 (0.541)	0.979*** (0.337)
<i>Panel D: 36 - Furniture; manufacturing n.e.c.</i>				
Industrial Employment	0.186** (0.089)	0.194*** (0.030)	0.396*** (0.093)	0.191*** (0.021)
<i>F-statistic</i>	139.96	419.03	162.40	208.94
Implied Multiplier	1.793** (0.863)	1.869*** (0.289)	3.828*** (0.898)	1.849*** (0.202)
Zone FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	12392	3028	3628	5552

Notes. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. The unit of observation is a manufacturing small firm. The sample is restricted to informal firms. The table shows the estimated coefficient and multiplier obtained when estimating a regression where the unit of observation is a manufacturing small informal firm, the dependent variable is the number of workers at these firms, and the main independent variable is the log of the number of industrial jobs in the sector specified in the panel heading. All columns present 2SLS estimates. Each column restricts the sample based on the 2-digit sector the small firm belongs to. The multiplier is derived considering the average number of small firms and the average of industrial employment in each zone. Standard errors are clustered at the zone level.

Table 5: Industrial Jobs and Service Jobs

	Categories of Service Employment						
	Services (All)	Services (Informal)	Retail (Informal)	Wholesale (Informal)	Recreational (Informal)	Transportation (Informal)	Public Admin.
Industrial Employment	0.0182 (0.0140)	0.0120 (0.0072)	0.0025 (0.0068)	0.0048*** (0.0017)	0.0061** (0.0023)	0.0004** (0.0002)	0.0039** (0.0018)
<i>F-statistic</i>	19.39	19.39	19.39	19.39	19.39	19.39	19.39
Zone FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Observations	484,354	484,354	484,354	484,354	484,354	484,354	484,354

Notes. * p-value< 0.1; ** p-value<0.05; *** p-value<0.01. This regression is based on data from the NLF surveys. The unit of observation is an individual. The sample includes the entire population aged 10 and above. The dependent variable is a dummy equal to one if an individual is employed in a given services sector category. The main independent variable is the log of the number of industrial jobs in the zone and year the small firm observation belongs to. All columns present 2SLS estimates. All regressions are weighed using sample weights as reported in the NLF survey data. Standard errors are clustered at the zone level.

Appendix for Online Publication

A Additional Tables and Figures

Table A.1: Small Firm Share of Economic Activity

Year	% Total Firms	% Total Emp.	% Total Prod.	% Total Wages	% Total Cap.
2002	97.67%	50.96%	2.54%	10.49%	11.18%
2004	97.53%	55.41%	9.63%	14.99%	11.76%
2007	97.02%	52.09%	9.29%	16.47%	12.05%
2010	96.47%	52.18%	9.55%	17.04%	11.41%
2013	97.99%	62.95%	16.56%	19.00%	10.68%

Notes: Data report the share of small firms in the total number of firms, total employment, total production, total wage bill and total capital, respectively. Shares are measured by combining information on the full sample of firms over the whole period covered in the analysis. Sample weights available from the SSIS have been used to scale the small firm sector to its universe.

Table A.2: Summary Statistics

Variable	Obs.	Weight	Mean	St. Dev.	Min	Max
<i>Panel A: Small Firms</i>						
Employment	31,032	253503.622	2.956	1.843	0	19
Wage Bill	22,279	189859.202	9680.445	15921.81	0	350000
Informal	31,032	253503.622	0.798	0.402	0	1
Year	31,032	253503.622	2010.316	3.888204	2002	2014
2-digit Sectors	20					
Zones	42					
<i>Panel B: Local Labor Markets</i>						
Industrial Jobs - All	166	n.a.	3845.273	11047.39	2	72015.75
15 - Food and Beverages	166	n.a.	1073.271	3077.755	0	24139.25
17 - Textiles	166	n.a.	643.964	1669.907	0	12419
18 - Apparel, Fur	166	n.a.	171.518	776.198	0	6682.25
19 - Leather, Luggage, etc.	166	n.a.	274.182	1101.86	0	7950.5
20 - Wood and Wood Products	166	n.a.	46.753	159.79	0	1198.5
22 - Publishing, Printing, etc.	166	n.a.	169.220	840.620	0	5797.5
24 - Chemicals and Chem. Products	166	n.a.	233.521	835.831	0	6191.25
25 - Rubber and Plastics Products	166	n.a.	272.669	1017.359	0	7668.75
26 - Non-metallic mineral products	166	n.a.	369.973	861.715	0	6014.25
27 - Basic Metals	166	n.a.	64.163	250.519	0	1559.75
28 - Fabricated Metal Products, etc.	166	n.a.	191.75	785.209	0	5315.5
36 - Furniture, n.e.c.	166	n.a.	158.630	435.123	0	2983.5

