Rural Spillovers of Urban Growth

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Abstract

As cities in developing countries continue to grow rapidly, there is little empirical evidence about how this affects growth in surrounding rural economies. We study the effects of shocks to labor demand in cities on village-level economic outcomes, using a new dataset with administrative data from multiple sources on the universe of urban and rural economies in India. We find that, over the period 1990-2013, urban shocks led to increases in aggregate economic activity and non-farm establishment size in villages located 20 km or farther away from their closest city. At the same time, distant villages experienced net population loss, as rural workers relocated closer to urban areas. Labor demand shocks in cities also led to a reconfiguration of the industry composition in surrounding rural economies, with the services sector gaining employment share in nearby villages, and the manufacturing sector gaining share in villages farther away.

Keywords: Urbanization in developing countries, geographic dispersion of shocks, urban-rural linkages.

JEL Codes: O14, O18, R11 R12

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1. Introduction

Urbanization is expected to accelerate dramatically in the developing world over this century. By 2100, forecasts project that urban population in these countries will reach 8 billion people, from 2.6 billion in 2010 (Fuller and Romer 2014.) However, an important fraction of the population will remain living in rural areas. How growth in cities will affect economic development in these areas is, a priori, ambiguous. City growth can lead to positive economic effects on their rural fringe, due to a larger demand for agricultural products or the decentralization of jobs in search for cheaper factors of production (Partridge et al. 2015.) However, it could also lead to negative effects on economic activity and living standards, particularly in distant villages, for which trade with the city is more costly (Storeygard 2016) and rural-urban migration can shrink the prime-age labor force.

This paper studies how employment growth in cities affects the economic development of surrounding rural areas in the long run. To this purpose, we use the Socioeconomic High-resolution Rural-Urban Geographic Dataset (SHRUG), a new dataset containing administrative data from multiple sources on the universe of urban and rural local economies in India for the period 1990-2013 (Asher et al. 2019). We construct shift-share shocks in the tradition of Bartik (1991) to capture exogenous variation in labor demand at the town level and examine the effects of these urban shocks on village-level outcomes at different distances from the city.

We find that employment growth in towns of population 100,000 or larger led to increased economic activity in nearby villages, as measured by night lights. The effects are concentrated in villages located 20 km and farther away. Meanwhile, the effects on the economic activity of nearby villages are negative, small, and not economically significant.

In response to urban shocks, relatively distant villages saw an increase in the average non-agricultural establishment size, with a marked drop in the employment share of establishments of less than 20 employees, and a concurrent increase in the share of larger establishments, particularly those with between 20 and 50 employees. These patterns are consistent with a reduction in the misallocation of factors of production, possibly implying efficiency improvements (Hsieh and Klenow, 2009).

At the same time, town-level shocks had negative effects on the population of distant villages and positive on the population of nearby villages. This suggests that there was a significant reallocation of workers out of agriculture in farther away locations. These effects are similar in nature to those brought about by the Prime Minister's Village Road Program (PMGSY) in the 2000s (Asher and Novosad 2018). However, in contrast with the case of rural road construction, urban labor demand shocks appear to have led to a significant fraction of these workers - disproportionally males - to permanently relocate to the city or its vicinities.

City growth also led to structural transformation in the surrounding rural areas. How the relative importance of different industries was affected varied noticeably with distance to the city. Distant villages experienced, along with the positive effects on non-agricultural employment and the negative effects on population, a change of their industry structure. We find that shocks to urban labor demand had a positive effect on the employment share of manufacturing and transportation, and a negative effect on the share of services. Meanwhile, nearby villages experienced a positive effect on the shares of services and construction, and a reduction in the manufacturing share.

These results are consistent with theory and existing international descriptive evidence. As countries develop, cities become increasingly inefficient locations for manufacturing due to congestion and rising labor and land costs, leading manufacturing establishments to first decentralize to suburban locations, and then relocate to smaller cities and rural areas (Henderson 2010). And while manufacturing tends to disperse, services tend to become more concentrated in cities (Desmet and Henderson 2015.) The geographical patterns of our industry composition results resemble those found in the U.S. by Desmet and Fafchamps

(2005), where during the period 1970-2000 most non-service job growth was concentrated in counties located 20 to 70 km away from large cities, while job growth in services took place mostly within 20 km. Our findings also align with those of Ghani et al. (2012), who document that in India formal plants moved away from cities and into rural areas, while informal employment moved from rural to urban areas over the period 1989-2005.

Shocks to smaller towns (with populations ranging from 10,000 to 100,000) generally produced qualitatively similar effects, albeit smaller in size and less precisely measured. Two important exceptions are the effects on aggregate employment on the number of establishments, both negative and statistically significant. These negative average effects are driven by nearby villages, suggesting that, in these cases, increased commuting to the city is a more important margin of adjustment than rural-urban migration.

This paper contributes to the large and growing literature on the effects of local labor demand shocks, which goes back to Bartik (1991), and Blanchard and Katz (1992). Recent works in this literature include Notowidigdo (2013), Beaudry et al. (2014), Bartik (2015), Diamond (2016), and Chauvin (2018). These studies generally abstract from the impacts of city-level shocks on the surrounding urban areas, and focus on cross-city mobility responses as the key arbitrage mechanism in the labor and the housing markets. In contrast, our paper explicitly focuses on the effects on the economic development of surrounding rural economies and considers rural-urban migration as one of they main adjustment mechanisms.[1]

We also contribute to a body of work studying the geography of employment growth by economic sector. The international literature has documented, relying mainly on descriptive and decomposition techniques, that there is a tendency of manufacturing to disperse and of services to concentrate both in the U.S. and Europe (Desmet and Fafchamps 2005, Desmet

[1]A standard theoretical assumption in this literature is that the distribution of workers and firms across locations is pinned down by local wages, costs of living, and amenities, following the canonical spatial equilibrium model of Rosen (1979) and Roback (1982). Chauvin et al. (2017) find no evidence that the (frictionless) spatial equilibrium assumption holds in India, plausibly because of the relatively small cross-city migration. The rural-urban migration margin may be a more important dimension in this low-urbanization context.

and Henderson 2015.) This tendency has been theoretically liked to increasing factor costs in urban areas (Henderson 2010) and sector-level heterogeneity in productivity gains from agglomeration (Duranton and Puga 2001, Desmet and Rossi-Hansberg 2009.) In India, while Ghani et al. (2012) find that manufacturing tends to relocate to rural areas, Desmet et al. (2015) argue that manufacturing is also concentrating, if at a slower rate than services. Our work introduces to this literature an identification strategy based on shocks at the city level, and finds results more in line with those of Ghani et al. (2012) and prior work in developed countries.

Finally, we contribute to the vast literature on the causes of economic growth in rural areas in low-income countries. This is a topic of major concern, as three quarters of the world's poor live in rural areas (Bank 2007). Further, researchers have documented large wage gaps between urban and rural areas (Gollin et al. 2014). Multiple recent papers have suggested that major infrastructural investments do not produce significant effects on living standards (Asher and Novosad 2018, Burlig and Preonas 2016). While cities are widely considered to be engines of economic growth, there is little work testing the causal effect of cities on rural areas. We thus provide not only new estimates of the size of urban-rural spillovers, but also contribute to the debate on how government spending in low-income countries should be distributed. Our findings suggest that investments in urban areas could benefit not only urban residents and migrants, but also nearby rural areas.

The rest of the paper proceed as follows. Section 2 provides an overview of the context and relevant descriptive information. Section 3 describes the data and the empirical strategy. Section 4 presents the results, and Section 5 concludes.

2. Overview

While the last 30+ years have seen rapid economic growth in India, there is widespread concern that the gains to such growth are concentrated among far too few. There is a sense that rural areas in particular are lagging behind. There have been numerous major programs targeted at improving rural growth and living standards. The success of such programs has been mixed. While there is evidence that the government's flagship rural workfare program (NREGA) has succeeded in alleviating the most extreme poverty and raising wages in rural labor markets (Imbert and Papp 2015), the massive Prime Minister's Rural Road Program did not have any noticeable effects on agriculture, firm growth or poverty (Asher and Novosad 2018). While agriculture is still the largest single source of labor demand in rural areas, over 2/3 of income is actually from non-farm work, and rural non-farm job growth has been stagnant (Chand et al. 2017).

