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ABSTRACT

Structural Transformation and Spillovers from Industrial Areas*

Like many developing countries, India features a variety of land-use restrictions that make it difficult to establish industrial firms on agricultural lands. Such policies have received some of the blame for the slow pace of industrialization, and there is widespread agreement on the need for reform. Traditional agrarian economies, however, have many features that may serve as barriers to industrialization, making it unclear that land-use reform would be sufficient for promoting manufacturing growth in rural areas. To better understand the role played by such regulations, we study the effects of the Industrial Areas (IAs) program in India, which facilitated the establishment of industrial firms in areas that had previously been restricted to agriculture. We find that IAs caused a large increase in the number of firms and employment, and that there were substantial spillovers to neighboring villages. Furthermore, IAs trigger a classic "structural transformation" of the economy, with a shift of workers from agricultural to non-agricultural employment, and the creation of numerous small manufacturing and agricultural firms.

JEL Classification: O12, O25, R2
Keywords: industrial areas, spillovers, labor market

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1 Introduction

Low levels of economic development are often attributed to a poor institutional environment. One variety of institutional barrier common in the developing world are zoning laws which restrict rural land to agricultural production, and require time-consuming bureaucratic approvals for non-agricultural firms seeking to use the land for other purposes. Political constraints against the wholesale reform of such regulations have led policymakers to enact piecemeal liberalization through a variety of localized land acquisition interventions, which are used to increase the supply of land available to non-agricultural firms in rural areas (Rajan, 2013). It is unclear, however, whether zoning restrictions are largely or even partly responsible for the slow pace of industrialization, as agrarian economies possess a variety of characteristics that may be inimical to economic development, including low levels of human capital, poor infrastructure, and remoteness from input and output markets.

In this paper, we use quasi-experimental methods to measure the impact the Industrial Areas (IA) program in the Indian state of Karnataka. This program involved government acquisition of agricultural land and its provision to large non-agricultural firms at market rates. Lacking many of the economic incentives offered with other land acquisition policies, such as special economic zones (SEZs), the IA program functioned as a *de facto* reform of local land-use restrictions. We find that this program was highly effective in promoting local development, demonstrating the potential for even overwhelmingly agrarian economies to attract large manufacturing enterprises. Moreover, the policy triggered a fundamental transformation of the surrounding economy, giving some of the first micro evidence on how traditional agricultural economies respond to the arrival of large industrial firms.

This paper adds to a growing literature documenting the substantial effects of land-use restrictions and property rights regimes on economic development (De Janvry et al., 2015; Ding and Lichtenberg, 2011; Besley and Ghatak, 2010; Galiani and Schargrodsky, 2011). In India, the slow pace of movement away from agricultural employment may in part be attributable to zoning laws and dysfunctional land markets that impede the establishment of large, non-agricultural firms in rural areas (Rajan, 2013). In lieu of politically difficult land-use reform, policy makers have resorted to the (legal) expropriation of agricultural land and its conversion to non-agricultural production, often under the auspices of industrial promotion programs (Kazmin, 2015).[1] Karnataka's IA program is an example of this policy approach, but differs from most others in the unusual degree to which it relies on market forces to attract manufacturing firms to rural areas.

Under the IA program, the government of Karnataka acquires and consolidates contigu-

[1]Such policies are made possible by India's 1894 Land Acquisition Act, which grants the state wide latitude in acquiring land for public purposes, with considerable flexibility in the interpretation of what constitutes public purpose.

ous parcels of privately-held land, which is rezoned for non-agricultural activities and made available to private firms for sale or lease at market rates (Government of India, 2009). The sites are selected according to a number of criteria, including proximity to towns, availability of electricity and other basic infrastructure, and the presence of uncultivated land. Most significantly, no financial incentives are offered to firms to locate their operations in the IAs, in stark contrast to other place-based policies, such as SEZs. Indeed, the program's conspicuous lack of incentives has led to its being described in a technical manual as "essentially a piece of real estate promotion" (Government of India, 2009). The intention of the policy, therefore, is to harness market forces to promote industrialization, with the government acting primarily as the facilitator of the necessary rezoning to enable non-agricultural production.

Two key research questions are addressed in this paper. First, we assess whether the primarily regulatory reforms embodied in the IA program are sufficient for attracting industrial firms, and thereby seek to shed light on the role of land-use policies in impeding economic development. Second, insofar as IAs are successful, we exploit the quasi-random creation of new industrial activity in rural areas to better understand the effects of formal-sector manufacturing firms on labor markets and firm growth in a traditional agrarian economy. Though the latter topic has been central to thinking in development economics since Lewis (1954), this paper provides some of the first empirical evidence for how this process unfolds.

Whether the IA policy will be effective in increasing industrial activity is highly uncertain, as the local economy may be unable to supply manufacturing firms with necessary factor inputs. For example, male literacy rates in these areas are just 49%, and the share of the population working as cultivators or agricultural wage laborers is 81%, potentially rendering the population unfit for manufacturing employment. The location of IAs may aggravate this problem, as their distance from manufacturing centers increases the cost of procuring inputs from established suppliers. Given the absence of financial incentives, the IA program will succeed insofar as land-use restrictions are the principal impediment to industrial production, rather than the characteristics of the local economy.

There is also uncertainty regarding the impact that the program will have on the economy in surrounding areas. The Lewis (1954) model famously predicts that the growth of modern manufacturing absorbs low-productivity workers from agriculture, and ultimately triggers the commercialization of the agricultural sector, and of the "traditional" economy more generally.[2] For the IA program to affect local labor markets, however, requires that workers have the necessary skills for manufacturing employment, and that some level of immobility in the labor market had previously prevented qualified workers from taking up manufacturing jobs elsewhere. Firm growth and the modernization of the traditional economy will likewise depend on the entrepreneurial ability of the local population, and the importance of local

[2]Lewis (1954) stresses that it is not only agriculture in which workers may have extremely low productivity.

agglomeration economies.

Evaluating the effects of such policies presents considerable empirical challenges. Causal identification depends crucially on (i) careful construction of valid counter-factuals to deal with their non-random placement, and (ii) accounting for possible negative and positive spillovers to nearby areas, which are of independent interest (see, e.g., Neumark and Kolko, 2010; Ham et al., 2011). The data we use is particularly well suited to such an analysis, giving village-level information on firms, workers, infrastructure and amenities across more than 20 years (1990 to 2013), as well as the precise locations and years of establishment of the IAs. In addition, Karnataka has more than 20,000 villages and a population of 61 million people, making it roughly the size of Italy or France, giving us a sufficiently large number of data points to detect even small effects.

We estimate the effects of IAs using a difference-in-differences identification strategy, with economic changes in areas receiving an IA between 1991 and 2011 compared to those in areas not receiving an IA. Balance tests indicate that the places that received the IAs were not dramatically different in 1991 than those that did not.[3] Moreover, controlling for the characteristics that determined the location of the IA removes virtually all other imbalances. Therefore, it is plausible that a simple difference-in-differences methodology that controls for these pre-requisite conditions will provide an unbiased estimate for the treatment effect.

Nevertheless, we adopt four principal strategies to address the non-random placement of IAs. First, we include controls for characteristics which determined the location of the IA, or which are correlated with potential growth, and interact them with time dummies. Second, we use a non-parametric coarsened exact matching (CEM) strategy to establish a more comparable control group (Blackwell et al., 2009), with additional robustness tests conducted using a variety of sample restrictions. Third, we use an event study framework to determine whether there are parallel trends in economic activity for control and treatment villages prior to the establishment of the IA, and a trend break for the treatment villages in the year the IA is established. Finally, we conduct placebo regressions in which control villages which have similar characteristics to the treatment villages are assigned treatment status. This exercise is conducted 1000 times, and the distribution of the treatment coefficients and t-statistics are compared to the values for the true treatment.[4]

All these approaches yield consistent evidence that IAs had large effects on local economies. The difference-in-differences specification yields similar results with or without the CEM procedure. The results are also largely unaffected by a variety of sample restrictions, including the exclusion of villages farther than 15 kilometers (kms) from the

[3] For example, 29% of IA villages have tap water, 38% have post offices, 30% have telephone connectivity, 85% have paved roads, and they are located 12kms on average from the nearest town.

[4] This method is the same as that used in Dell and Olken (2017).

IA, and the exclusion of IAs close to large towns. The event study analysis verifies parallel trends in nighttime light density (the only variable we observe on a year–by–year basis) across control and treatment villages prior to the IA, and displays a striking divergence for treatment villages starting in the year of IA establishment. Finally, the placebo regressions yields test statistic distributions in which the true statistics have low p-values, indicating that the results found in this paper were highly unlikely in the absence of the IA program.

Having established the direct effect of IAs, we then turn our attention to the impact of IAs on the structure of the economy in nearby areas. Using the economic and demographic censuses, as well as night lights data, we estimate spillovers using difference-in-differences specifications that compare economic outcomes in villages at intervals of (0-1], (1-2], (2-3], and (3-4] kms from the IA to those further away, and include the full set of controls. As before, we use a variety of strategies to allay concerns arising from non-random placement, including: the use the CEM algorithm; restricting the sample alternatively to villages close to the IA or far from large towns; and running placebo regressions based on proximity to control villages similar to the treatment villages. All of these exercises give results quite similar to those of the baseline specification.

We document two main results capturing the effects of IAs on economic activity. First, we find that IAs have been highly successful in promoting economic development. Depending on the choice of control villages, we find that IAs established between 1991-2011 led to an increase of between 37 and 57 percent in the number of firms, and an increase of approximately 80 percent in the number of workers.

Second, using a variety of control groups, and flexibly accounting for treatment effects at discrete distance intervals from the IAs, we document substantial economic spillovers due to the creation of the IAs. There is an increase in the number of firms and employees up to a distance of 4 kms from the IAs. While the majority of firms within the IAs are within the manufacturing sector, those outside the IAs are evenly divided across the manufacturing and agricultural sectors,[5] with a small number of retail, transportation, and hospitality firms as well. In the local labor markets, there is a decrease in the share of male workers involved in agriculture, and a symmetric increase in those working in non-agricultural wage labor. The magnitude of these changes is largest in villages overlapping the IA, and falls monotonically with distance from the IA up to a distance of 4 kms. The decline in agricultural work is largely driven by a falling share of men cultivating their own land, with only a small change in the share of the population engaged in agricultural wage labor.

These results indicate that the IAs have triggered a more general structural transformation of the local economy, in the spirit of the classic Lewis (1954) model. The reduction in

[5]The economic census includes both firms producing agricultural goods and firms producing animal products under the rubric of "agriculture."

agricultural employment is primarily driven by individuals moving away from the cultivation of their own land, rather than through a decline in agricultural wage labor. Despite the decline in the agricultural work force, there is a substantial *increase* in agricultural firms evident for up to 4 kms from the IA. There also occurs an increase in the number of manufacturing and service sector firms at similar distances from the IA, underlining the potential for rapid economic growth even in places dominated by traditional agriculture.

Several village characteristics play an important role in mediating the effect of the IAs, shedding light on the likely mechanisms. Villages with higher literacy rates experience larger growth in the number of firms, consistent with models emphasizing the importance of human capital in entrepreneurship. There in no association between literacy rates and labor market outcomes, however, implying that the newly created factory jobs are low-skilled. Importantly, we also find that villages in which banks were absent at baseline witness a larger increase in the number of firms, suggesting that the relaxation of credit constraints due to the incomes earned in IAs may have been a significant factor in the growth of entrepreneurial activity.

The innovative approach employed here for studying the topic of structural transformation in the context of policies relaxing land-use barriers constitutes a novel contribution to the development literature. By studying a program that entailed the exogenous introduction of large-scale manufacturing in largely agricultural economies, we are able to assess the influence of industrialization on the agricultural sector, and the channels by which this occurs. Moreover, because the IAs worked primarily through the relaxation of land-use restrictions, their success starkly highlights the role of regulations in impeding economic development. These findings are consistent with a growing body of research demonstrating the importance of land-use restrictions (De Janvry et al., 2015) and property right regimes (Besley and Ghatak, 2010; Galiani and Schargrodsky, 2011) for economic development.

These findings also speak to a literature that examines the factors that impede structural transformation and industrialization in rural areas of developing countries. Though inadequate infrastructure is often cited as one key bottleneck to rural development (United Nations, 2013), recent research from India has found limited effects of rural infrastructure on local manufacturing activity. Road construction, for example, has a positive effect on the movement of workers out of agriculture and into wage labor, but has muted effects on firms' growth (Asher and Novosad, 2017b). Rural electrification has also been shown to only have small effects on local economic activity, despite a large increase in electricity consumption as proxied by night-time illumination (Burlig and Preonas, 2016). The contrast between these results and the large effects we find for the IAs suggests that one potential reason infrastructure improvements have not yielded more substantial local impacts on firm creation may be related to land-use regulations that hinder the establishment of large firms.

We also shed light on one of the central issues in development economics: namely, the significant productivity gap between the agricultural and manufacturing sectors in developing countries, and the processes by which development induces convergence across the two sectors (Lewis, 1954; Gollin et al., 2013). While a substantial literature has argued for the importance of agricultural modernization in facilitating industrialization (Rostow, 1960; Shaw-Taylor, 2001; Gollin et al., 2016; Bustos et al., 2016), others have stressed the role played by industrialization in spurring agricultural modernization through the freeing up of labor, increases in demand for food, and relaxation of credit constraints (Lewis, 1954; Allen, 2009; Rozelle et al., 1999). Our study clearly shows that industrialization can trigger a fairly rapid commercialization of the agricultural sector, despite a shift of labor away from agricultural employment.