Notes. The table shows the summary statistics of all variables used in the analysis. Those in Panel A are weighted by survey weight.

Table A.3: Small Firm Sample Characteristics

	All		Formal		Informal	
	Obs.	Freq.	Obs.	Freq.	Obs.	Freq.
<i>Panel A: Small Firms by 2-digit Sector</i>						
15 - Food and Beverages	15,230	49.08	2,838	44.14	12,392	50.37
17 - Textiles	1,572	5.07	179	2.78	1,393	5.66
18 - Apparel, Fur	3,492	11.25	463	7.20	3,029	12.31
19 - Leather, Luggage, etc.	311	1.00	51	0.79	260	1.06
20 - Wood and Wood Products	274	0.88	69	1.07	205	0.83
22 - Publishing, Printing, etc.	607	1.96	143	2.22	464	1.89
24 - Chemicals and Chem. Products	9	0.03	6	0.09	3	0.01
25 - Rubber and Plastics Products	16	0.05	2	0.03	14	0.06
26 - Non-metallic mineral products	542	1.75	204	3.17	338	1.37
27 - Basic Metals	64	0.21	34	0.53	30	0.12
28 - Fabricated Metal Products, etc.	3,879	12.50	1,053	16.38	2,826	11.49
36 - Furniture, n.e.c.	5,006	16.13	1,378	21.43	3,628	14.75
Others	30	0.10	10	0.17	20	0.08
<i>Panel A: Small Firms by Year</i>						
2002	2,424	7.81	452	7.03	1,972	8.02
2006	3,997	12.88	595	9.25	3,402	13.83
2008	9,990	32.19	1,951	30.34	8,039	32.68
2010	3,512	11.32	621	9.66	2,891	11.75
2014	11,109	35.80	2,811	43.72	8,298	33.73

Notes. The table shows the number and frequency of small firm observations by sector and by year.

Table A.4: Robustness Checks – Average Wage

	Log of Avg. Wage					
	Excluding Addis		Leave-Out Instrument		Instrument at $t + 1$	
	Formal	Informal	Formal	Informal	Formal	Informal
Industrial Employment	0.066 (0.110)	0.151** (0.068)	0.072 (0.111)	0.146** (0.069)	-0.680 (0.791)	-0.242 (0.560)
<i>F-statistic</i>	9.40	6.67	8.66	6.77	0.48	0.30
Zone FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	3901	12327	4837	14728	2886	10256

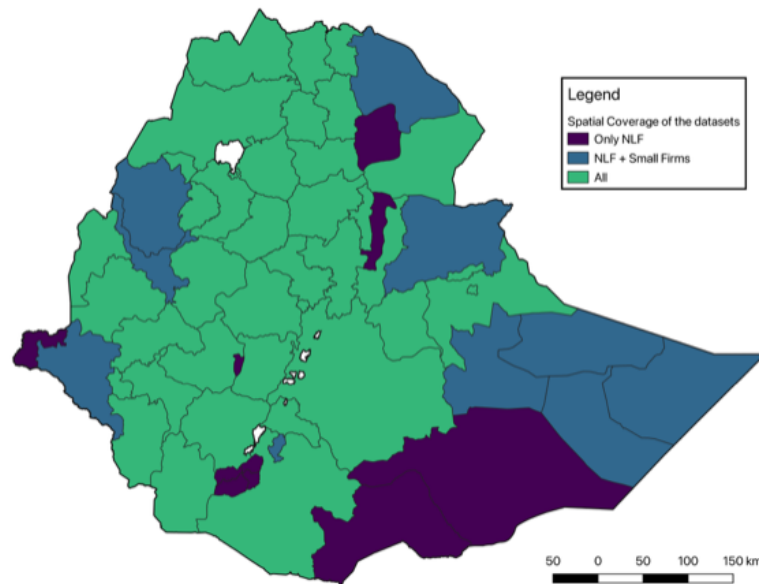
Notes. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. The unit of observation is a manufacturing small firm. The dependent variable is the log of average wage at these firms. The main independent variable is the log of the number of industrial jobs in the zone and year the small firm observation belongs to. All columns present 2SLS estimates. Columns 1 and 2 exclude the Addis Abeba zone from the sample. In columns 3 and 4, industrial employment in the zone itself is excluded when calculating aggregate nationwide employment by industry in the calculation of the instrument. In columns 5 and 6, the instrument is predicted employment in the next wave of the small firm-level data. Standard errors are clustered at the zone level.