India's cities, on the other hand, have grown rapidly, if not nearly as fast as China's. According to the Population Census, the population share in urban areas increased from 23.3% in 1981 to 31.2% in 2011. Chand et al. (2017) estimate that while cities accounted for just 29.1% of the labor force in 2011-12, they generated 53.1% of output. Around the world, economic growth has generally been accompanied and driven by urbanization, as workers move out of agriculture into more productive work in manufacturing and services, which both tend to be more productive in urban areas and their environs. In this paper, we provide evidence on the magnitude of the effect of urban growth on the rural economy, and the conditions in which rural areas may most benefit from linkages to growing urban centers.

3. Data and empirical strategy

3.1. The SHRUG dataset

The Socioeconomic High-resolution Rural-Urban Geographic Dataset on India (SHRUG) is a new administrative data source describing socioeconomic development in India at the village and town level for the period 1990 to the present. It combines data from multiple different sources: demographic and location amenities from the Population Census (1991, 2001, 2011), firms and employment from the Economic Census (1990, 1998, 2005, 2013), and annual estimates of agricultural production and total output from satellite imagery. Importantly, it provides these data in a consistent form over time. Villages and towns are combined as needed to have unchanging borders since 1990, using an identifier called the SHRUG ID or shrid. New industrial codes, called shrics, are also generated to be consistent from the first to last round of the economic census.

The Economic Census is a comprehensive enumeration of all non-farm economic establishments in India: private and public, formal and informal, manufacturing and services, urban and rural. For consistency across rounds, the SHRUG drops all establishments in agriculture, government administration and defense before generating employment by shric. It is this shric-level employment across the four rounds of the Economic Census that will provide the basis for the primary independent and dependent variables in this analysis.

The Population Census is a decennial enumeration of India's population. Among many other things, it contains village-level data on both demographics (population by age and social group, number of workers, etc.) and village amenities (schools, health centers, electrification, etc.). We use these variables as both outcomes and controls, as described below.

Finally, we use lights at night as a proxy for total economic activity. They have the advantage of being a high resolution annual measure over a 20+ year period (**?**). They come as gridded data, which we match to shrids using GIS data for all Indian villages.

The appendix includes summary statistics and correlation tables for the main variables of interest. Tables A.1 and A.2 show summary statistics for town-level and village-level variables (measured in 1990/1991), respectively. Tables A.3 andA.4 present correlations across the town-level and village-level variables, respectively.

3.2. Urban bartik shocks

We capture town-level exogenous variation in labor demand using a shift-share shock in the tradition of Bartik (1991). Shocks are calculated at the shrid level as:

$$Bartik_{s,t-t_0} = \sum_n s_{si,t_0} \times (\log emp_{-s,it} - \log emp_{-s,it_0}) \tag{1}$$

where s indexes localities (shrids), i indexes industries (shrics), s_{si,t_0} is the employment share of industry i in shrid s at the base period, and $emp_{-s,it}$ is the national employment in industry i and time t, excluding locality s. Shrids with zero employment and shrids with a single industry dominating local employment (share higher than 90%) are excluded. Our analysis focuses on the period $t_0 = 1990$ and $t = 2013$. Appendix Figure A.1 shows the distributions of the shock for urban shrids (towns) for this period.

Intuitively, the Bartik shock leverages the national employment growth at the industry level to predict the employment growth in the locality, considering the shares that each industry had in local employment at the base year. It measures what local employment growth would have been in the locality over the period of interest if local firms' had grown at the same rate as firms in the same industry elsewhere in the country.

The shock performs well at predicting town-level employment growth over this period. Table 1 reports regressions of local employment growth on the shock with and without controls. The coefficients on the shock are positive and statistically significant even without controls (Appendix Figure A.2 displays the raw data and the bivariate regression.) Controlling for the starting employment levels increases slightly the size of the coefficient, and improves the precision with which it is measured. Both the coefficient and the standard error remain the same after the introduction of state fixed effects. The coefficient suggests that a 10 percent increase in predicted employment growth in a town is associated with a 5.5 percent increase in actual employment between 1990 and 2013.[2]

[2]Coefficients in the US literature tend to be larger than one, and coefficients in developing countries (such

Table 1: First-stage for the period 1990-2013 (Dependent variable: log difference in total employment)

	(1)	(2)	(3)
Bartik shock 1990-2013	0.46***	0.55***	0.55***
	(0.14)	(0.08)	(0.08)
Log of total employment		-0.28***	-0.29***
		(0.02)	(0.01)
Constant	0.29**	2.17***	2.23***
	(0.13)	(0.18)	(0.13)
Observations	3,711	3,711	3,711
R-squared	0.01	0.28	0.29
State fixed effects	No	No	Yes

Note: Shrid-level regressions restricted to urban observations. Standard errors clustered at the state level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

3.3. Empirical specification

We measure the average effect of the 1990-2013 Bartik shock to the closest town of population 100,000 or larger on changes in rural outcome j over (roughly) the same period. Specifically, we estimate the regression:

$$\Delta_{t-t_o} Outcome_{jr} = \alpha + \beta_j \, Bartik_{u,t-t_0} + \delta \, Controls_{r,t_0} + \eta \, Controls_{u,t_0} + \gamma_s + \Delta_{t-t_o} \epsilon_{jru} \quad (2)$$

where subindex r denotes rural shrids, and subindex u urban shrids, γ_s are state fixed-effects, α is a constant an ϵ_{jr} an error term. For outcome variables, t and t_0 vary, due to data availability, depending on the original source: For economic census outcomes $t = 2013$ and $t_0 = 1990$, for all population census outcomes $t = 2011$ and $t_0 = 1991$, and for night lights $t = 2013$ and $t_0 = 1994$. Standard errors are clustered at the state level.

as Brazil) have been shown to be smaller. This may have to do, among other things, with higher "metropolitan dominance" in developing countries (larger cities attract disproportionally more migrant workers for the same shocks, but there are relatively more small-city observations in the samples).

In our preferred specification we use a set of village-level and town-level controls, all measured at t_0. At the town level, we control for the log of total population of the distance (in km) to the village. At the village level, we control for baseline economic activity (log of total employment, average establishment size, and share of private workers in total employment, all from the 1990 economic census), geographic location (longitude and latitude of the village centroid), and demographic characteristics (log of population, share of females in population, share of children younger than 7 in population, share of scheduled castes and scheduled tribes in population, and share of literates in population aged 7 or older, all calculated from data of the 1991 population census.) In addition, we introduce industry structure controls, in order to compare villages that are broadly similar in their economic composition. These include the share of main workers and share of marginal workers in total population (from the population census) and the shares of manufacturing and services in employment (from the economic census.) Lastly, in specifications where the base year level of the dependent variable is not already part of the main set of controls, we add it to account for mean regression.

All shrids identified as an outlier in any of the rounds of the Economic Census from 1990 through 2013, or in any of the rounds of the Population Census from 1991 through 2011, are dropped. Economic Census outliers are defined as villages with 0 nonfarm employment, villages that have a non-agricultural employment share of 0.45 or if growth in the non-agricultural employment share is outside of the 1st and 99th percentiles. Population Census outliers are defined as villages with 0 population.

4. Results

In this section we present our empirical results. We first present evidence on how urban demand shocks affect the economic activity in nearby villages. Second, we turn our attention to the effects on population and employment, which are useful to understand the role of migration, commuting and the decentralization of economic activity as possible mechanisms behind the aggregate economic activity effects. Third, we discuss results on the effects on the industrial composition of villages' non-agricultural employment. Lastly, we look at the robustness of the results to different specifications.