This paper also contributes to the literature on the effects of place-based policies in developed and developing economies. Much of the previous literature has focused on SEZs, which include substantial financial incentives from the state to induce firms to locate in the economic zones. The IA policy, in contrast, primarily relies on the local relaxation of land-use policies, allowing market forces and private entrepreneurship to assume a driving force in achieving structural transformation. By striking a balance between government intervention and market forces (Rodrik, 2004), the IA policy provides a model of immense significance to policy makers in poor countries, and one which can be implemented at relatively low cost. To the best of our knowledge, our study is the first paper looking at the impact of a place-based policy that leans so heavily on regulatory policy rather than financial incentives.

The remainder of the paper is organized as follows. In Section 2, we provide a review of the existing literature, and in Section 3 we give background details on land-use regulations and IAs in Karnataka. Section 4 presents the datasets we employ in this paper, and Section 5 provides our empirical specification. Section 6 presents our results and we conclude in Section 7.

2 Literature

Our paper makes an important contribution to a central topic in development economies: the "structural transformation" of traditional agrarian economies. In addition to shedding light on the role of industrial production in triggering this process, we also contribute to the debate over the causal relationship between industrialization and the commercialization of agriculture. While some have argued for agricultural commercialization as a pre-requisite to industrialization (e.g., Rostow, 1960), others view agricultural commercialization as the result of the population's shift into manufacturing (e.g., Lewis, 1954). This debate harkens back to an earlier one within economic history between those viewing land enclosure and the commercialization of agriculture as playing an essential role in driving the industrial revolution, and others arguing that the commercialization of agriculture was in fact caused by the increased demand for food to feed populations moving to urban-based manufacturing employment (see Allen, 1992, 2009).[6]

A more general question concerns the necessary conditions under which structural transformation may occur. An influential body of thought has emphasized the importance of human capital for achieving structural transformation (United Nations, 2013). However, the earlier development literature gave little emphasis to this issue, while economic historians have documented the low levels of education of the early industrial labor force (Sanderson, 1972; Nicholas and Nicholas, 1992). Our paper contributes to this literature by documenting the large shift in the agricultural work force into manufacturing in the presence of IAs, despite low levels of human capital and an economy dominated by traditional agriculture. However, we also find that the effect of the IAs on entrepreneurship is greater where literacy rates are higher, giving some evidence for the importance of human capital.

Our work also contributes to the literature on the state-led efforts to promote development through the creation of various types of economic zones. A particularly influential strand in this literature has focused on programs such as State Enterprise Zones (ENTZ)[7], which are primarily prevalent in developed economies. For example Neumark and Kolko (2010) focus on California's ENTZ and like many other studies fail to find any state-specific effects on employment by using geographically aggregated data.[8] On the other hand, Ham et al. (2011) find strong statistically significant effects of the much more aggressive Enterprise Community program and the Empowerment program (EZ). Additionally, Busso et al. (2013) also find, using a different methodology, that the EZ program had important effects. Other papers have looked at programs in European countries, finding ambiguous results. These studies include the "Regional Selective Assistance" in the United Kingdom (Criscuolo et al., 2012), the French EZs (called Zones Franches Urbaines) (Mayer et al., 2015; Givord et al., 2013) and Italy's Law 488/1992 (Bronzini and de Blasio, 2006).

A more recent literature has begun to focus on place-based policies in developing countries. Several papers have documented substantial effects for SEZs in China (Wang, 2013; Cheng, 2014; Lu et al., 2015; Alder et al., 2016). A somewhat smaller body of research has explored the effects of place-based policies in India, such as Chaurey (2016) using location-based tax incentives, and Hyun and Ravi (2017) using SEZs, both of which have also concluded that such policies are highly effective. However, aggressive intervention by the state

[6]These two perspectives have been referred to as "agrarian fundamentalism" and "agricultural revolution," respectively. A case study of agricultural reforms in Spelsbury, England, reveals how agrarian fundamentalism could prove counter-productive for increasing agricultural yields (Allen, 1992).

[7]These are neighborhoods receiving tax breaks and job subsidies.

[8]Similarly, Greenbaum and Engberg (2004), and Bondonio and Greenbaum (2007) find no effects of economic zones (EZs) on employment growth as well.

in costly implementation of place-based policies with such high pecuniary and administrative obligations, as found with SEZs, can be difficult for developing economies. As such, our paper makes an important contribution in understanding whether place-based policies consisting primarily of local institutional reforms through land zoning can be successful in promoting industrialization.

A crucial question with respect to place-based policies is the extent of the spillovers they generate. Such spillovers may take the form of traditional Marshallian agglomeration economies (Ellison and Glaeser, 1999; Rosenthal and Strange, 2004; Ellison et al., 2010; Greenstone et al., 2010; Kline and Moretti, 2014a), or perhaps operate on the demand side through income channels (Rosenstein-Rodan, 1943; Murphy et al., 1989). The evidence assessing spillovers from such program, however, is at best mixed. For example, Criscuolo et al. (2012) (UK regional selective assistance), Neumark and Kolko (2010) (California enterprise zones), and Martin et al. (2011) (clusters in France) find no effects on local spillovers. On the other hand, Zheng et al. (2017), and Alder et al. (2016) find evidence for positive spillovers of Chinese SEZs and industrial parks, and Greenstone et al. (2010) find large agglomeration effects on incumbent plants in US counties that attracted a large manufacturing plant. We add to the existing research by documenting large spatial spillovers for IAs on economic activity (firms, employment, and structural transformation), operating at distances of up to 4 kms from the IAs.

3 Background

In the last twenty years, industrial production in India has increasingly shifted from urban to rural areas, with a disproportionate share of this movement accounted for by firms in the formal sector (Ghani et al., 2012). This trend towards rural production has been impeded, however, by a variety of rules and regulations limiting the use of agricultural land for non-agricultural activities (Morris and Pandey, 2007).[9] The IA policy represents one of several tools and approaches which the state governments have employed for overcoming these barriers. We first provide information of the land-use policies and then discuss the industrial programs in more detail.

[9]The common All-India Law for Preservation of the Agricultural Lands, instituted at the time of independence and revised several times since, places numerous restrictions on the transfer of agricultural land to a non-agriculturist, where the latter is defined as an individual not involved in the cultivation of crops and lacking family ties to agriculture. However, the transfer of land and the changing of land usage is strictly under the jurisdiction of state governments, giving states significant power to acquire land but by compensating owners in a fair manner and using it for various non-agricultural projects.

3.1 Land-use in Karnataka

Karnataka's land-use rules were laid out in the Karnataka Town and Country Planning Act (hereafter, KTCPA) of 1961. Though a variety of amendments have been made to the the Act, the principal rules persist with only minor modifications. Land-use rules can be summarized as follows.

First, the KTCPA invokes the national Land Acquisition Act to establish the power to the state to acquire land as deemed necessary for the purpose of planning and development. To ensure fairness for landowners, an amendment was made to this rule requiring that compensation for any acquired land be based on market value on the date of publication of improvement or development schemes. In addition, the government must provide a "grant of solatium," increasing the compensation by 15% in the light of the compulsory nature of acquisition.

Second, the KTCPA also references the national Land Revenue Act in stipulating that permission from the Deputy Commissioner must be obtained in order to use agricultural land for non-agricultural purposes, and defines the fees for land-use conversion. This act reflects the power of the state in determining if the change of land-use is to be granted. However, given the political economy of India, where agricultural interests are fiercely protected, such changes in land-use are difficult to achieve, even for large businesses.[10] In addition, the associated fees and taxes can represent a substantial cost to small- and medium-size businesses, discouraging them from pursuing a change in land-use.

Changes in land-use are far less difficult in cases where the change is from one non-agriculture zoning to another. However, because the associated act (the Land Revenue Act) was vague regarding the circumstances under which a change in land-use was permitted, the KTCPA provided greater clarity on the this matter. In particular, it was stipulated that, if the change of land-use is from commercial or industrial to residential, or from industrial to commercial; and if the stipulated fee is paid and the Local Planning Authority is informed prior to effecting the change; then permission for such change of land-use or development shall be deemed to have been given.

Finally, the KTCPA states that there is no need for change of land-use if the new economic activity is undertaken by the current land owner, and the original economic activity also continues to occur. For example, if a farmer wants to establish a small mechanic shop on a share of his agricultural land, then this would be permitted. These rules, therefore, establish a land-use regime in which the greatest regulatory friction arises from the conversion of agricultural land to non-agricultural activities, with allowances made for small-scale, non-agricultural economic activities undertaken by farmers/dwellers. This feature of the land-use

[10] A recent, well-publicized example of these hurdles was the failure by Tata to secure land for a major production plant in the state of West Bengal.

regulations will be important for interpreting the results presented later.

3.2 Industrial Programs and IAs in Karnataka

Since independence, the Indian state has played a large role in shaping the economy via various industrial policies. The main objective of these policies is to provide regulations and procedures for the development and management of industrial undertakings throughout the country, with close control over the respective roles of the state and private sectors. One approach to promoting industrialization has been through the creation of a variety of Industrial Estates (IE), a general label subsuming a number of place-based policies. Included in this are: IAs, export processing zones (EPZs), special economic zones (SEZs), and industrial parks and complexes. The various types of of IEs differ according to their economic objectives, the incentives offered, and the economic activities they promote.

These programs began in 1955 with the founding of the first IE in Rajkot, Gujarat,[11] and soon spread to the other states of India. Competition between states has led to a broad convergence over time in industrial policy, with states providing similar promotions and incentives.[12] Despite the relative uniformity of industrial policy, however, the execution and implementation of policy has been far more uneven, which may have contributed to the extreme regional imbalances that characterize industrial production in India.

In this paper, we study the effects of IAs in Karnataka between the years 1991–2011. IAs represent one of the less *dirigiste* of the industrial policies pursued by the state, relying primarily on the operation of market forces, with primarily regulatory support from the state via rezoning the land use from agriculture to non-agriculture activities.

Karnataka's IA program began with the Karnataka Industrial Development Act (KIAD) of 1966, which mandated the speedy and orderly establishment of IAs for the promotion of industrial production. Since then, the state has developed around 160 IAs covering an area of 76,136 acres. The spatial distribution of IAs can be seen in Figure A1, and their relation to census towns, major roads, and geographic features in Figure A2.[13]

A central challenge in this program is to determine a suitable site for the IA, the responsibility for which lies with the Karnataka Industrial Areas Development Board (KIADB). Selection of the site is based on a number of criteria, such as the presence of suitable infras-

[11] Industrial Estates were not an Indian innovation, but were instead borrowed from the British, and had indeed long existed in various forms in the advanced, industrial economies. These would include such areas as IAs, parks, zones, districts, and so on, all of which refer to geographical units set aside for primarily industrial activity, though with significant variation in terms of incentives offered across various types of industrial estates as well as across countries.

[12] As noted by Saez (2002) the inter-jurisdictional competition between states of India is not only in terms of implementing industrial policies but is pervasive on various dimensions and primarily stemming from the economic liberalization policies of 1990s in India.

[13] www.kiadb.in

tructure, proximity to markets, and the promotion of backwards areas.[14] Once a site has been selected, the government uses the Land-Acquisition Act to acquire land from the current owners and re-zone the area to allow industrial activities which prior to acquisition are not allowed. The plot is then developed with basic utilities such as power system, recycling, and infrastructure and finally leased or sold to firm owners.

The principal benefit for firms is that the re-zoning of the land by the state obviates the need for individual firms to engage in the costly and time-consuming efforts necessary for identifying a suitable plot of land, and securing the necessary approval for converting it to non-agricultural activities. IAs are also established in locations with the requisite infrastructure, relieving a bottleneck that often hinders economic activity. Additional benefits of establishing operations in IAs are not very significant and may include some additional amenities to allow more suitable working conditions. Crucially, IAs lack the strong financial incentives that are present with other types of place-based policies, such as subsidies, tax exemptions, customs privileges, and relaxation of labor codes. More succinctly, the government describes the IA program in a technical manual as "essentially a piece of real estate promotion" (Government of India, 2009).

The protocols guiding the placement of IAs leads to the selection of areas that are endowed with sufficient infrastructure, and yet simultaneously economically underdeveloped. For the purpose of our study, this poses the challenge of specifying a suitable comparison group and identification strategy for the estimation of the effects of IAs on both the areas in which they are situated, as well as the spillovers to adjacent areas. We address this challenge and discuss it in detail in Section 5 by providing the balanced sample for the control and treatment while also controlling for various variables at the baseline; and employing several econometric approaches to construct various control samples.

4 Data

We use four different datasets in our analysis. First, we use the list of IAs available from Karnataka Industrial Areas Development Board (KIADB), that provides us with the year and location (up to the village level) in which the IA was set up. We match the information on these IAs to the Economic Census and the Population Census at the village-level. The next data set we employ is the Economic Census for the years 1990 and 2013. The Economic Census (EC) of India is a complete enumeration of all economic establishments except those engaged in non-commercial crop production and plantation, and includes both formal and

[14]See Section A1 in Appendix A for additional details on the protocols for selection.

informal firms irrespective of firm size.[15] The EC provides us with information on the number of firms, number of workers, social caste and gender of owner, and the industrial classification for the firms at the village level. We match villages in the EC data to the population/demographic censuses (DC) for 1991 and 2011. The DC provide us with village-level information on the shares of the population working in agricultural and non-agricultural sectors, literacy rates, and public goods (paved roads, banking facilities etc.). Finally, we make use of night-time lights data as a proxy for economic activity at the village-level.[16] The satellite data on night-time lights are collected by the National Aeronautics and Space Administration's (NASA) Defense Meteorological Satellite Programs Operational Linescan System (DMSP-OLS) via a set of military weather satellites that have been orbiting the earth since 1970. In the night-time lights data, each pixel is encoded with a measure of its annual average brightness on a 6-bit scale from 0 to 63.