Table A.5: Heterogeneity by Industrial Job Category

Sector	<i>F</i> -statistic	IV Estimate	Multiplier
15 - Food products and beverages	43.04	0.057 (0.044)	0.065 (0.051)
17 - Textiles	52.35	0.006 (0.007)	0.012 (0.013)
18 - Apparel; dressing and dyeing of fur	15.65	0.096*** (0.010)	0.682*** (0.068)
20 - Wood and of products of wood and cork, except furniture	7.98	0.028 (0.081)	0.729 (2.122)
22 - Publishing, printing and reproduction of recorded media	16.32	-0.103 (0.069)	-0.746 (0.497)
26 - Other non-metallic mineral products	55.80	0.006 (0.026)	.021 (0.088)
28 - Fabricated metal products, except machinery and equipment	18.97	0.074 (0.055)	0.474 (0.348)
36 - Furniture; manufacturing n.e.c.	181.40	0.186*** (0.036)	1.431*** (0.281)

Notes. * p-value< 0.1; ** p-value<0.05; *** p-value<0.01. The table shows the estimated coefficient and multiplier obtained when estimating a regression where the unit of observation is a manufacturing small informal firm, the dependent variable is the number of workers at these firms, and the main independent variable is the log of the number of industrial jobs in the sector specified in each row. All are 2SLS estimates. The multiplier is derived considering the average number of small firms and the average of industrial employment by sector in each zone. Standard errors are clustered at the zone level.

Figure A.1: Map of Zones in Ethiopia



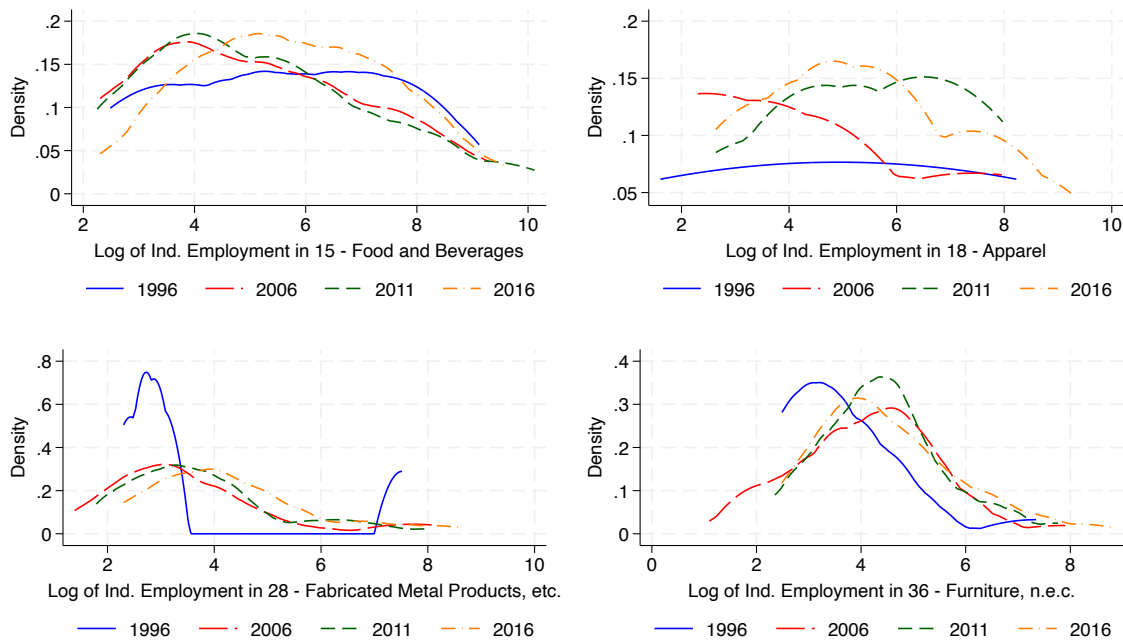
Notes. The map shows the boundaries of zones in Ethiopia. These are level 2 administrative units, below regions and above woredas or districts. It also shows using different colors those zones that are represented in worker-level NLF data, small firm-level SSIS data, and medium and large firm-level LMMS data.