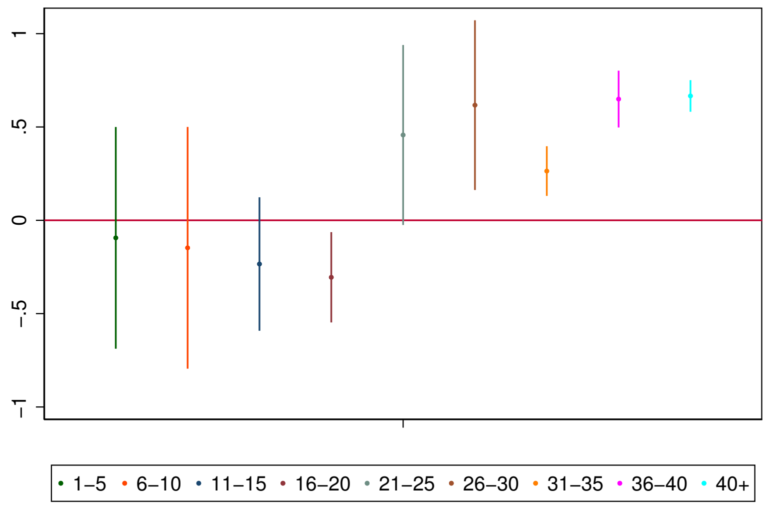
Equation 2 allows us to estimate the average reduced-form effects on village-level outcomes of shocks to labor demand in the closest town of population 100,000 or larger. In addition to estimating the average effects, we study how the effects vary over distance by restricting the estimation to different distance-to-town brackets.

4.1. Effects on economic activity

We start by looking at the effects of town-level shocks on the economic activity of nearby villages. In principle, shocks to labor demand in urban areas could either help or hurt economic activity on the rural fringe. On one hand, cities generate demand for rural products, and urban growth can lead to growth in nearby rural economies that supply them (Partridge et al. 2015.) Moreover, as cities develop, urban land and labor become more costly, creating incentives for firms to relocate to suburban or rural areas (Desmet and Henderson 2015.) On the other hand, growing cities can stimulate rural urban migration, draining valuable human resources from villages (prime age and relatively high-skills workers), and hurting their development prospects.

Both positive and negative effects on rural economic activity can vary with distance to the city. Transport costs make it harder for rural areas located farther away to benefit from increased urban demand of their products. Villages located close to the city may gain if firms decide to relocate to suburban areas as production costs in the city increase, but not if firms chose to relocate to more distant rural areas. Prime-age workers of nearby villages may choose to commute rather than to relocate to the city, increasing local consumption and overall economic activity, but this option becomes less appealing at higher distances, where migration becomes the most cost-efficient way for rural workers to take advantage of growing labor opportunities in the city.

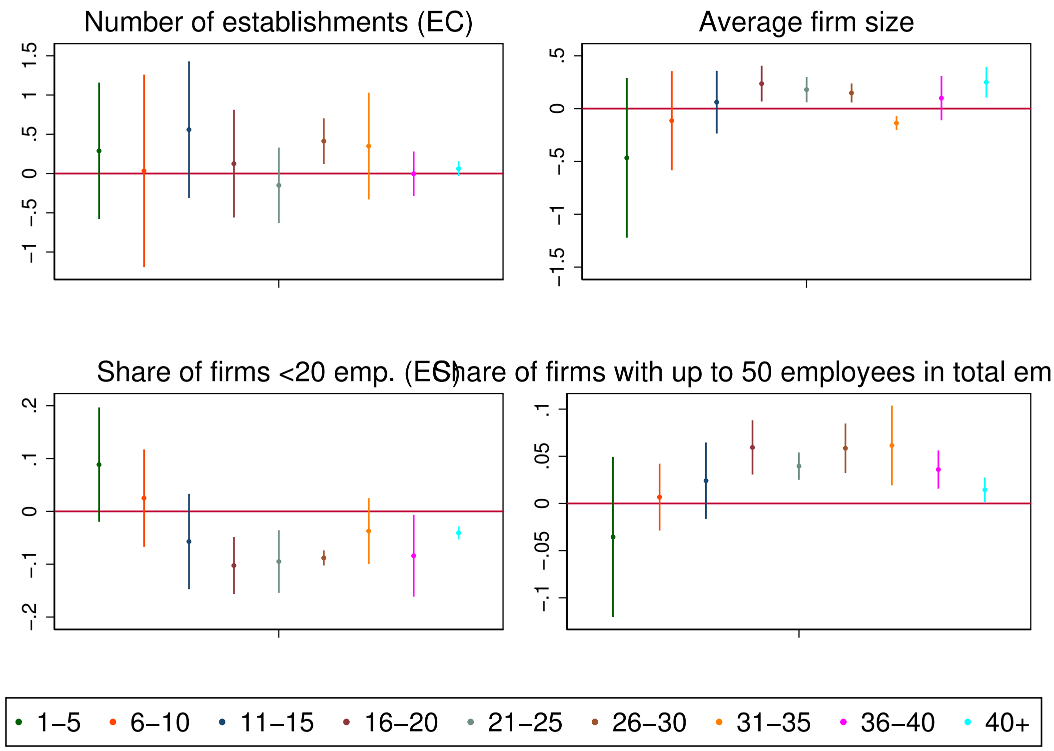
Figure 1: Effects of urban Bartik shocks on rural nightlights



Source: Own calculations using Shrug data.

We first consider aggregate productivity in rural economies. Following the work of Henderson et al. (2012) a growing number of studies have used night lights satellite data as a measure of aggregate economic activity in contexts where reliable Gross Domestic Product (GDP) measures are not available. Using this data, we look at the 1994-2013 growth in total night lights luminosity of Indian villages. Figure 1 depicts estimates and 95% confidence intervals for coefficient β_j in equation 2, calculated at different ranges of distance from the closest city of population 100,000 or larger. It shows that, at relatively small distances from the city, the effects of urban labor demand shocks on rural economic activity are negative, small, and not economically significant. However, among villages located 20 km or farther away, we find positive and statistically significant effects, with point estimates ranging from 0.3 to 0.7. This implies that a 10 percent increase in predicted employment growth in the city is associated with a 3 to 7 percent increase in night lights luminosity in distant villages over a twenty years period.

Figure 2: Effects of urban Bartik shocks on establishment size



Source: Own calculations using Shrug data.

Next, we look at village economic activity in terms of number and size of non-farm establishments using Economic Census data. Figure 2 reports coefficients and 95% confidence intervals for four different measures. The results suggests that the positive aggregate economic activity effects measured with night lights are related to increases in establishment size rather than in the number of establishments. Indeed, the point estimates for the number of establishments effect, depicted in the upper-left graph, are sometimes positive but not statistically significant. In contrast, average firm size effects, shown in the upper-right graph, are mostly positive and statistically significant at larger distances.

The firm size effect is more apparent in the bottom two graphs of Figure 2. They show that shocks to urban labor demand lead to decreases in the employment share of firms with less than 20 employees, and increases in the employment share of firms that have between 20 and 50 employees, among villages located farther away from the city.