5 Methodology

Our principal empirical strategy for identifying the effects of IAs is a difference-in-differences design. The unit of analysis is the village, denoted by i at time t where $t \in \{1991, 2011\}$ for variables from the Demographic Census, and $t \in \{1990, 2013\}$ for those from the Economic Census. The regression is specified as:

$$y_{i,t} = \alpha + \beta(IA_i \times post_t) + \gamma_1 IA_i + \gamma_2 post_t + X_i\Gamma_1 + (post_t \times X_i)\Gamma_2 + \eta_i + \varepsilon_{i,t}. \quad (1)$$

IA_i is a dummy variable indicating that the village's boundary overlaps with that of an IA, and $post_t$ is a dummy indicating $t = 2011$. X_i is a vector of baseline controls, described below. η_i denotes the village (i) fixed effect. Our dependent variable, $y_{i,t}$, captures the economic outcome related to the firm or labor market at the village level. Error terms are clustered at the village level, in order to account for serial correlation in unobservables.

The location identifier in the economic census gives only the village in which a firm is located, and does not indicate whether the firm is located within an IA. To identify which firms are located within the IA, we use maps of each village and IA boundaries. Villages whose boundaries overlap with an IA are assigned a value of 1 for the IA_i indicator (treatment village), and all other villages are assigned a value of 0 (control village). Insofar as spillovers to neighboring villages are smaller than the effect of the IA itself, this will lead to a slight

[15] Asher and Novosad (2017a) and Asher and Novosad (2017b) are recent papers using the Economic Census data.

[16] Henderson et al. (2012), Hodler and Raschky (2014), Michalopoulos and Papaioannou (2013), and Storeygard (2016) find the use of night-time lights data as a useful proxy for development for regional analysis in countries with poor quality income data, and Pinkovskiy and Sala-i Martin (2016) shows that light density at night is a robust proxy of economic activity.

downward bias of the treatment effect. We therefore exclude villages within 4 kms of the IA from the control, as our specifications classify these as "spillover" villages rather than control villages.

An important innovation of our study is the ability to identify economic spillovers to neighboring areas. In addition to the inherent interest of understanding how IAs affect the surrounding economy, accounting for spillovers is necessary for identifying the cumulative effect of IAs. For this purpose, we estimate the difference-in-differences specification as before, but include additional indicator variables denoting disaggregated distance intervals from the IA, each of which is interacted with the year indicators:

$$\begin{aligned} y_{i,t} = \alpha + \sum_{j=1}^{5} \beta_{1,j}(1[dist \in bin_j] \times post_t) + \sum_{j=1}^{5} \beta_{2,j}(1[dist \in bin_j]) + \gamma_2 post_t + \\ X_i\Gamma_1 + (post_t \times X_i)\Gamma_2 + \eta_i + \varepsilon_i. \end{aligned} \tag{2}$$

Our primary spillover specification will include indicator variables for villages whose boundaries overlap those of the IA ("within IA"), as well as for villages at distances of (0-1], (1-2], (2-3], and (3-4] kms. The coefficients of interest are for the distance-post interaction terms, given by $\beta_{1,1}, ..., \beta_{1,5}$. As noted above, we lack information on the precise location of firm activity, which leads us to attribute some of the spillovers induced by the IA in adjacent areas to the IA itself. This means that the indicator variable for distances of (0-1] kms will be an underestimate of the true magnitude of the immediate spillover from the IA.

Several strategies are employed for establishing causal identification. In brief, we first compare control and treatment villages according to baseline (1991) characteristics, and show that the samples are largely balanced once accounting for the criteria used for site selection. We then show that there existed parallel trends in economic activity prior to the establishment of the IAs. Next, we perform a variety of robustness tests on the treatment effects estimated using equations (1) and (2) to account for possible biases introduced by non-random placement of the IAs. Finally, we conduct placebo regressions in order to determine whether control villages with characteristics similar to the treatment villages experienced growth rates comparable to those of the treatment villages. We present the corresponding results in the next section.

The principal threat to identification is the presence of differential trends, which may bias results even where treatment groups are similar according to baseline (1991) characteristics. To address this possibility, we use an event study framework comparing trends in night-time light density (the only variable for which we have annual data) across control and treatment villages prior to and after the establishment of IAs.[17] For this exercise, we regress light

[17]Night-time light illumination is well suited to this task, as it has been used frequently as a proxy measure

density in each year on light density eight years prior to the establishment of the IA, and plot the mean residuals disaggregated by treatment status. For each village, the time since the establishment of IA is based on the year in which the nearest IA was established.

Three measures are taken to address potential biases introduced into the estimated treatment effects from non-random placement of IAs. First, all specifications include a battery of control variables and their interaction with time dummies. The list of control variables includes: IA site selection variables (paved roads, railway stations, post office or telephone, the percentage of land that is forested, and quadratics in distance to the nearest town and distance to IAs established before the study period); and variables correlated with potential growth (log population, the presence of a primary school, the share of male workers employed in non-agricultural wage labor, and the share of the population that belong to the scheduled castes).[18] Second, the baseline regressions are re-estimated using the coarsened exact matching (CEM) algorithm,[19] which establishes balance on all selected variables. Third, we restrict the sample to villages within 15 kms of the IA, and then villages more than 10 kms from the nearest town, while continuing to use the CEM algorithm.

Finally, we conduct placebo regressions in which control villages which have characteristics predictive of receiving an IA are randomly assigned treatment status. Specifically, we regress the treatment variable on: distance from town, presence of a paved road, presence of a railway station, presence of a phone or post office, percentage of land that is forested, the share of the population that works in non-agricultural employment outside the household, log population, and district fixed effects. We then randomly assign treatment status to 50 villages which are in the 95th percentile of predicted treatment, conditional on their being at least 15 kms away from the true treatment villages. Finally, we calculate the distance of each village to these placebo treatment villages, and rerun the baseline regressions using these distances, with indicator variables included for intervals of (0-1], (1-2], (2-3], and (3-4] kms. This procedure is repeated 1000 times, and the distribution of the treatment coefficients and t-statistics compared to the respective values for the true treatment villages.[20]

6 Results

Table 1 assesses the similarity of control and treatment villages according to a number of baseline characteristics. Column (1) gives the mean level of the indicated variable in control villages, and column (2) the mean for treatment villages. Column (3) gives the difference across the two samples, estimated using a regression of the indicated variable on a dummy for

of aggregate economic activity (Pinkovskiy and Sala-i Martin, 2016).

[18]Electrification is omitted from the vector of controls, as virtually all villages were electrified at baseline.

[19]We provide step by step algorithm for CEM (Blackwell et al., 2009) in Section A2 of Appendix A.

[20]This method is the same as that used in Dell and Olken (2017).

IA villages. In Column (4) we add controls for characteristics which determined the location of the IA (paved roads, railway stations, post office or telephone, the percentage of land that is forested, and distance to the nearest town), or which are correlated with potential growth (log population and the share of male workers employed in non-agricultural wage labor).[21] We then repeat the balance test in column (5) using the non-parametric coarsened exact matching (CEM) strategy, which reweights observations so as to generate balance across control and treatment groups (Blackwell et al., 2009). The results show that the samples are largely balanced with the inclusion of the control variables, or when using CEM method.

To provide additional confidence in our identification strategy, we use an event study framework to determine whether there were parallel trends in light density prior to the establishment of the IA, and a subsequent trend break in villages where the IA was established. In Figure 1, we plot the mean level of light density for treatment and control villages against a time variable indicating the number of years since the IA was established. Treatment villages are those whose boundaries overlap those of the IAs, and control villages are all villages more than 4 kms from the IA. As is apparent, light density shows no trend differential across control and treatment groups in the years leading up to the creation of the IA, after which there is a sharp spike in light density in the treatment villages.

The balance in baseline characteristics strengthens our confidence in the identification strategy, as do the results of the event study analysis. We turn now to the main results of this paper, using the difference-in-differences estimator to estimate the effects of IAs on the local economy.

6.1 Economic outcomes

6.1.1 Firms

Figures 2.1 and 2.2 preview the results of this paper. In these figures, we plot the coefficients and 95% confidence intervals from the distance-post interaction terms from specification 2, with villages 15-20 kms from the IA as the omitted group. There is a large and statistically significant increase in the (log) number of firms and workers within the IAs, and (monotonically declining) spillovers at distances up to 4 kms away.

Table 2 gives the direct and spillover effects of the IAs using the difference-in-differences specification. In all regressions we include a vector of control variables associated with IA placement, or which are potentially correlated with long-term growth, as well as village fixed effects, and cluster standard errors at the village level. In column (1) is given the effect

[21] This vector of control variables is slightly more parsimonious than that included in the regression specifications. Specifically, it uses a linear in distance to nearest town rather than a quadratic, excludes the distance to pre-1991 IAs, and excluded the percent of the population that belong to the scheduled castes.

of the IA only on villages with overlapping boundaries (denoted by "within IA"), while in column (2) dummies are included to account for spillovers at intervals of (0-1], (1-2], (2-3], and (3-4] kms.[22] In both specifications the control group is all villages more than 4 kms from the IA. The outcome variables are the (log) number of firms in panel A and the (log) number of workers in panel B.

The baseline regressions show the IAs to have been associated with a 56 percent increase in the number of firms, and an 83 percent increase in the number of workers employed by firms within villages overlapping the IA.[23] There are also substantial spillover from the IA, with an increase in the number of firms of approximately 21-40 percent, and an increase in the number of workers of approximately 24-45 percent. These spillovers extend up to 4 kms from the IA, and are decreasing with distance.[24]

To account for non-random placement of the IAs, we re-estimate the treatment effects using the CEM algorithm. This is done in two ways. In the first, we impose no sample restrictions on the algorithm while searching for control villages ("all-state" matches), the results for which are given in column (3). We next modify the algorithm to restrict the search to villages which are in the same district as the the respective IA villages (column 5). Using the CEM with all-state matches yields virtually identical results to the baseline specification, despite a substantial decline in the sample size.[25] When using the CEM with within-district matches, there is some attenuation of the estimated treatment effect for firms, but little change to the results for workers, despite a fall in the sample size of nearly 90%.

Additional robustness checks are performed imposing further restrictions on the sample, the results of which are given in Appendix Table B1. Again using the CEM algorithm, we first restrict the control villages to those which are no more than 15 kms away from the IA; and, second, restrict the sample to villages that are more than 10 kms from the nearest town. The results are largely unchanged when limiting the sample to villages within 15 kms of the IA, and even increase when limiting the sample to villages more than 10 kms from the nearest town.

As another robustness check, we conduct placebo regressions in which treatment status is randomly assigned to control villages with baseline characteristics similar to those in which the IAs were established.[26] We randomly assign treatment status to 50 villages, then run the

[22]The selection of these distance intervals is motivated by patterns found in figures 2.1 and 2.2.

[23]Note, since our dependent variable is logged, the effect represented by coefficient β is precisely $\exp^{\beta}$ % change.

[24]Results using block fixed effects are qualitatively similar to the results shown in this paper.

[25]Because the CEM generates matches based on a single treatment group, it is necessary to estimate the spillover effects using separate regressions. Therefore, the coefficients given in column (3) are from five independent regressions, in each of which the treatment group is defined as those villages within the indicated distance bin, and the control sample includes all villages more than 4 kms from the IA.

[26]See Section 5 for a further discussion of how these villages are selected.

baseline regressions with spillovers using the distance of each village to the nearest placebo treatment village. This is done 1000 times, and the distribution of coefficients and t-statistics of the five treatment dummies is plotted in Appendix Figure B1. The true coefficients and t-statistics are displayed in these figures using a vertical line. Insofar as the p-values for the true statistics is sufficiently low, this counts as evidence against the results being driven by characteristics driving the site selection. In this case, the p-values for the true coefficients range from a high of 0.02 to a low of 0.00, while the p-values for the true t-statistics is always below 0.00. As is apparent, the true coefficients and t-statistics are extreme outliers in the distribution of placebo statistics, increasing our confidence in the estimated treatment effects.

The subsequent analysis uses the same specification as that in column (2) of Table 2, with the full sample of villages and a vector of time-interacted control variables to account for site selection and characteristics associated with potential growth. This approach is justified by the balance shown between control and treatment groups when including control variables (shown in Table 1), as well as the stability of the estimated coefficients across a number robustness tests (shown in Tables 2 and Table B1). It should be emphasized, however, that the results given below are robust to the employment of the CEM algorithm and sample restrictions discussed above.

6.1.2 Labor Markets

We next explore the effects of the IA on labor markets. For this exercise, we use the demographic census (DC), which gives the occupations of individuals living within villages. One key constraint in this analysis is that the 1991 and 2011 censuses have different disaggregation of occupations. While both include agricultural labor and cultivation, as well as household-based business, the 2011 census aggregates together all other non-agricultural businesses outside the household, which in the 1991 census are disaggregated into eight categories. These include: livestock, forestry, and fishing; mining and quarrying; manufacturing and processing; construction; trade and commerce; transportation, store, and communication; and other. We therefore aggregate all these occupations for the 1991 census, and label this as "non-agricultural wage labor".[27]

Table 3 gives the effects of the IAs on labor market outcomes, disaggregated by gender. The labor market variables are the (log) number of workers in the agricultural and non-agricultural sectors (in columns (1)–(2) for men and columns (5)–(6) for women), as well as the share of workers in these two sectors (in columns (3)–(4) for men and columns (7)–(8) for women). The IAs are associated with a 45 percent increase in the number of men

[27]It is possible that some of this work is salaried employment, or is compensated in-kind but this provides one possible way to make the two censuses comparable in terms of variables.

engaged in non-agricultural wage labor and a 29 percent decrease in agricultural employment. As a share of the labor force, 14 percent more men are engaged in non-agricultural wage labor, and 15 percent fewer are engaged in agricultural labor. As before, we find evidence for substantial spillovers within the labor markets. There is a 20 percent increase in men working as non-agricultural wage laborers at a distance of 3-4 kms from the IA. The share of the labor force engaged in agricultural employment and non-agricultural wage labor show corresponding changes. In Appendix Table B2, we estimate the treatment effects for male workers when using the CEM algorithm, with and without within-district matching, as in Table 2. The results are robust to this method. For parsimony, this exercise is not repeated in the subsequent analysis.