Figure A.2: Industrial Jobs Across Zones Over Time



Notes. The figure plots the distribution of the (log) total number of industrial jobs across zones over time.

Figure A.3: Industrial Jobs Across Zones by Category Over Time



Notes. The figures plot the distribution of the (log) total number of industrial jobs by category across zones over time.

B Additional Robustness Checks

In this section, we perform additional robustness checks to support our shift-share identification strategy. Our placebo checks follow the recommendations in the shift-share econometric literature, particularly those suggested by [Goldsmith-Pinkham, Sorkin and Swift \(2020\)](#) and [Borusyak, Hull and Jaravel \(2022\)](#). We regress industry- and zone-level outcomes of small firms in period t on the corresponding-level regressors or instruments from industrial firms in period $t + 1$ to see if we can detect any placebo effect. The primary outcome variables we use for placebo checks are employment and the value of production (output) of small firms.

For industry-level checks, where the shift-share identification is motivated by the exogeneity of industry-level industrial job growth ([Borusyak, Hull and Jaravel, 2022](#)), we implement the following specification

$$y_{iszt} = \beta ind_{s,t+1} + \alpha_s + \theta_z + \delta_t + \varepsilon_{it},$$

where y_{iszt} is the outcome of the small firms i in sector s , zone z , and year t . $ind_{s,t+1}$ is the national level of industrial employment in sector s in year t from LMMS data. Since SSIS data is available in 2002, 2004, 2007, 2010, 2013, we obtain values for $ind_{s,t+1}$ in 2004, 2007, 2010, 2013, 2015.

Following both [Goldsmith-Pinkham, Sorkin and Swift \(2020\)](#) and [Borusyak, Hull and Jaravel \(2022\)](#), we also perform zone-level checks by implementing the specification

$$y_{iszt} = \beta \widehat{ind}_{z,t+1} + \alpha_s + \theta_z + \delta_t + \varepsilon_{it}$$

Here, $\widehat{ind}_{z,t+1}$ is the shift-share IV defined in equation (2).

The results for both industry- and zone-level checks are reported in Appendix Table B.1. None of the estimated coefficients are statistically significant at standard levels. Future nationwide industrial employment or predicted zone-level industrial employment are not systematically correlated with small firms' current employment or output. Moreover, in their simulation [Borusyak, Hull and Jaravel \(2022\)](#) find that shift-share identification based on industry shocks works well with about 20 independent industries. This is consistent with our empirical context here, where we use 20 2-digit industries to construct our shift-share instrument.

Table B.1: Placebo Checks

	Industry Level		Zone Level	
	Employment	Output	Employment	Output
$ind_{s,t+1}$	0.009 (0.008)	5.023 (10.787)		
$\widehat{ind}_{z,t+1}$			-0.019 (0.066)	-9.238 (40.165)
Zone FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	22778	10884	20980	10343

Notes. * p-value< 0.1; ** p-value<0.05; *** p-value<0.01. The unit of observation is a small manufacturing firm. The dependent variables are the level of employment and the value of production (output) at these firms. Columns 1 and 2 show placebo checks at the industry/sector level. Columns 3 and 4 show placebo checks at the zone level. Standard errors are clustered at the zone level.