Table 2: Effects of urban Bartik shocks on economic activity

	Shocks to large towns (population 100k+)		Shocks to small towns (population 10k-100k)	
	(1)	(2)	(3)	(4)
Total nightlights	0.22*	0.22*	0.08	0.04
	(0.11)	(0.11)	(0.12)	(0.16)
Number of establishments	0.25	0.24	-0.33***	-0.36***
	(0.17)	(0.17)	(0.11)	(0.13)
Average establishment size	0.05	0.07	0.10**	0.08
	(0.07)	(0.06)	(0.05)	(0.06)
Share of establishments with up to 20 employees	-0.04*	-0.04**	-0.01	0.00
	(0.02)	(0.02)	(0.01)	(0.01)
Share of establishments with up to 50 employees	0.03***	0.03***	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Share of establishments with up to 100 employees	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Share of establishments with more than 100 employees	0.01*	0.01**	0.00	-0.00
	(0.01)	(0.01)	(0.00)	(0.00)
Excludes villages located 5km away from the city or closer	No	Yes	No	Yes

Note: Shrid-level regressions restricted to urban observations. Standard errors clustered at the state level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 2 reports estimates of the average effects of urban labor demand shocks on rural economic activity outcomes, including villages at any distance from their closest town. Column 1 corresponds to the same specification used in the figures 1 and 2. Across nearby and distant villages, a 10 percent increase in predicted employment growth in the closest city led to an average 2.2 percent increase in night lights luminosity over the period of analysis. The coefficient is only significant at the 10% level, which is consistent with the presence of positive and significant effects among distant villages and negative (though non-significant) effects among villages close to the city. This highlights the importance of tracking the effects of urban shocks at different distances. In this and other outcomes, statistically significant and economically meaningful effects at certain distances may be outweighed by effects at different distances going in the opposite direction.

The results in column 1 of Table 2 also show that the effects on establishment size hold in the average. In response to a one percent increase in predicted employment growth in the closest city, surrounding villages experienced, on average, a 4 percentage points decrease in the employment share of establishments with less than 20 employees, alongside a 3 percentage points increase in the share of establishments with 20 to 50 employees, and a 1 percentage point increase in the share of establishments with more than 100 employees.

Previous studies in different contexts have also found positive geographic spillovers of urbanization and/or localized economic shocks. Schmitt and Henry (2000) find that city size and urban employment growth positively affect rural employment and population growth in France. Berdegué et al. (2015) document, both in Chile and Colombia, that rural areas close to a small or medium cities grew faster than rural areas that were isolated over 10-year periods. More recently, Feyrer et al. (2017) find that oil and gas productivity shocks related to the U.S. fracking book during the 2000s and 2010s led to significant and persistent increases in production and wages in other industries, and that only 20% of the effects are captured by the county where production was located, and 54% within 100 miles.

In contrast, the distance gradient of the effects is at odds with what we would have expected from reading the existing literature. The productivity advantage of cities tends to attenuate rapidly over relatively small distances, and then continue to decline slowly over longer distances (Rosenthal and Strange 2003.) Cities in developing countries have been show to benefit significantly more from global economic shocks if they are effectively closer to their primate port city (Storeygard 2016). In order to shed light on why in our context the effects on aggregate economic activity are concentrated in more distant towns, we turn to the analysis of population, employment, and industry composition effects.

4.2. Population and employment effects

When a city experiences a positive economic shock, at least part of the increased labor demand tends to be satisfied by workers who were previously residing elsewhere. In high-income countries, which are typically highly urbanized, most of these migratory adjustments come from other cities. In contrast, in low-urbanization contexts, a significant part of the added workforce come from rural areas. Individuals from villages close to the city do not necessarily need to relocate in order to take advantage of the urban job opportunities, as long as there is a reasonably efficient commuting technology available. Meanwhile, for individuals living in distant villages, migration is likely to be the best alternative.

Rural migration and commuting responses to urban shocks map into lower employment levels in the villages, as long as migrants and commuters were previously employed in their place of origin. However, this may not be the case if rural areas were experiencing excess supply of labor. In the former case, migration could lead to lower aggregate productivity in the village, as they loose a key factor of production. The tendency of migrants to be positively selected - having higher levels of education and experience, and longer prime-age years of work ahead of them - can aggravate these negative effects. In the latter case, however, migration could improve aggregate productivity, reducing rural population for whom the marginal productivity is below the average.

Our population results suggest that labor demand shocks in cities led to strong migratory responses, with people from distant villages relocating to the proximities of the city. As shown in the upper-left graph of Figure 3, a ten percent urban shock led to decreases in population of around two percent among villages located 30 km or farther away from their closest town, along with (less precisely measured) increases of similar magnitudes in the population of villages located up to 20 km away. It appears that the bulk of the migrants were males, as suggested by the upper-right graph in Figure 3. A one percent urban shock was associated with increases in the share of females in the population of distant villages in de order of two percentage points, whereas the share of females in the population of villages located closer to the city decreased. As in the case of night lights, the effects on distant villages roughly cancel out with the effects on nearby villages, and the aggregate average effects (shown in Table 3, column 1) are close to zero and statistically non-significant.

Figure 3: Effects of urban Bartik shocks on population and employment

Source: Own calculations using Shrug data.

Along with the migration effects, urban labor demand shocks led to increases in non-farm employment. The two bottom graphs of Figure 3 show the coefficient estimates and confidence intervals for the aggregate employment and private employment regressions. Point estimates are mostly positive in villages located farther than 10 km away from their closest city, albeit imprecisely measured. When we pool villages at any distance from the city together in column 1 of Table 3, precision increases, particularly when measuring private employment effects. A 10 percent increase in predicted urban employment growth led to a 4 percent increase in private non-farm employment in surrounding rural economies.

Table 3: Effects of urban Bartik shocks on population and employment

	Shocks to large towns (population 100k+)		Shocks to small towns (population 10k-100k)	
	(1)	(2)	(3)	(4)
Total population (PC)	-0.03	-0.04	0.02	0.03
	(0.03)	(0.03)	(0.01)	(0.02)
Share of females in population	0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Aggregate employment (EC)	0.30*	0.31*	-0.22**	-0.27**
	(0.15)	(0.15)	(0.09)	(0.10)
Private employment (EC)	0.40**	0.42**	-0.29**	-0.30*
	(0.16)	(0.16)	(0.14)	(0.17)
Total main workers (PC)	-0.04	-0.06*	0.05	0.07
	(0.04)	(0.03)	(0.06)	(0.07)
Share of females in main workers	0.01	0.01	0.04*	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)
Total marginal workers (PC)	-0.61***	-0.63***	-0.07	-0.14
	(0.10)	(0.10)	(0.23)	(0.21)
Share of females in marginal workers	-0.06**	-0.06**	-0.02	-0.02
	(0.03)	(0.03)	(0.02)	(0.02)
Excludes villages located 5km away from the city or closer	No	Yes	No	Yes

Note: Shrid-level regressions restricted to urban observations. Standard errors clustered at the state level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

The fact that distant towns experienced both non-farm employment growth and population losses suggest that the migration effects were driven by rural agricultural workers. The strong negative effect on the population of individuals categorized as marginal workers in the population census (also shown on Table 3, column 1) is consistent with this interpretation.