Female labor force participation was also affected, with a 48 percent increase in women working in non-agricultural wage labor, and (a statistically insignificant) 5.7 percent fewer working in agriculture. These translate to an 8.7 percent increase in the share of female workers engaged in non-agricultural wage labor, and a 6.5 percent decline in those engaged in agriculture (again, statistically insignificant). The (log) number of women working in non-agricultural wage labor shows spillovers of a somewhat smaller magnitude than those found for men, ranging from 13 percent to 18 percent, and the coefficients are measured less precisely. As a share of the labor force, there is even less evidence for spillovers in the labor force composition of women.

Figure 3 depicts the labor market effects of the IAs, again taking villages located 15-20 kms from the IA as the comparison group, and limiting the sample to villages within 35 kms of the IA. In Figure 3.1, we see that the percentage of the male labor force engaged in non-agricultural employment experiences the largest increase in villages within the IA, and that this effects falls monotonically up to a distance of 7 kms from the IA. This is accompanied by a nearly symmetric shift in agricultural employment as a share of the work force (Figure 3.2). Interestingly, we see in Appendix Table B3 that the reduction in agricultural employment is driven primarily by a reduction in the share of workers cultivating land they own or rent presented in column (2), with only a small decline in the share of individuals working as agricultural wage laborers presented in column (3).

6.2 Mechanisms

6.2.1 Firm characteristics

Having looked at the direct effects and spillovers from IAs, it is important to understand the mechanisms behind these effects. For example, do IAs bring in large firms, that then lead to spillovers? What industrial sectors are attracted by these IAs? What characteristics of the local economy are important for successful IAs? And do these IAs bring about a change in the ownership structure of firms (by disadvantaged sections of the society)? We explore these questions in detail in the following subsections.

Tables 4 and 5 show the effects of the IAs disaggregated by the size and sector of firms. Results are given using both logs and levels of the outcome variable. The latter is justified by the frequent occurrence of observations taking value of zero.[28] In addition, levels are of independent interest, as it is not clear that the treatment effect should be expected to scale to the baseline level of the outcome variable.

In Table 4, we see in column (1) that there is an increase in the number of firms employing 99 or more employees within the IA: for every three villages overlapping an IA, two villages will have a firm of such a size. There is no increase in the number of such firms in neighboring villages. There is remarkably a little increase in the number of firms employing between 10 and 99 workers, either within the IA or in the nearby villages. Firms with fewer than 10 employees, however, witness explosive growth, both within the IA and in villages up to 4 kms away. In the second panel we look at the number of workers in firms within each firm-size category. There is an increase of 300 workers per village in firms with more than 99 employees, meaning that the average large firm created in the IA has 450 employees. There is an increase of 50 workers at firms with fewer than 10 individuals, meaning that the average firm of this size employs 2 individuals.[29] The log results are consistent with these findings, though there is more noise when looking at firms with more than 99 or 10-99 employees, due to the large number of zeros.

The size distribution of newly created firms highlights both the efficacy of the program, and the constraints on economic activity outside the IAs. The vast majority of the employment generated within the IAs occurs within the largest firms, as intended by policy makers. Outside the IAs, however, all growth occurs for firms with a small number of employees, with no evidence of an increase in the number of firms employing more than 10 employees. The lack of growth in medium and large sized firms outside the IAs is consistent with the barriers to undertaking non-agricultural economic activity that motivated the creation of the IAs. Smaller firms, however, may operate within homes and other small buildings, and are not required under the KTCPA act to secure the alterations of land zoning as is necessary for larger enterprises. Land use restrictions therefore pose no obstacle to the large number of newly created small firms in the commercial agriculture sector.

Table 5 takes as the outcome variable the number of firms in manufacturing, commercial agriculture, and a variable aggregating retail, restaurants, and transport (abbreviated as "rrt") presented in columns (1)–(3), respectively. These are measured in both logs and

[28]For log outcomes, we take the log of the value plus 1.

[29]In Appendix Table B4, we can see that most of the new firms in this size category indeed have just 1 or 2 employees.

levels. Manufacturing shows large increases up to 4 kms (3 kms) from the IA, and increases up to 4 kms (2 kms) for rrt when we use logs (levels).

Interestingly, there is also evidence of substantial spillovers for commercial agriculture firms. This is somewhat surprising if we think that spillovers should arise from the traditional mechanisms invoked for explaining agglomeration economies. One plausible explanation for this result is that the income generated by employment in IAs allows households to overcome the credit constraints that had previously prevented them from making the capital investments necessary for establishing their own firms. It is plausible that the increase in agricultural firms is due to the larger demand for agricultural products in areas adjacent to the IAs. However, it is also plausible that the relative integration of markets for agricultural products (Donaldson, 2017) renders local demand less important to producers of agricultural products. We next look at the characteristics of the local economy that may have mediated the effects of the IAs, such as human capital, infrastructure, and the presence of financial institutions.

6.2.2 Village characteristics

In Table 6, we explore the effect of baseline village characteristics on the subsequent effects of the IAs on firms and workers. Here we focus on three factors: literacy, presence of banks, and paved roads. Literacy is measured using an indicator taking the value of 1 where literacy rates are above the median at baseline, while banks and paved roads are captured with indicator variables taking a value of 1 when these are present in the village at baseline. Each of these is interacted with the distance indicators and the post variable, as well the interaction of the post and distance indicators (post $\times$ distance). To control for correlations between the variables, we include all the interacted terms in a single regression.[30] Panel A takes as the outcome the log and level of the number of all types of firms, while panel B has as the outcome the log number and percent of male workers in non-agricultural employment. The results for individual regressions are displayed across three columns, with each column giving the coefficients from the interaction of the post $\times$ distance terms with the variable indicated at the head of the column. For example, columns (1)–(3) come from a single regression with log firms as the outcome, and the three columns give the coefficients of the post $\times$ distance terms interacted with literacy, banks, and paved roads, respectively.

The most striking heterogeneities are those for literacy rates and the presence of banks. Literacy rates above the median are associated with a far higher rate of firm creation, consistent with models stressing the correlation of human capital and entrepreneurship (Lucas Jr,

[30]Because each of these variables might be correlated with the population size, we always include interactions of the latter (logged) with the treatment variables and time dummies (i.e. post $\times$ distance $\times$ log(population)).

1978; Moretti, 2004). We also find that the presence of banks at baseline is associated with a smaller effect of the treatment. This is consistent with a credit channel, whereby previously credit-constrained households are now able to use the income from factory jobs to finance the creation of new businesses. As can be seen, much of the effect is driven by an increase in commercial agriculture firms, suggesting that households had previously practiced traditional, subsistence agriculture due to the lack of capital necessary for engaging in market-oriented commercial agriculture.

6.2.3 Finance

To shed further light on the role of credit access in driving the effects of the IA, we next explore the sources of financing for newly created firms. The vast majority of firms in Karnataka rely upon self-financing (69 percent), with only 3 percent receiving bank financing, and 17 percent government financing.[31] Because the increase in firms was larger where banks were absent, we would expect that the increase in firms would consist primarily of self-financed firms. However, the government may have provided additional support to local firms in order to strengthen the efficacy of the IAs, or private lenders may have become more active in areas with IAs.[32]

To assess the relative importance of these various sources of finance, we again estimate specification 2, using as the outcome the log or level number of firms using different sources of credit.[33] These results are given in Table 7. In columns (1)–(3) the outcome variable is defined as the (log) number of firms self-, government-, and bank-financed, respectively; and in columns (4)–(6), the outcome is the level of firms financed by same three sources. We find that the majority of newly created firms are self-financed. However, within the IA, there is large increase in the number of firms which receive financing from banks. In results not shown, we find that it is the largest firms which receive bank financing, with smaller firms being generally self-financed.

These findings are consistent with the thesis advanced previously in this paper, that the growth in firms is driven in part by the relaxation of credit constraints due to the additional income from the new employment opportunities within the IAs. It is likely that demand channels also contribute to the increase in firms – particularly for firms in rrt – as the higher incomes from manufacturing employment are used for the consumption of locally produced goods and services.

[31] Authors' calculations, using the Economic Census data.

[32] Most commercial banks in India are owned by the government, which supply most of the credit in the country.

[33] Because we do not have information on the source of firm financing for 1990 census, we use the 1998 measures for the baseline.

6.2.4 Income – Night lights

The IAs have apparently been remarkably successful in triggering an economic transformation of the local economy. To assess the magnitude of this transformation, one would require data on wages and output, which is unavailable at the village level. We therefore use the nighttime light illumination as a proxy for aggregate village-level income.[34]. We saw earlier in the event study analysis that there was a large increase in light density in IA villages in comparison to control villages. We now use the difference-in-differences specification to assess the direct and spillover effects of the IAs on light density.

In Figure 4, we estimate specification 2, with nighttime light density as the outcome variable. As with regressions for labor force composition, there is strong evidence for increased light density at distances up to 7 kms from the IAs. In Table 8 the coefficients for each of the distance bins are estimated. In column (1) the outcome variable is light density measured in levels, and in column (2) in logs. For the log regressions, to handle zeros we take the log of 1 plus the light density. There is a statistically significant increase in light density within the IAs, with a level increase of 13.5, and a log increase of 0.43. This increase in light density extends out for several kms from the IAs. Because log outcomes can be sensitive to the linear transform to which the variable is first subject to, in column (3) we limit the sample to observations that lacked light at the baseline, and use as the outcome a dummy taking a value of 1 for any light; and in columns (4) and (5) we limit the sample to villages that had light at the baseline, and measure the outcome in levels and logs.

Pinkovskiy and Sala-i Martin (2016) note the close correspondence between the percentage increase in GDP and the percentage increase in light density in India. In the spirit of this observation, we estimate a back-of-the-envelope calculation of the effects of IAs on GDP using the percentage change in light coverage. Using log light density as the outcome, villages within the IA experience a 43.2 percent increase in village's GDP, while villages at intervals of 0-1, 2-3, and 3-4 kms experience increases in village's GDP ranging from 0 to 10 percent. The increase in incomes is also accompanied by a greater accumulation of assets. In Appendix Table B5 we find evidence for an increase in television, scooter, and bicycle ownership up to four kms from the IA, suggesting that households have used the additional income to purchase consumer durables.[35]

[34] This measure has been extensively employed in the past literature (see Pinkovskiy and Sala-i Martin (2016) for a discussion of this literature)

[35] These estimates are based on a single cross-sectional regression using data from the 2011 economic census, as these variables were not collected in earlier years of the census.

6.3 Social impacts

We next examine whether the economic effects documented in this paper have been socially inclusive. In India, many state program include explicit policies to encourage the participation of minority groups and vulnerable populations, lest existing social exclusions be perpetuated in the program's implementation. Because the IA program lacked any such targeting for marginalized groups, it is interesting to know whether members of these communities benefited. We therefore examine the effect of the IA program on two particularly salient marginalized communities: women and scheduled castes (SC).

Table 9 shows the change in firm ownership and manufacturing employment for women in Panel A. In columns (1) and (2), the outcome variable is the (log) number of firms owned by women, and the (log) number of employees working for firms owned by women. We provide the level number in columns (3) and (4). In column (2) and (4) we can see that there is a substantial increase in the number of women working for firms (in the nearby villages).[36] Our results also show in columns (1) and (3) that there is a substantial increase of female-owned firms, though the coefficients are less precisely measured.

Table 9 also gives the effects of IAs for SC-owned firms and employment in Panel B. SC firm ownership increased by 4 firms within the IA, and by approximately 1 firm per village up to 2 kms away. This represents a small increase in the overall share of firms in these villages. The increase in the number of workers at SC-owned firms is approximately 13 per village within the IA, and between 5-8 workers per village up to distances of 4 kms (but estimated with less precision). Using log outcomes, there is a 60 percent increase in workers at SC-owned firms in villages within the IA, which declines monotonically to a 18 percent increase in villages at an interval of 3-4 kms.

7 Discussion and Conclusion

Our findings indicate that the IA program has been remarkably effective. Despite the overwhelmingly agricultural structure of the economy, low levels of human capital, and the relatively modest policies included in the program, IAs led to large increases in the manufacturing work force. In addition, the program triggered a broader restructuring of the local economy, with workers up to 4 kms away shifting from agricultural to non-agricultural employment, and agriculture itself being increasingly commercialized.

We also shed light on some of the mechanisms at play in the pace of structural transfor-

[36]The 1990 economic census excluded information on female firm ownership, preventing the use of the difference-in-difference estimator with 1990 as the baseline. We therefore estimate a difference-in-differences using 1998 and 2013 as the two time periods. In an alternative specification not presented, we also simply use the cross-section of 2013. In both exercises the estimated coefficients are relatively consistent.

mation. Most conspicuously, we find that the absence of banks is associated with the largest increase in entrepreneurship in areas surrounding the IAs, suggesting that credit constraints had previously played a role in suppressing entrepreneurship. In addition, we find that firm creation is largest in villages with higher literacy rates, pointing to the importance of education for entrepreneurship. Interestingly, there is no evidence that baseline literacy rates were important in labor force outcomes. Finally, the shift to commercial agriculture despite a decline in the agricultural labor force highlights the role of industrialization in triggering the modernization of the agricultural sector, as long posited by development economists and economic historians.

These economic changes are associated with an increase in light density of a fairly large magnitude, as well as an increase in asset accumulation. This suggests that the movement out of subsistence agriculture has been accompanied by an increase in social welfare. Though this is not surprising, it should be noted that such land acquisitions are often criticized for a heavy-handed displacement of agricultural labor, which may be counter to the interests of the local community. In results not shown, we find some validation for these concerns, with villages overlapping the IA experiencing a 17 percent decline in cultivated land. However, a significant share of this decline is likely due to a voluntary shift out of agriculture, as villages close to the IA, and not subject to any acquisition from the state, also experience 6-7 percent declines in cultivated land.[37]

Though the IA program has proven strikingly successful, there are two findings that point to some of the limitations to conducting industrial policy in rural areas, at least in the short run.

First, the number of individuals employed by firms within the IAs far exceeds the number of workers from nearby villages reported in the demographic census as being employed at such firms. A back-of-the-envelope calculation indicates that of the 800 employees working within the IAs, only about 220 of them were drawn from nearby villages. This means that the new firms are drawing a large share of their employment from outside the local labor markets. Though this may indicate that the local population lacks the skills necessary for such employment, it is equally plausible that the new manufacturing jobs simply offer an insufficient wage premium for drawing more workers out of agriculture.[38]

Second, it is striking that within the IAs there occurs a small increase in the number of very large firms, and a large increase in the number of firms with 1 or 2 employees, but little increase in firms of middling size (3-99). The lack of mid-size firms indicates that the advantages conferred by the IAs are insufficient to attract mid-size firms from elsewhere,

[37] These numbers come from (2) with acres of cultivated land (from the demographic census) as the outcome variable.

[38] See Blattman and Dercon (2017) on the inadequacy of the manufacturing wage premium to offset the dis-amenities of manufacturing employment for a substantial share of workers in the informal sector.

and that the local population lacks the requisite entrepreneurial skill or access to credit to establish such firms. Outside the IAs, all firm growth occurs for firms with only small labor forces, suggesting that the land-use restrictions that had originally motivated the IA program continue to be binding outside the IAs, so that firm growth is constrained to smaller firms with less need for large plots of land.[39]

The remarkable success of the IA program suggests that the extensive agricultural zoning found throughout India, though ostensibly protecting the interests of agriculturalists, ultimately comes at the expense of economic development. This program should be seen as complementary to more traditional policies facilitating the movement of labor to economic opportunities in urban areas (Kline and Moretti, 2014b), such as road construction (Asher and Novosad, 2017b), investments in human capital, and improved urban governance. Given India's substantial frictions in labor mobility (Topalova, 2010; Munshi and Rosenzweig, 2016), however, and the relatively slow pace of urbanization, the IA program represents an attractive approach to achieving the structural transformation of the economy.

[39]As mentioned previously, agricultural households are free to engage in non-agricultural activities on a share of their land, so long the primary use of the land remains agricultural.

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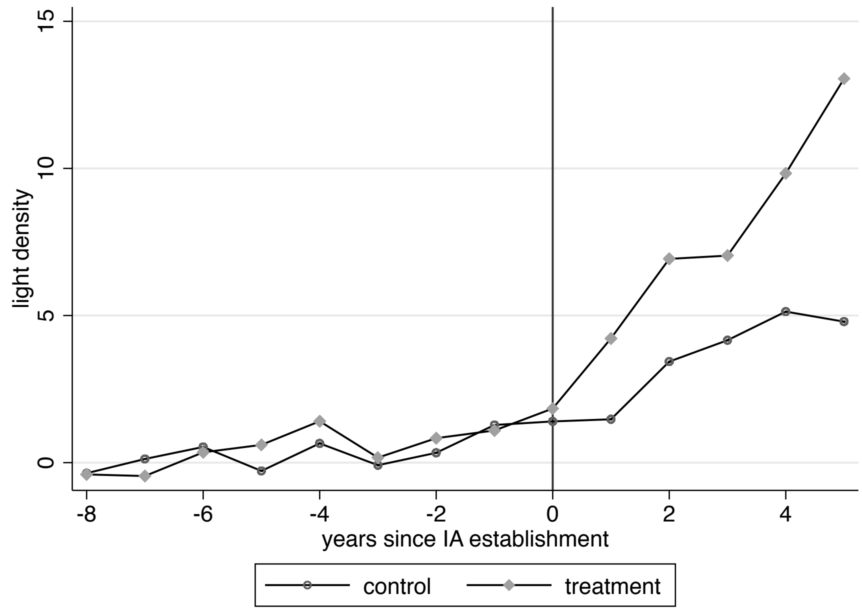
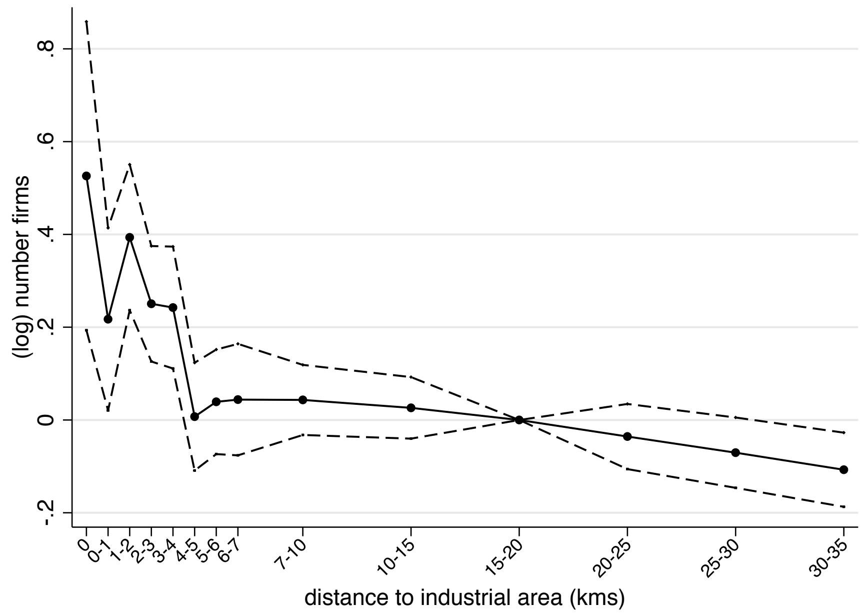
Figure 1: Event study using Light Density

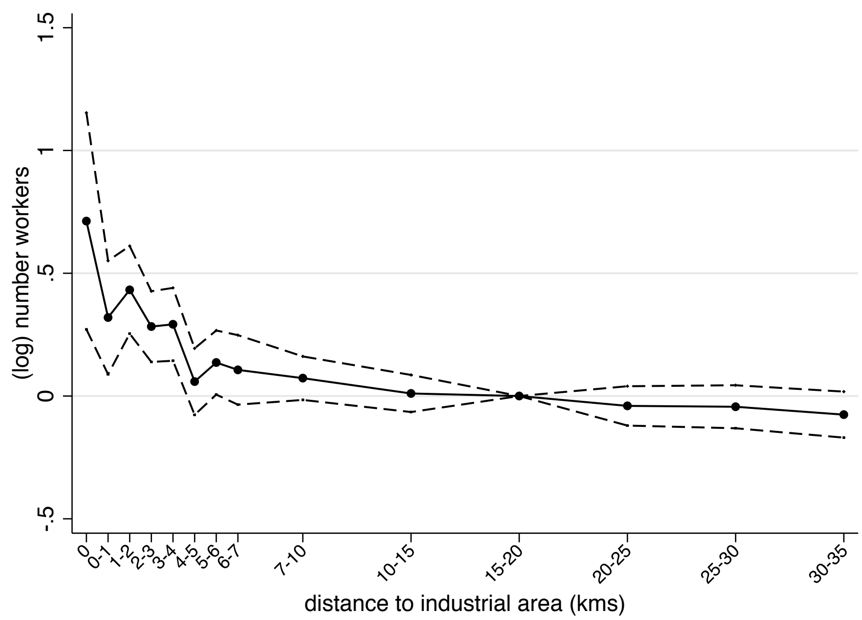


Notes: Figure 1 plots average light density disaggregated by treatment status against the number of years since the establishment of the nearest Industrial Area. Treatment villages are villages in which an IA was established. Control villages are all villages more than 5 kms from the IA. Light density each year is measured as the residual from a regression of light density on baseline light density (8 years prior to the establishment of the IA).

Figure 2: Effects of IAs on Firms and Workers



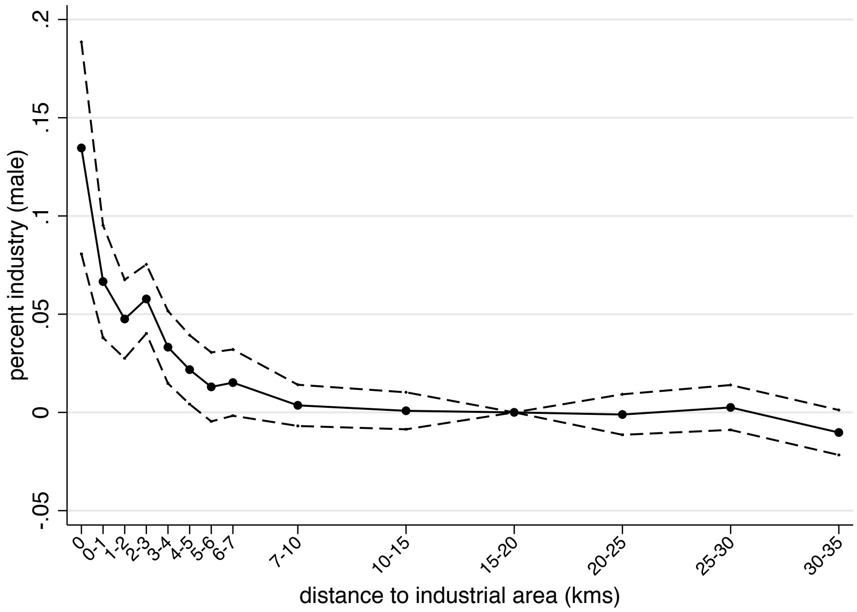
2.1: Firms



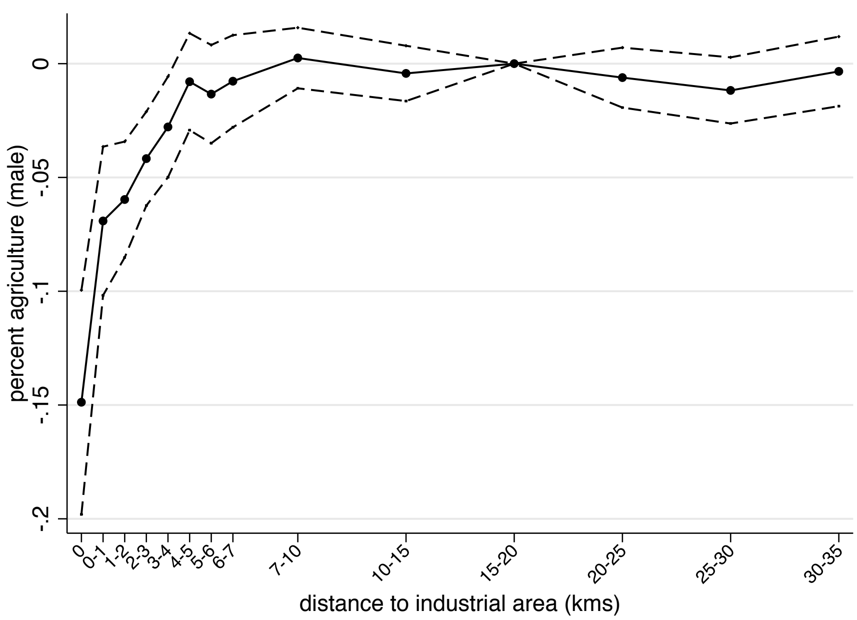
2.2: Workers

Notes: Figure 2 plots the coefficients of the distance-post interaction terms from the difference-in-differences regression given in Specification (2). In Figure 2.1 the outcome variable is (log) number of firms, and in Figure 2.2 (log) number of workers. The x-axis measures the distance (in kms) of the village from the IA, where "0" refers to villages whose boundaries overlap those of the IA, and the omitted category is villages 15 – 20 kms from the IA. The dashed lines indicate the 95% confidence interval.