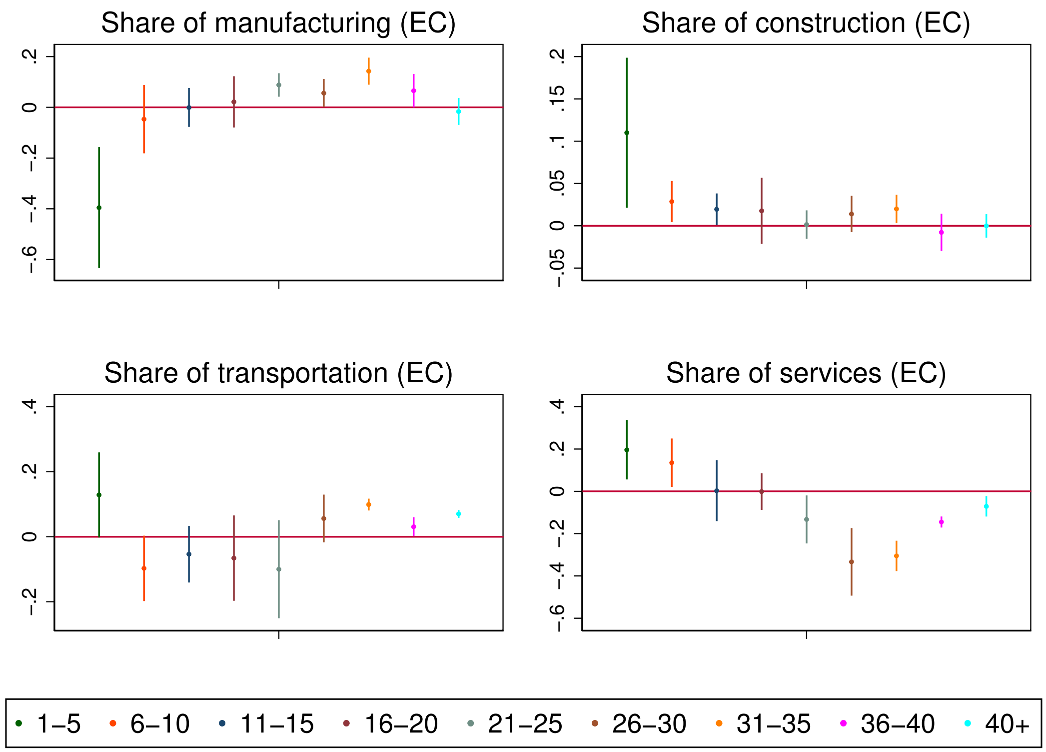
4.3. Industrial composition effects

As urbanization and development progress, urban areas grow. And as they grow, land becomes more expensive, and workers demand higher wages (Desmet and Henderson 2015). Moreover, manufacturing industries tend to be more mature, and benefit relatively less from agglomeration economies than younger service industries (Duranton and Puga 2001, Desmet and Rossi-Hansberg 2009). Cities become increasingly inefficient locations for manufacture, leading manufacturing establishments to relocate. In the U.S. and other developed countries, they first tend to move to suburban areas, and eventually to rural areas (Henderson 2010). At the same time, commercial establishments and services tend to move closer to higher-income urban customers. Because of these dynamics, we should expect city-level shocks to lead to transformation in the industry structure of their rural economies of influence.

In India, during the period of our analysis, shocks to urban labor demand led to a reconfiguration of the industry composition of surrounding rural economies. Figure 4 presents our results for the shares of broadly-defined industries in local employment. It shows that, in distant villages, manufacturing industries gained a larger share in employment at the expense of device industries following a shock. Meanwhile, in villages located close to the city, it was service industries which grew, while the share of manufacturing shrunk. As in previous cases, opposite effects at different distances from the city offset each other, and we don?t find statistically significant effects on these variables for the average village (Table 4, column 1.)

Figure 4 also reports our estimates of the effects of urban shocks on the shares of construction and transportation in village employment. We find that, in response to labor demand shocks in the city, the share of transportation in employment increased in distant villages, as well as in the villages located in close proximity to the city (within 5 km.) This is consistent with our economic activity and population results. As distant villages increased their economic activity, particularly in manufacturing, trade with the city likely fueled demand for transportation. And the fact that rural migrants moved to villages right at the outskirts of the city and aggregate economic activity in those villages did not increase, suggest that these migrants worked in the city and commuted. Rural-urban migration would have also increased housing demand in the proximities of cities, which may explain the increase in the share of construction in these areas' employment.

Figure 4: Effects of urban Bartik shocks on rural industrial composition



Source: Own calculations using Shrug data.

Existing research has documented changes in the geographic distribution of industries that resonate with our results. In the U.S., Desmet and Fafchamps (2005) finds that during the period 1970-2000 non-service employment grew faster in counties located 20 to 70 km away from large cities, whereas employment growth in services took place largely within 20 km. Services establishments appear to be concentrating at a higher rate than manufacturing disperses (Desmet and Fafchamps 2006.) Similar changes have been observed in European regions, where services have concentrated and manufacturing has dispersed (Desmet and Henderson 2015.)

In the context of India, Ghani et al. (2012), document that between 1989 and 2005 formal plants relocated from cities towards rural areas, while informal employment moved from rural to urban areas. This is at odds with the findings of Desmet et al. (2015), who find that manufacturing is also concentrating, although at a slower rate than services. Our findings more in line with the former.

Table 4: Effects of urban Bartik shocks on industrial composition

	Shocks to large towns (population 100k+)		Shocks to small towns (population 10k-100k)	
	(1)	(2)	(3)	(4)
Share of manufacturing	-0.00	0.02	-0.09*	-0.08*
	(0.04)	(0.03)	(0.04)	(0.04)
Share of construction	0.02**	0.01**	-0.01**	-0.01*
	(0.01)	(0.00)	(0.01)	(0.00)
Share of transportation	-0.00	-0.01	0.01	0.01
	(0.03)	(0.03)	(0.01)	(0.02)
Share of retail and wholesale trade	0.03	0.04	0.00	0.00
	(0.04)	(0.03)	(0.02)	(0.02)
Share of services	-0.05	-0.07	0.09**	0.09
	(0.05)	(0.04)	(0.04)	(0.05)
Excludes villages located 5km away from the city or closer	No	Yes	No	Yes

Note: Shrid-level regressions restricted to urban observations. Standard errors clustered at the state level in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4.4. Robustness

In this section we look at the robustness of the results to different sample compositions. We begin by restricting our analysis to villages whose closest town had a population between 10,000 and 100,000. Estimates of the average effects (including villages at all distances) are reported in column 3 of tables 2 , 3, and 4. Figures reporting estimates and 95% confidence intervals for regressions restricted to different distance brackets are included in the Appendix.

In most cases, shocks to small towns lead to qualitatively similar effects on village economies as did shocks to large towns, although smaller in size and less precisely measured. Two important exceptions are the average effects on the number of establishments and aggregate employment, both of which are negative and significant in the case of small towns.

A plausible explanation is that, at this scale, the number of new jobs created in the city are not large enough to spark significant rural-urban migration effects, and increased commuting to the city is a more important margin of adjustment. As appendix figures A.5 and A.6 show, these negative average effects are driven by nearby villages. If a significant number of rural workers living close to to the city chose to abandon their prior occupation and started commuting to the city -including those previously employed in their own single-employee small business- then we would observe at the same time decreases in employment and the number of establishments, without significant population effects. This would also help explain the positive and significant effect on average establishment size reported in column 3 of Table 2.

Treating towns and very close villages as different economic units may be inappropriate, as they both can be part of the same integrated urban labor market. To assess the sensitivity of our results to this concern, we replicate our analysis excluding villages for which the closest town is located 5 km away or closer. The results are reported in columns 2 and 4 of tables 2 , 3, and 4.

We observe that, in the case of shocks to large towns (population 100,000 or larger), the results are virtually identical when we exclude the villages located closest to the town. There are some small differences in the point estimates in the case of shocks to small towns, but the direction and statistical significance of the coefficients do not change. This is in line with our prior observation that, in the case of small towns, the results are driven by the effects on nearby villages.

In future work, we will further explore the robustness of our results to alternative specifications and sample compositions.

5. Conclusion

Many developing countries around the world are growing rapidly, but this growth is concentrated in urban areas, consistent with earlier periods of economic growth in more advanced economies. Yet the majority of the world's poor live in rural areas. How much and under what circumstances does urban growth contribute to economic growth in rural areas?

In this paper, we provide evidence on such urban-rural linkages by estimating the spillovers from urban areas to nearby villages in India. To do so we use a new dataset, the SHRUG, which provides economic data for 5,000 towns and 600,000 villages, from 1990 to the present. Causal identification comes from the Bartik shock, where urban growth is predicted by demand shocks to urban industries.

We find that rural villages are strongly affected by urban growth. Population reallocates from further to nearby villages, while economic activity moves in the opposite direction. This suggests that nearby villages are being incorporated into urban labor markets while more remote villages experience increased integration in goods markets.

In concurrent work, we are generating further evidence on how these changes affect rural living standards. As importantly, we will test for how complementary investments (roads, electricity, human capital) affect the incidence of the urban-rural spillovers that we have documented in this paper. In addition to highlighting the role of complementary investments on the geographic propagation of economic development, We hope that such evidence will prove useful to policymakers seeking to spend scarce resources in ways that will maximize the ability of rural households to benefit from rising productivity and demand in urban locations.