Figure 3: Effects of IAs on Workers by Sector



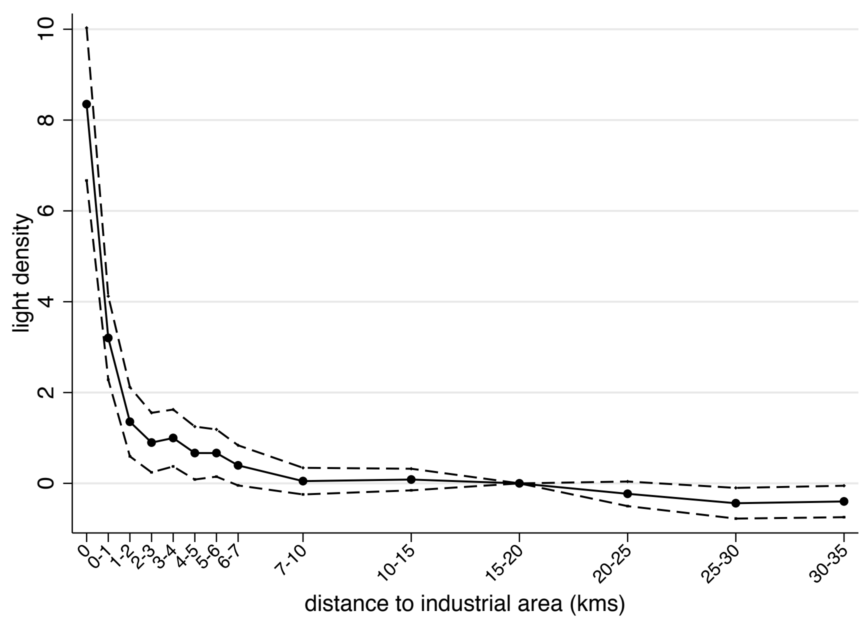
3.1: Workers (Male) Industry



3.2: Workers (Male) Agriculture

Notes: Figure 3 plots the coefficients of the distance-post interaction terms from the difference-in-differences regression given in Specification (2). In Figure 3.1 the outcome variable is the percent of male workers in non-agricultural wage labor, and in Figure 3.2 the percent of male workers in agriculture. The x-axis measures the distance (in kms) of the village from the IA, where "0" refers to villages whose boundaries overlap those of the IA, and the omitted category is villages 15 – 20 kms from the IA. The dashed lines indicate the 95% confidence interval.

Figure 4: Effects of IAs on Light Density



Notes: Figure 3 plots the coefficients of the distance-post interaction terms from the difference-in-differences regression given in Specification (2). The outcome variable is light density. The x-axis measures the distance (in kms) of the village from the IA, where "0" refers to villages whose boundaries overlap those of the IA, and the omitted category is villages 15–20 kms from the IA. The dashed lines indicate the 95% confidence interval.

Table 1: Balance Table

	control	treatment	treat - control		
	(1)	(2)	(3)	(4)	(5)
demographics					
log population	6.4	6.718	0.319***		0.033
			(0.120)		(0.119)
pct population Scheduled Caste	0.194	0.201	0.008	0.011	0.012
			(0.019)	(0.021)	(0.019)
pct male workers in agriculture	0.806	0.749	-0.057***	0.013	0.017
			(0.019)	(0.019)	(0.024)
pct male workers non-agr wage labor	0.020	0.060	0.039***		0.006
			(0.005)		(0.008)
pct male literacy	0.485	0.525	0.040**	0.023	0.015
			(0.016)	(0.018)	(0.017)
infrastructure (unrelated to IA site)					
primary school present	0.859	0.917	0.058	-0.028	-0.007
			(0.036)	(0.029)	(0.028)
high school present	0.387	0.552	0.165***	0.052	0.014
			(0.050)	(0.041)	(0.054)
market present	0.048	0.062	0.014	-0.021	-0.052*
			(0.022)	(0.017)	(0.030)
bus stand present	0.671	0.812	0.141***	-0.009	-0.022
			(0.048)	(0.043)	(0.042)
communication facility	0.673	0.812	0.140***	-0.016	-0.022
			(0.048)	(0.043)	(0.042)
post office present	0.313	0.385	0.072	0.011	0.023
			(0.047)	(0.013)	(0.052)
telephone present	0.165	0.302	0.137***	0.048	0.02
			(0.038)	(0.030)	(0.048)
telegraph office present	0.095	0.219	0.124***	0.026	0.019
			(0.030)	(0.024)	(0.042)
firm outcome variable					
no. employed (EC 1990)	3.582	4.262	0.680***	-0.027	-0.164
			(0.161)	(0.129)	(0.180)
land use					
log total land	6.067	6.128	0.061	0.009	-0.053
			(0.101)	(0.076)	(0.106)
pct land cultivated	0.659	0.694	0.034	-0.013	-0.021
			(0.026)	(0.021)	(0.021)
pct land uncultivated	0.13	0.163	0.032**	0.013	0.019
			(0.014)	(0.016)	(0.016)
pct land waste	0.116	0.125	0.009	-0.001	0.002
			(0.015)	(0.017)	(0.016)
pct cultivated land irrigated	0.19	0.183	-0.007	-0.019	-0.01
			(0.023)	(0.025)	(0.026)
pct land forest	0.094	0.018	-0.076***		0
			(0.022)		(0.003)
infrastructure (related to IA site)					
distance from town (kms)	15.534	12.021	-3.513***		-0.475
			(0.984)		(0.755)
paved roads	0.648	0.854	0.206***		0.021
			(0.049)		(0.039)
railroad	0.008	0.083	0.075***		0
			(0.009)		(0.020)
tap water	0.179	0.292	0.113***	0.035	0.022
			(0.039)	(0.038)	(0.049)
electricity	0.953	1	0.047**	-0.006	0.009
			(0.022)	(0.018)	(0.010)
controls				yes	
CEM					yes

Note: Columns (1) and (2) give the mean values of the indicated variables for control and treatment villages, respectively. Control villages are all villages more than 4 kms from the nearest Industrial Area (IA). Treatment villages are those villages whose boundaries overlap those of the IA. The coefficients in column (3) come from a regression of the indicated variable on the treatment indicator. Column (4) includes controls for (log) population, share of male workforce in non-agricultural wage labor, percent of land that is forested, distance from nearest town, the presence of a paved road, presence of a railroad station, and presence of either a post office or telephone connectivity. Column (5) uses the coarsened exact matching (CEM) weighting scheme (see section A2 in Appendix A for more details). *** p<0.01, ** p<0.05, and * p<0.1.

Table 2: Effect of IAs on Number of Firms and Employees

			coarsened exact matching			
			all-state match		within-district match	
			treatment	sample	treatment	sample
	baseline regression		effect	size	effect	size
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: log firms						
within IA	0.559***	0.549***	0.570***	8020	0.366*	848
	(0.154)	(0.154)	(0.171)		(0.202)	
0-1 kms		0.207**	0.168	15050	-0.023	1962
		(0.093)	(0.102)		(0.127)	
1-2 kms		0.395***	0.333***	18812	0.234**	3278
		(0.072)	(0.078)		(0.102)	
2-3 kms		0.240***	0.232***	20470	0.137*	4718
		(0.055)	(0.062)		(0.074)	
3-4 kms		0.217***	0.165**	21508	0.069	4836
		(0.060)	(0.066)		(0.078)	
R-squared	0.796	0.795				
N	32090	35444				
Panel B: log workers						
within IA	0.828***	0.812***	0.840***	8020	0.839***	848
	(0.219)	(0.218)	(0.242)		(0.282)	
0-1 kms		0.321***	0.312**	15050	0.213	1962
		(0.109)	(0.124)		(0.160)	
1-2 kms		0.449***	0.372***	18812	0.351***	3278
		(0.086)	(0.094)		(0.117)	
2-3 kms		0.259***	0.253***	20470	0.205**	4718
		(0.070)	(0.080)		(0.095)	
3-4 kms		0.242***	0.175**	21508	0.085	4836
		(0.069)	(0.075)		(0.093)	
R-squared	0.778	0.777				
N	32090	35444				

Note: Regression results are for the post-distance interaction terms using specifications (1) and (2) for direct and spillover effects, respectively. The outcome variables are (log) number of firms and (log) number of workers. The sample for column (2) are villages within the IA and villages more than 4 kms from the IA. The sample for column (3) is all villages. A vector of time-interacted controls is included for characteristics determining site selection or correlated with potential growth. Village fixed effects are included. Robust standard errors (clustered at village level) are shown in parentheses. *** p<0.01, ** p<0.05, and * p<0.1. Column (3) gives the results using the coarsened exact matching (CEM) method based on treatment covariates that determined site selection of the IAs, and uses all villages within the state to determine the best match. Column (5) uses the CEM method, but restricts matches to villages within the same district. Separate regressions are run for each distance interval, with the sample restricted to villages within the indicated interval and villages more than 4 kms from the IA. The adjacent column gives the respective sample size for these regressions. (See Section A2 in Appendix A for more details.)

Table 3: Effect of IAs on Labor Force

	men				women			
	log		percent		log		percent	
	Non-Agr	Agr	Non-Agr	Agr	Non-Agr	Agr	Non-Agr	Agr
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
within IA	0.449***	-0.285***	0.143***	-0.150***	0.478***	-0.057	0.087**	-0.065
	(0.147)	(0.077)	(0.027)	(0.025)	(0.150)	(0.211)	(0.039)	(0.058)
0-1 kms	0.328***	-0.097**	0.065***	-0.065***	0.178*	-0.054	0.037	-0.023
	(0.072)	(0.045)	(0.014)	(0.016)	(0.098)	(0.121)	(0.024)	(0.033)
1-2 kms	0.209***	-0.096**	0.046***	-0.053***	0.154**	0.113	-0.002	0.006
	(0.062)	(0.039)	(0.010)	(0.012)	(0.078)	(0.100)	(0.018)	(0.026)
2-3 kms	0.241***	-0.054**	0.052***	-0.033***	0.104*	0.024	0.002	0.030
	(0.048)	(0.026)	(0.008)	(0.010)	(0.058)	(0.076)	(0.014)	(0.022)
3-4 kms	0.199***	-0.031	0.030***	-0.022**	0.130**	0.180**	0.014	0.019
	(0.049)	(0.031)	(0.009)	(0.011)	(0.059)	(0.079)	(0.012)	(0.021)
R-squared	0.875	0.911	0.819	0.767	0.836	0.769	0.729	0.588
N	40836	40836	40832	40832	40836	40836	40114	40114

Note: Regression results are for the post-distance interaction terms using specification (2). The outcome variables are (log) number and share of workers in agricultural and non-agricultural employment, disaggregted by gender. A vector of time-interacted controls is included for characteristics determining site selection or correlated with potential growth. Village fixed effects are included. Robust standard errors (clustered at village level) are shown in parentheses. *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Table 4: Effect of IAs by Firm Size

	firm size (levels)			firm size (logs)		
	> 99	10 - 99	< 10	> 99	10 - 99	< 10
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Number of firms						
within IA	0.712**	1.735	26.050**	0.212**	0.221	0.530***
	(0.280)	(1.170)	(12.214)	(0.082)	(0.138)	(0.153)
0-1 kms	-0.048	0.154	14.555**	-0.018	0.081	0.199**
	(0.035)	(0.219)	(7.064)	(0.017)	(0.058)	(0.093)
1-2 kms	-0.018	0.128	21.478***	-0.002	0.050	0.392***
	(0.022)	(0.173)	(5.488)	(0.011)	(0.046)	(0.073)
2-3 kms	-0.028*	0.005	9.053***	-0.011	0.020	0.239***
	(0.014)	(0.133)	(3.364)	(0.007)	(0.038)	(0.055)
3-4 kms	-0.014	-0.112	4.499	-0.002	-0.018	0.216***
	(0.019)	(0.131)	(3.256)	(0.010)	(0.034)	(0.060)
R-squared	0.553	0.581	0.733	0.563	0.629	0.792
N	35442	35442	35442	35442	35442	35442
Panel B: Number of workers						
within IA	307.976***	59.922	49.885*	0.861**	0.568	0.586***
	(111.754)	(37.411)	(25.857)	(0.372)	(0.349)	(0.167)
0-1 kms	8.301	-1.359	23.615**	-0.088	0.268	0.326***
	(13.529)	(5.918)	(10.662)	(0.104)	(0.163)	(0.101)
1-2 kms	74.194*	-1.516	39.191***	0.060	0.095	0.439***
	(43.962)	(3.970)	(10.478)	(0.088)	(0.122)	(0.082)
2-3 kms	-28.328	-3.492	20.594***	-0.082	0.013	0.303***
	(52.985)	(3.045)	(6.720)	(0.058)	(0.107)	(0.063)
3-4 kms	16.950*	-3.820	10.311	0.010	-0.052	0.263***
	(10.266)	(3.211)	(7.490)	(0.060)	(0.096)	(0.066)
R-squared	0.501	0.595	0.711	0.551	0.637	0.781
N	35448	35448	35448	35448	35448	35448

Note: Regression results are for the post-distance interaction terms using specification (2). The outcome variables are the number of firms and workers in each firm size category, given in both logs and levels. and share of workers in agricultural and non-agricultural employment, disaggregted by gender using the Economic Census. A vector of time-interacted controls is included for characteristics determining site selection or correlated with potential growth. Village fixed effects are included. Robust standard errors (clustered at village level) are shown in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.

Table 5: Effect of IAs by Firm Sector

	firm sector					
	logs			levels		
	manu	comm agr	rrt	manu	comm agr	rrt
	(1)	(2)	(3)	(4)	(5)	(6)
within IA	0.419**	0.517**	0.498***	9.763	0.867	12.229***
	(0.177)	(0.237)	(0.149)	(6.030)	(4.413)	(4.356)
0-1 kms	0.253**	0.312**	0.101	8.067	1.560	3.151
	(0.099)	(0.156)	(0.081)	(5.199)	(3.172)	(1.949)
1-2 kms	0.266***	0.473***	0.234***	4.047	11.872***	2.847**
	(0.071)	(0.109)	(0.070)	(2.684)	(3.805)	(1.425)
2-3 kms	0.143**	0.334***	0.122***	5.443**	3.443	0.092
	(0.059)	(0.091)	(0.044)	(2.325)	(2.213)	(0.652)
3-4 kms	0.103*	0.339***	0.084*	-0.968	5.382**	0.456
	(0.059)	(0.092)	(0.050)	(1.296)	(2.347)	(0.791)
R-squared	0.760	0.728	0.840	0.598	0.690	0.768
N	35438	35848	35438	35438	35848	35438

Note: Regression results are for the post-distance interaction terms using specification (2). The outcome variables are the number of firms in the indicated sectors, given in both logs and levels. "manu" denotes manufacturing, "comm agr" denotes commercial agriculture (inclusive of livestock) and, "rrt" refers to restaurant, retail and transport services. A vector of time-interacted controls is included for characteristics determining site selection or correlated with potential growth. Village fixed effects are included. Robust standard errors (clustered at village level) are shown in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.

Table 6: Heterogeneous Effect of IAs on Firms

	log firms			level firms		
	literacy	bank	paved road	literacy	bank	paved road
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All firms						
var X within IA	-0.285	-0.181	-0.253	20.895	-40.248	15.064
	(0.302)	(0.544)	(0.402)	(26.782)	(45.548)	(17.223)
var X 0-1 kms	0.513**	-0.123	0.040	43.381***	27.450	2.645
	(0.204)	(0.281)	(0.255)	(14.005)	(36.145)	(14.458)
var X 1-2 kms	0.224	-0.579***	0.154	19.075*	-39.329*	2.326
	(0.164)	(0.185)	(0.170)	(11.558)	(22.274)	(8.815)
var X 2-3 kms	0.304**	-0.620***	0.265*	28.105***	-53.997***	-2.210
	(0.120)	(0.210)	(0.147)	(6.879)	(17.896)	(6.396)
var X 3-4 kms	0.035	-0.241	0.289*	1.941	-1.647	-0.920
	(0.134)	(0.229)	(0.158)	(7.111)	(25.729)	(6.500)
	log workers			percent workers		
Panel B: Non-agr labor						
var X within IA	-0.645**	-0.171	0.356	-0.042	-0.039	0.100
	(0.282)	(0.445)	(0.413)	(0.058)	(0.097)	(0.076)
var X 0-1 kms	-0.373**	-0.394	0.176	-0.045	-0.074	0.023
	(0.149)	(0.315)	(0.190)	(0.031)	(0.067)	(0.037)
var X 1-2 kms	-0.122	-0.104	0.018	0.016	-0.042	-0.013
	(0.143)	(0.188)	(0.169)	(0.023)	(0.037)	(0.025)
var X 2-3 kms	-0.009	0.124	-0.070	0.006	0.031	-0.033
	(0.099)	(0.229)	(0.120)	(0.017)	(0.055)	(0.022)
var X 3-4 kms	-0.088	-0.015	0.129	0.027	-0.000	-0.014
	(0.105)	(0.150)	(0.131)	(0.017)	(0.034)	(0.020)

Note: Regression results are for the interaction of the variable at the column head with the post-distance interaction terms using specification (2). The outcome variables are the number of firms, in logs and levels, and the (log) number and share of male workers in non-agricultural wage labor. Coefficients in columns (1)–(3) come from a single regression, as do those of column (4)–(6). A vector of time-interacted controls is included for characteristics determining site selection or correlated with potential growth. The interaction of (log) population with the post-interaction term is also included. Village fixed effects are included. Robust standard errors (clustered at village level) are shown in parentheses. *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Table 7: Effect of IAs on Firms by Finance Type

	log firms financed by:			level firms financed by:		
	self	govt	bank	self	govt	bank
	(1)	(2)	(3)	(4)	(5)	(6)
within IA	0.258	0.059	0.451***	5.649	-0.006	5.307*
	(0.175)	(0.144)	(0.151)	(10.211)	(2.618)	(2.973)
0-1 kms	0.334***	0.051	0.090	16.138**	-0.761	0.346
	(0.107)	(0.079)	(0.067)	(7.555)	(0.739)	(0.370)
1-2 kms	0.482***	0.136**	0.062	14.107***	0.616	0.540
	(0.087)	(0.062)	(0.055)	(4.593)	(0.560)	(0.416)
2-3 kms	0.351***	0.070	0.024	7.686**	0.493	-0.149
	(0.073)	(0.047)	(0.038)	(3.032)	(0.451)	(0.216)
3-4 kms	0.280***	0.054	-0.007	3.635	0.755	-0.665*
	(0.072)	(0.051)	(0.042)	(2.924)	(0.702)	(0.385)
R-squared	0.770	0.754	0.602	0.736	0.596	0.602
N	38480	38480	38480	38480	38480	38480

Note: Regression results are for the post-distance interaction terms using specification (2). The outcome variables the number of firms receiving finance from the sources indicated in the column head, in logs and levels. A vector of time-interacted controls is included for characteristics determining site selection or correlated with potential growth. Village fixed effects are included. Robust standard errors (clustered at village level) are shown in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.

Table 8: Effect of IAs on Night Lights

	full sample		0-light	> 0 light	
	level	log	any	level	log
	(1)	(2)	(3)	(4)	(5)
within IA	13.506***	0.432***	-0.046	13.546***	0.568***
	(1.368)	(0.068)	(0.035)	(1.475)	(0.068)
0-1 kms	3.128***	0.098**	0.058***	3.019***	0.158***
	(0.633)	(0.042)	(0.022)	(0.775)	(0.044)
1-2 kms	2.437***	-0.021	0.012	2.698***	0.047
	(0.499)	(0.032)	(0.029)	(0.616)	(0.036)
2-3 kms	1.265***	0.039	-0.002	1.465***	0.029
	(0.338)	(0.029)	(0.018)	(0.471)	(0.031)
3-4 kms	2.470***	0.099***	0.046***	3.505***	0.113***
	(0.394)	(0.027)	(0.014)	(0.575)	(0.035)
R-squared	0.856	0.893	0.898	0.840	0.893
N	39934	39934	18848	21086	20956

Note: Regression results are for the post-distance interaction terms using specification (2). The outcome variable are nighttime light density, measured in levels, logs, and as an indicator for access. A vector of time-interacted controls is included for characteristics determining site selection or correlated with potential growth. Village fixed effects are included. Robust standard errors (clustered at village level) are shown in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.

Table 9: Effect of IAs on Female- and SC-owned firms

	log		level	
	firms	workers	firms	workers
	(1)	(2)	(3)	(4)
Panel A: Female owned firms				
within IA	0.296	0.475**	6.273	50.287
	(0.181)	(0.238)	(4.290)	(36.170)
0-1 kms	0.125	0.060	7.472*	3.627
	(0.107)	(0.126)	(3.865)	(5.366)
1-2 kms	0.350***	0.443***	2.939	38.348
	(0.077)	(0.087)	(1.792)	(32.770)
2-3 kms	0.222***	0.236***	3.905**	8.083*
	(0.065)	(0.076)	(1.737)	(4.283)
3-4 kms	0.169***	0.180**	-0.446	0.228
	(0.064)	(0.076)	(1.057)	(1.937)
R-squared	0.737	0.720	0.759	0.603
N	38480	38480	38480	38480
Panel B: SC-owned firms				
within IA	0.492**	0.595**	4.463*	12.709**
	(0.198)	(0.237)	(2.356)	(6.007)
0-1 kms	0.189*	0.310**	0.608	5.583
	(0.105)	(0.125)	(0.896)	(4.771)
1-2 kms	0.296***	0.363***	1.129**	8.034
	(0.080)	(0.099)	(0.574)	(4.896)
2-3 kms	0.151**	0.205***	0.282	6.523
	(0.062)	(0.074)	(0.519)	(5.214)
3-4 kms	0.164**	0.178**	0.353	4.808
	(0.064)	(0.077)	(0.479)	(4.580)
R-squared	0.671	0.665	0.632	0.501
N	35436	35436	35436	35436

Note: Regression results are for the post-distance interaction terms using specification (2). The outcome variables the number of firms owned by women (SCs) and the number of employees at these firms, in logs and levels. A vector of time-interacted controls is included for characteristics determining site selection or correlated with potential growth. Village fixed effects are included. Robust standard errors (clustered at village level) are shown in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.

Appendix A: For Online-Publication

The purpose of this appendix is two-fold: first it briefly explains how the IA sites are selected and provides the spatial distribution of Industrial areas (IAs) throughout the state of Karnataka. Second, it provides CEM algorithm (Blackwell et al., 2009) as applied in our context.

Section A1: Protocols for site selection

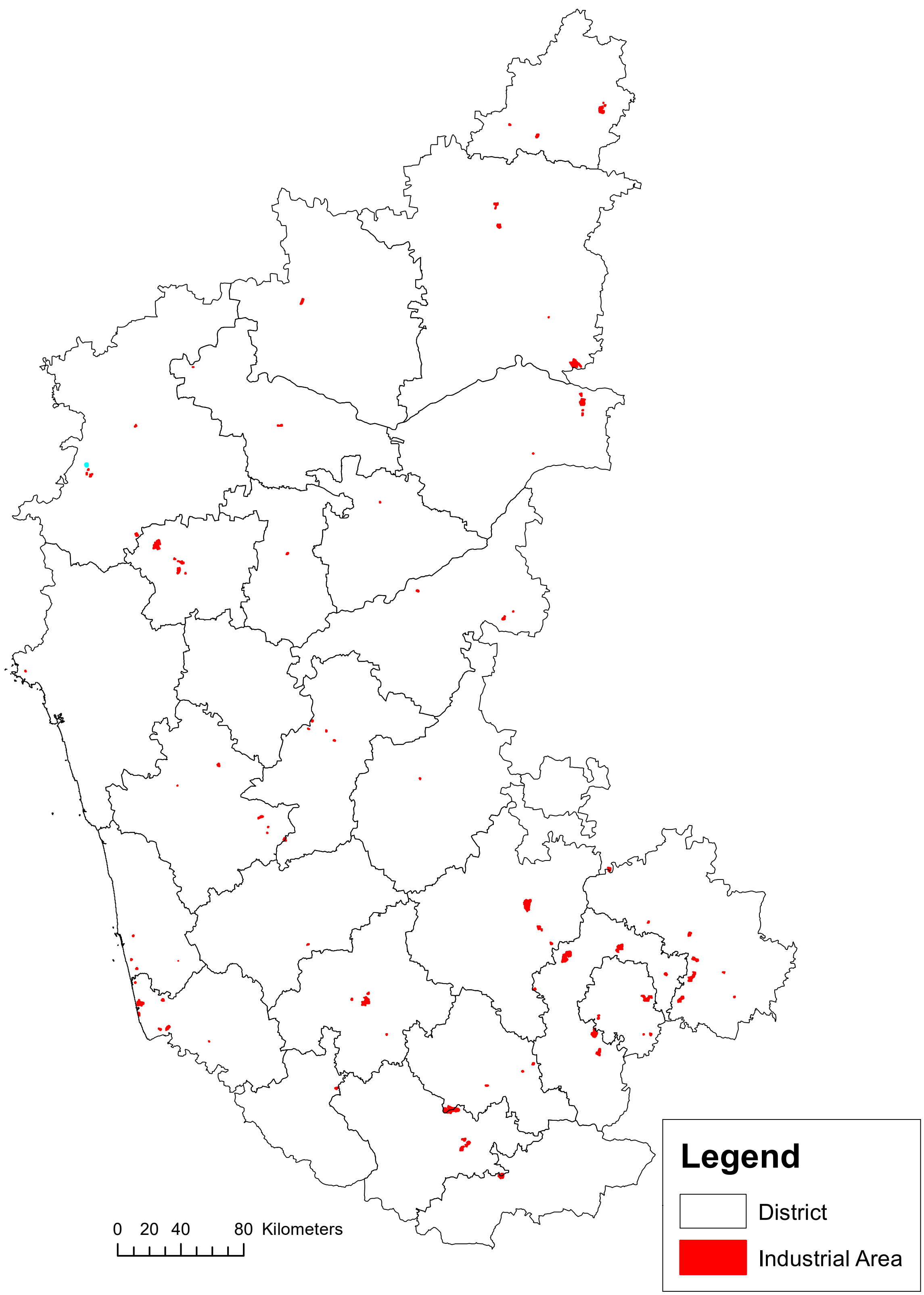
The various policies and authorities that influence the site of the IA can be summarized as follows:

- The All-India Government policy to establish the IAs in the backward regions plays a role in the selection process.
- Additionally, the selection of site for the IA must be in accordance with the industrial policy of the Government of Karnataka.
- The selection of site must be in conjunction with the recommendation of Joint Director, District Industry Center, Government of Karnataka along with District officer.
- In some cases, the recommendation comes directly from the District Authority i.e., Deputy Commissioner for establishment of the IA in their district.
- For any recommended site, the local public representative must consider the available resources such as land, skill of the population, accessibility of raw materials to allow for the minimum amenities needed for the establishment of IAs.
- Moreover, for any recommended site the connectivity via road, railways, airport as well as sea port must be considered in selecting the site.