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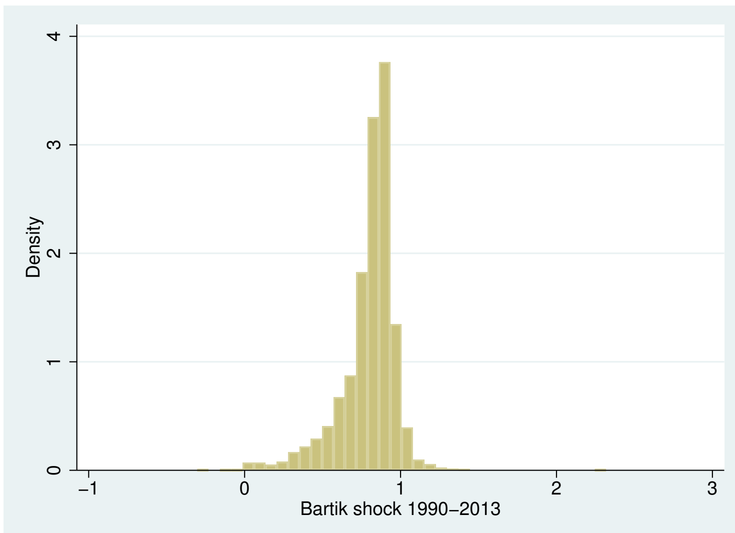
Appendix

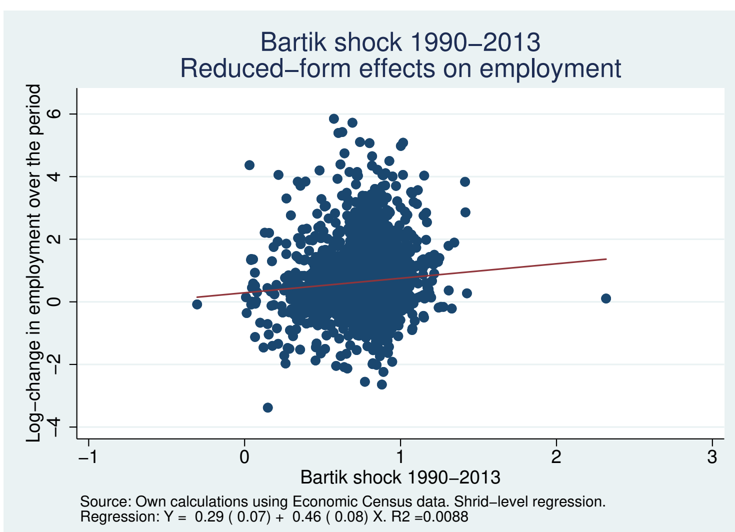
A. Figures

Figure A.1: Distribution of urban Bartik shocks



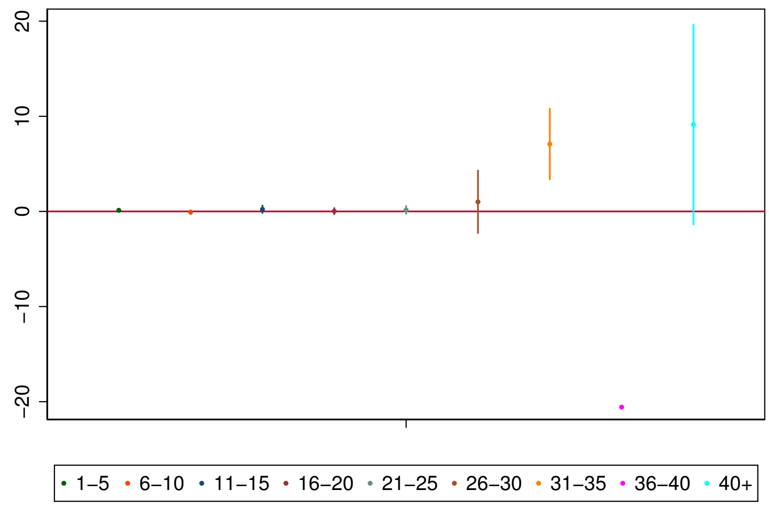
Source: Own calculations using Shrug data.

Figure A.2: First-stage of urban Bartik shock



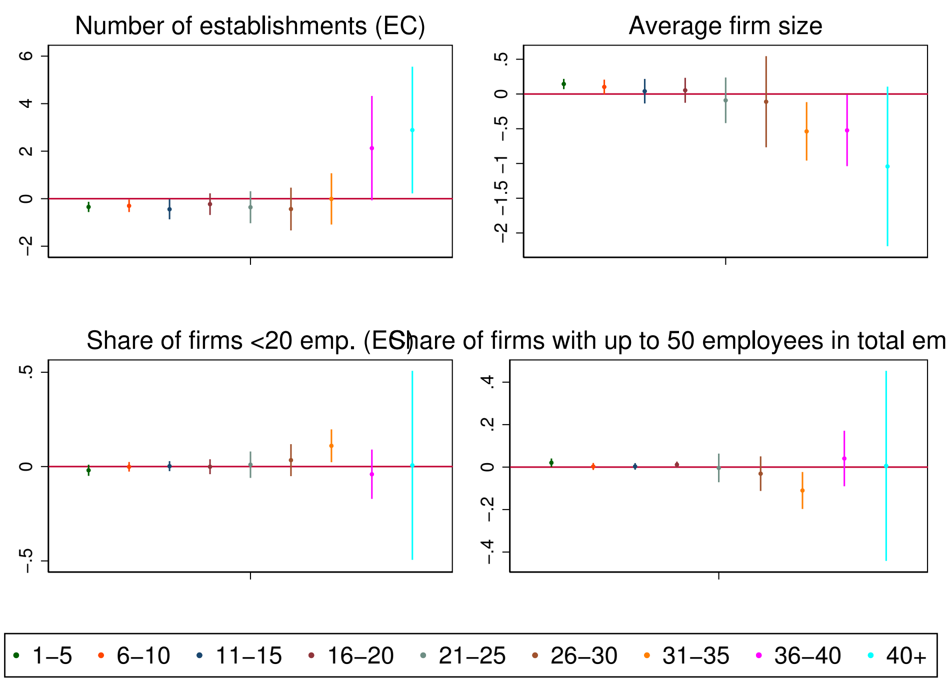
Source: Own calculations using Shrug data.

Figure A.3: Effects of urban Bartik shocks on rural nightlights, small towns



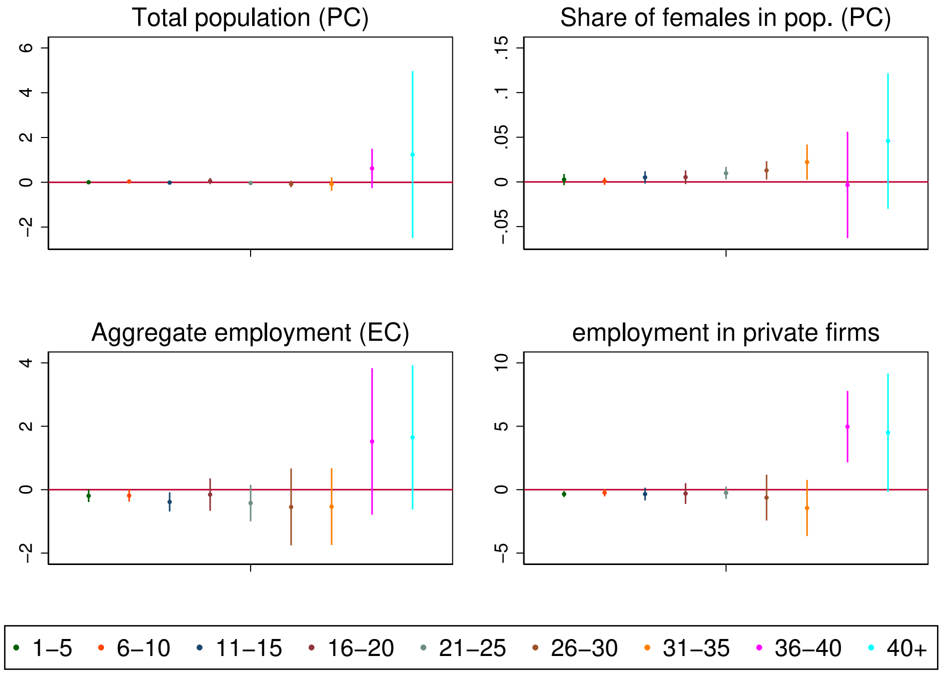
Source: Own calculations using Shrug data.

Figure A.4: Effects of urban Bartik shocks on establishment size, small towns



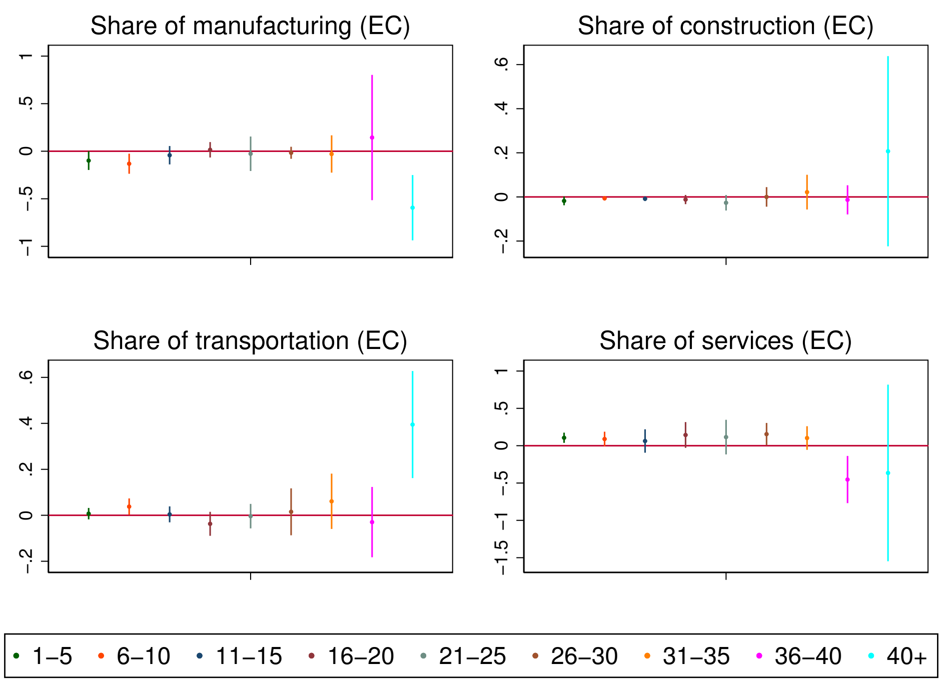
Source: Own calculations using Shrug data.

Figure A.5: Effects of urban Bartik shocks on population and employment, small towns



Source: Own calculations using Shrug data.

Figure A.6: Effects of urban Bartik shocks on rural industrial composition, small towns



Source: Own calculations using Shrug data.

B. Tables

Table A.1: Summary statistics, towns

	Mean	Std. Dev.	Min	Max
Bartik shock 1990-2013	0.8	0.17	-0.3	2.32
Total night light: calibrated	285.13	914.01	0	26503.34
Total employment	4204.43	36995.68	0	2.15E+06
Employment in private firms	3612.28	32234.03	0	1.88E+06
Number of firms	1361.21	7434.07	0	412831
Average firm size	2.68	1.94	1	41.81
Share of private sector in employment	0.86	0.13	0.03	1
Share of firms with up to 20 employees in total employment	0.84	0.17	0.04	1
Share of firms with up to 50 employees in total employment	0.07	0.08	0	0.83
Share of firms with up to 100 employees in total employment	0.03	0.06	0	0.9
Share of firms with more than 100 employees in total employment	0.05	0.13	0	0.96
Share of manufacturing in employment	0.34	0.19	0	1
Share of construction in employment	0.01	0.03	0	0.48
Share of transportation and storage in employment	0.04	0.05	0	0.77
Share of wholesale and retail trade in employment	0.31	0.13	0	1
Share of services in employment	0.29	0.13	0	1
Total population	29720.23	179714.15	14	9.93E+06
Total main workers	8628.27	60320.58	7	3.43E+06
Total marginal workers	276.18	1182.09	0	64610
Total population below age 7	4830.23	25261.47	3	1.35E+06
Share of females in population	0.48	0.03	0.23	0.68
Share of children aged 0-6 in population	0.17	0.04	0.02	0.34
Share of females in children aged 0-6	0.48	0.02	0.33	0.68
Share of scheduled castes in population	0.15	0.12	0	0.99
Share of females in scheduled castes	0.48	0.04	0	0.8
Share of scheduled tribes in population	0.04	0.11	0	1
Share of females in scheduled tribes	0.46	0.13	0	1
Share of scheduled castes and tribes in population	0.19	0.15	0	1
Share of females in scheduled castes and tribes	0.48	0.03	0	0.8
Share of literates in population age 7 or older	0.65	0.16	0.06	0.99
Share of females in children aged 0-6	0.38	0.07	0	0.82
Share of main workers in total population	0.29	0.05	0.07	0.75
Share of females in main workers	0.14	0.1	0	0.71
Share of cultivators in main workers	0.14	0.12	0	0.91
Share of females in cultivators	0.12	0.14	0	1
Share of agricultural labourers in main workers	0.16	0.12	0	0.84
Share of females in agricultural labourers	0.24	0.19	0	1
Share of cultivators and agricultural labourers in main workers	0.31	0.19	0	1
Share of females in cultivators and agricultural labourers	0.19	0.16	0	1
Share of marginal workers in total population	0.02	0.02	0	0.2
Share of females in marginal workers	0.73	0.25	0	1

Sources: Own calculations with shrug data.

Table A.2: Summary statistics, villages

Variables of interest (measured in 1990 / 1991)	Mean	Std. Dev.	Min	Max
Total night light: calibrated	14.22	33.21	0	1985.05
Total employment	41.65	128.2	0	9241
Employment in private firms	35.54	115.45	0	9035
Number of firms	20.97	55.72	0	3237
Average firm size	1.91	2.41	1	318
Share of private sector in employment	0.76	0.29	0	1
Share of firms with up to 20 employees in total employment	0.98	0.12	0	1
Share of firms with up to 50 employees in total employment	0.02	0.09	0	1
Share of firms with up to 100 employees in total employment	0.01	0.06	0	1
Share of firms with more than 100 employees in total employment	0	0.05	0	1
Share of manufacturing in employment	0.32	0.3	0	1
Share of construction in employment	0.01	0.04	0	1
Share of transportation and storage in employment	0.02	0.08	0	1
Share of wholesale and retail trade in employment	0.25	0.25	0	1
Share of services in employment	0.38	0.31	0	1
Total population	1121.1	1543.72	1	70816
Total main workers	391.96	534.36	0	34597
Total marginal workers	50.34	104.39	0	2837
Total population below age 7	215.32	279.85	0	10182
Share of females in population	0.48	0.04	0	1
Share of children aged 0-6 in population	0.2	0.04	0	0.78
Share of females in children aged 0-6	0.49	0.07	0	1
Share of scheduled castes in population	0.18	0.2	0	1
Share of females in scheduled castes	0.48	0.08	0	1
Share of scheduled tribes in population	0.14	0.29	0	1
Share of females in scheduled tribes	0.48	0.11	0	1
Share of scheduled castes and tribes in population	0.32	0.3	0	1
Share of females in scheduled castes and tribes	0.48	0.06	0	1
Share of literates in population age 7 or older	0.39	0.19	0	1.18
Share of females in children aged 0-6	0.25	0.13	0	1
Share of main workers in total population	0.36	0.11	0	1
Share of females in main workers	0.21	0.19	0	1
Share of cultivators in main workers	0.6	0.26	0	2.71
Share of females in cultivators	0.16	0.2	0	1
Share of agricultural labourers in main workers	0.26	0.23	0	1
Share of females in agricultural labourers	0.31	0.26	0	1
Share of cultivators and agricultural labourers in main workers	0.86	0.16	0	3.38
Share of females in cultivators and agricultural labourers	0.22	0.2	0	1
Share of marginal workers in total population	0.05	0.09	0	1
Share of females in marginal workers	0.87	0.23	0	1

Sources: Own calculations with shrug data.

Table A.3: Correlations among town variables (1990/1991)

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	Total night light: calibrated	1																						
2	Total employment	0.66	1																					
3	Number of firms	0.72	0.99	1																				
4	Average firm size	0.09	0.06	0.04	1																			
5	Share of private sector in employment	-0.05	0	0	-0.17	1																		
6	Share of manufacturing in employment	0	0.01	0	0.31	0.36	1																	
7	Share of construction in employment	-0.01	-0.01	-0.01	-0.01	-0.04	-0.11	1																
8	Share of transportation and storage in employment	0.05	0.02	0.03	-0.02	-0.2	-0.26	0.07	1															
9	Share of wholesale and retail trade in employment	-0.02	-0.01	0.01	-0.38	0.17	-0.6	-0.09	-0.04	1														
10	Share of services in employment	0.01	-0.01	-0.01	-0.16	-0.48	-0.66	-0.01	0.01	-0.01	1													
11	Total population	0.74	0.98	0.99	0.05	-0.01	0	-0.01	0.02	0	0	1												
12	Total main workers	0.71	0.99	0.99	0.05	-0.01	0	-0.01	0.02	0	0	1	1											
13	Total marginal workers	0.65	0.93	0.92	0.03	-0.01	0.01	0	0.01	-0.03	0.01	0.92	0.93	1										
14	Total population below age 7	0.77	0.97	0.99	0.05	-0.01	0	-0.01	0.02	0.01	0	1	0.99	0.91	1									
15	Share of females in population	-0.05	-0.03	-0.03	-0.08	0.16	0.1	0.01	-0.01	-0.15	0	-0.03	-0.03	0.04	-0.04	1								
16	Share of children aged 0-6 in population	-0.08	-0.05	-0.06	-0.08	0.1	0.09	-0.08	-0.06	0.14	-0.21	-0.06	-0.06	-0.08	-0.04	-0.23	1							
17	Share of scheduled castes in population	-0.05	-0.04	-0.05	0.02	-0.12	-0.07	0.02	0.04	-0.02	0.08	-0.05	-0.04	-0.04	-0.05	-0.14	0.11	1						
18	Share of scheduled tribes in population	0.11	0.06	0.07	0.08	-0.18	-0.18	0.09	0.09	-0.07	0.28	0.07	0.06	0.11	0.06	0.23	-0.73	-0.14	1					
19	Share of scheduled castes and tribes in population	-0.01	0.01	-0.01	0.17	-0.02	0.2	0.08	0.01	-0.28	-0.07	-0.01	0.01	0.01	-0.02	-0.13	-0.23	0.15	0.01	1				
20	Share of literates in population age 7 or older	-0.17	-0.08	-0.11	-0.12	-0.03	-0.02	-0.03	-0.07	0.04	0.03	-0.1	-0.09	-0.05	-0.11	-0.01	0.29	0.14	-0.38	0.07	1			
21	Share of main workers in total population	-0.17	-0.09	-0.12	-0.1	0.12	0.01	-0.06	-0.06	0	0.06	-0.1	-0.09	-0.06	-0.11	0.24	0.1	0.09	-0.22	0.05	0.21	1		
22	Share of cultivators in main workers	-0.22	-0.11	-0.15	-0.14	0.06	0	-0.06	-0.08	0.02	0.06	-0.13	-0.12	-0.07	-0.14	0.15	0.25	0.15	-0.38	0.08	0.76	0.79	1	
23	Share of agricultural labourers in main workers	-0.09	-0.04	-0.06	-0.02	-0.04	0.06	0.03	-0.01	-0.15	0.02	-0.05	-0.04	0.12	-0.06	0.13	-0.04	0.07	0.05	0.13	0.28	0.02	0.19	1

Source: Own calculations with shrid data.

Table A.4: Correlations among village variables (1990/1991)

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	Total night light: calibrated	1																						
2	Total employment	0.39	1																					
3	Number of firms	0.38	0.92	1																				
4	Average firm size	0.05	0.13	0.01	1																			
5	Share of private sector in employment	0.03	0.12	0.14	-0.01	1																		
6	Share of manufacturing in employment	0.01	0.09	0.05	0.15	0.46	1																	
7	Share of construction in employment	0.03	0.03	0.03	0	0.05	-0.05	1																
8	Share of transportation and storage in employment	0.02	0.02	0.03	0.01	-0.04	-0.11	0.01	1															
9	Share of wholesale and retail trade in employment	0	-0.02	0.02	-0.15	0.32	-0.34	-0.04	-0.06	1														
10	Share of services in employment	-0.03	-0.11	-0.11	-0.04	-0.71	-0.63	-0.07	-0.08	-0.41	1													
11	Total population	0.47	0.72	0.76	0.04	0.11	0.04	0.01	0.02	0.06	-0.1	1												
12	Total main workers	0.49	0.7	0.74	0.04	0.11	0.05	0.02	0.01	0.04	-0.09	0.95	1											
13	Total marginal workers	0.23	0.32	0.35	0	0.01	0.02	0.02	0.01	0.01	-0.03	0.45	0.41	1										
14	Total population below age 7	0.42	0.63	0.68	0.04	0.12	0.05	0	0.01	0.07	-0.11	0.97	0.91	0.43	1									
15	Share of females in population	-0.04	0.01	0.02	-0.04	-0.07	-0.04	0.03	0.02	-0.05	0.06	-0.03	-0.02	0.04	-0.05	1								
16	Share of children aged 0-6 in population	-0.11	-0.11	-0.11	-0.01	0	0.03	-0.03	-0.04	0.03	-0.04	-0.06	-0.1	-0.03	0.06	0.05	1							
17	Share of scheduled castes in population	-0.09	-0.08	-0.09	-0.02	-0.12	-0.07	-0.02	-0.02	-0.04	0.09	-0.14	-0.11	-0.02	-0.13	0.04	0.12	1						
18	Share of scheduled tribes in population	0.16	0.17	0.18	0.03	0.01	-0.03	0.05	0.08	-0.01	0.02	0.12	0.1	0.03	0.05	0.09	-0.39	-0.28	1					
19	Share of scheduled castes and tribes in population	0.04	0	0	-0.03	-0.05	0	0.03	-0.03	-0.06	0.04	-0.06	0.12	-0.11	-0.09	0.01	-0.17	0.2	-0.14	1				
20	Share of literates in population age 7 or older	-0.2	-0.24	-0.25	-0.06	-0.18	-0.03	-0.02	-0.04	-0.08	0.13	-0.23	-0.25	-0.01	-0.22	0.02	0.08	-0.01	-0.2	-0.04	1			
21	Share of main workers in total population	0.1	0.06	0.07	-0.01	0.11	-0.01	0	-0.01	0.09	-0.06	0.13	0.18	-0.06	0.13	-0.02	0.01	0.11	-0.06	0.2	-0.78	1		
22	Share of cultivators in main workers	-0.18	-0.3	-0.3	-0.1	-0.12	-0.07	-0.03	-0.09	0	0.11	-0.2	-0.15	-0.1	-0.17	0	0.14	0.15	-0.4	0.22	0.5	0.14	1	
23	Share of agricultural labourers in main workers	-0.05	-0.05	-0.05	-0.04	-0.08	-0.02	0.02	0	-0.04	0.04	-0.09	-0.11	0.53	-0.09	0.11	0.01	0.11	-0.06	-0.2	0.16	-0.19	-0.01	1

Source: Own calculations with shrid data.