Enumeration of Industrial areas

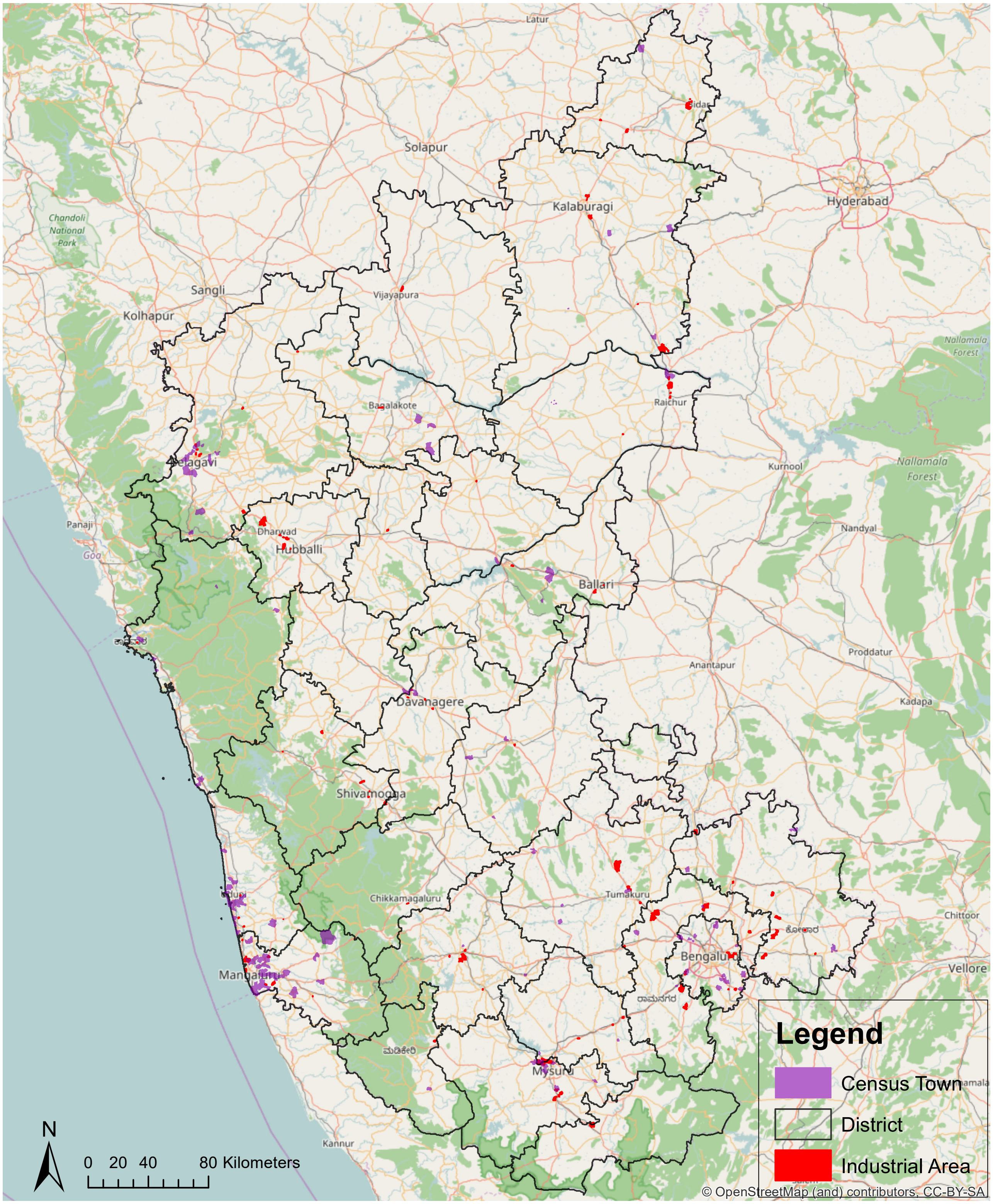
All of the IAs used in this study are established between 1991–2011 and have been active since inception. Figure A1 provides the spatial distribution of IAs in Karnataka while Figure A2 in addition also provides the census towns in relation to the IAs.

Figure A1: Spatial Distribution of Industrial Areas in Karnataka



Note: This figure shows the spatial distribution of Industrial Areas as in our sample. Source: http://kiadb.in/industrial-areas/

Figure A2: Spatial Distribution of Industrial Areas and Census Towns in Karnataka



Note: This figure shows the spatial distribution of Industrial Areas as in our sample along with the census town . Source: http://kiadb.in/industrial-areas/

Section A2: Coarsened Exact Matching (CEM) Algorithm

We apply the CEM algorithm (CEM) (Blackwell et al., 2009) as follows:

1. First temporarily coarsen the pretreatment covariates, X, into meaningful bins.

   In our context, the row vector of covariates is as follows:X = [log population, percentage of forest land, distance from towns, presence of paved roads and, presence of railroads].

   We also exclude all villages that are less than 4 kms from the IA so as to account for the possible spillover effects in step 4. For the binary variable, there are only two bins, while for the continuous variables we use the default number of bins. The results are unchanged when manually constructing the bins based on contextual considerations.

2. Next, select a sample from the untreated group as a control group if the coarsened covariate for the untreated group matches that of the treated group.

   Our treated group of villages includes all villages that overlap with the IA while the untreated group includes villages that do not overlap with the IA and are at least 4kms away from the IA. Our control group, therefore, is a subsample of the untreated villages, and which matches the treated villages for the specified covariates. For robustness analyses, in addition to these specified covariates we also use various restrictions that only allow the control group to be selected from untreated villages that are either in the same district as that of the treated village, or less than 15 kms away from the IA or greater than 10 kms away from the town.

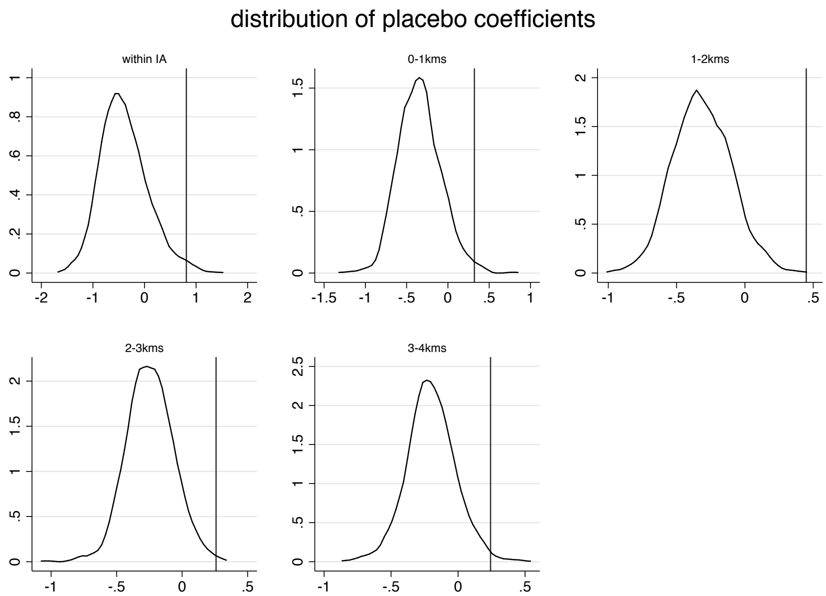
3. Use the control group constructed from steps 1 and 2 to estimate the treatment effect by using the uncoarsened data.

4. For the spillover effect, repeat steps 1 and 2 to construct additional control groups which are comparable to the group of observations where spillover is possible.

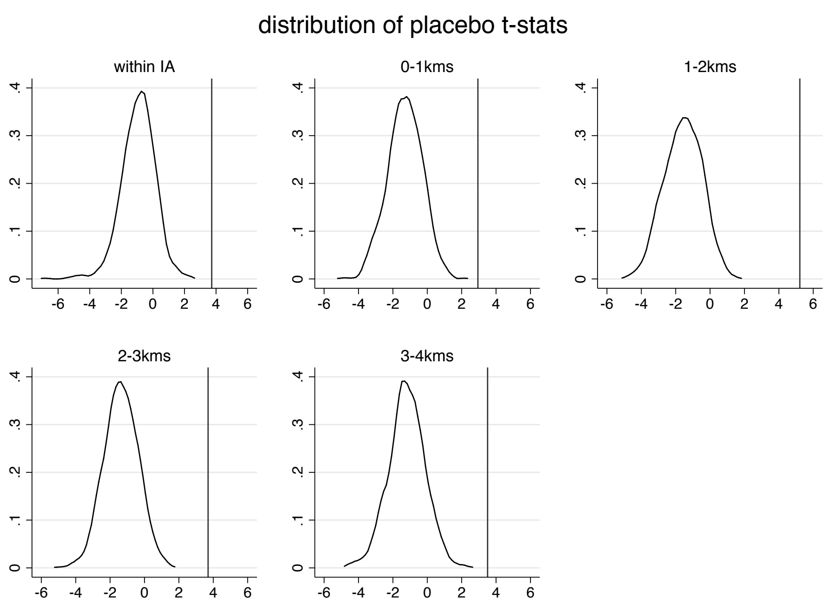
   In our context, villages that qualify to have a potential spillover effect are defined using each villages proximity from the IA. Since the pretreatment covariates for these villages differ with the distance from the IA, for every kms we construct a comparable group of control villages. We then estimate the spillover effect.

Appendix B

Figure B1: Placebo Test



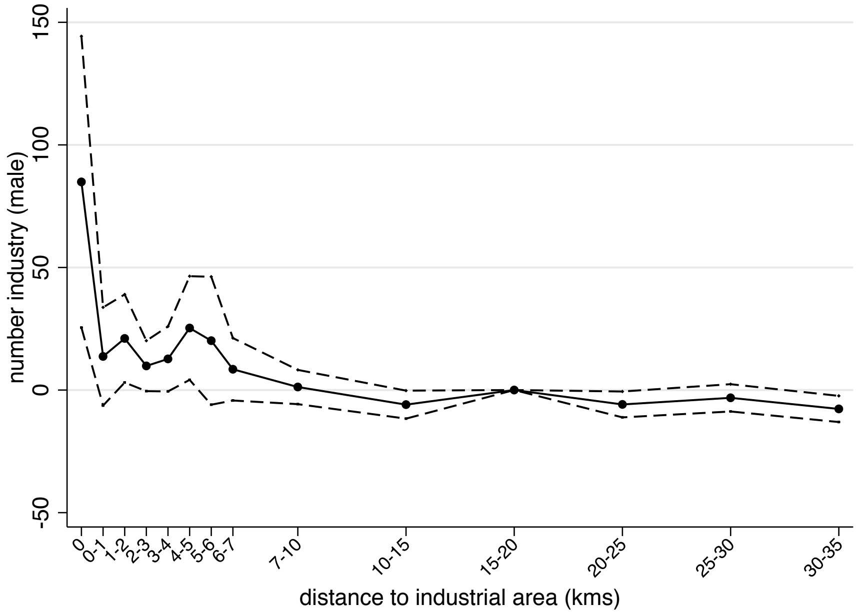
B1.1: Placebo Coefficients



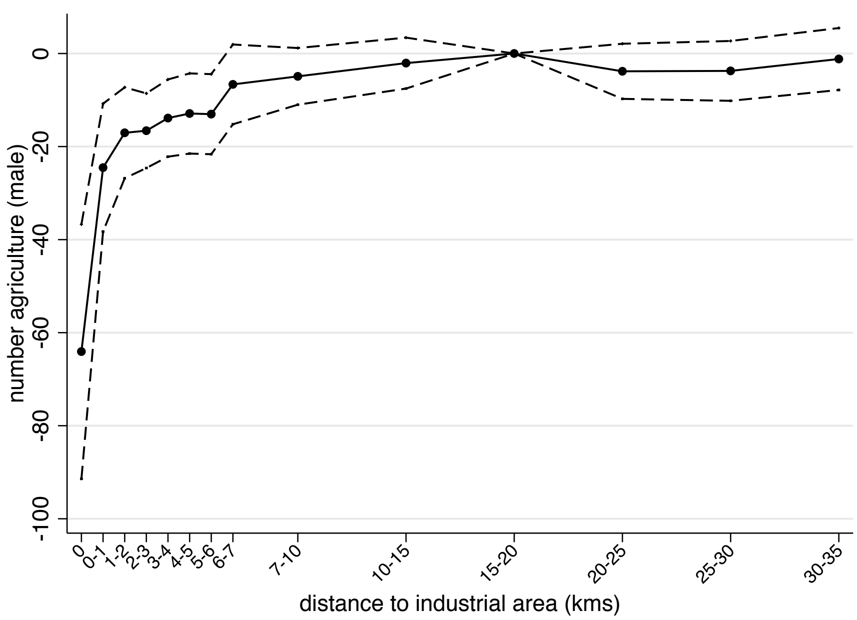
B1.2: Distribution of t-statistics

Notes: Figure B1 shows the distribution of coefficients and t-statistics for the 1000 regressions placebo regressions. In each regression, 50 control villages with infrastructure characteristics similar to treatment villages are assigned treatment status, and Specification (2) used to generate coefficients and t-statistics. The vertical line indicates the coefficients and t-statistics for the true treatment villages.

Figure B2: Effects of IAs on Workers



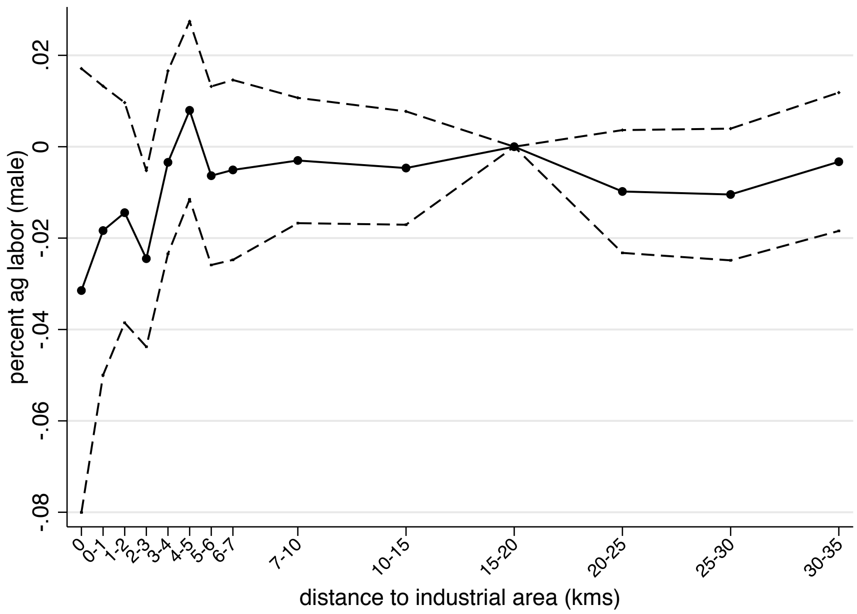
B2.1: Workers: Male Non-Agriculture



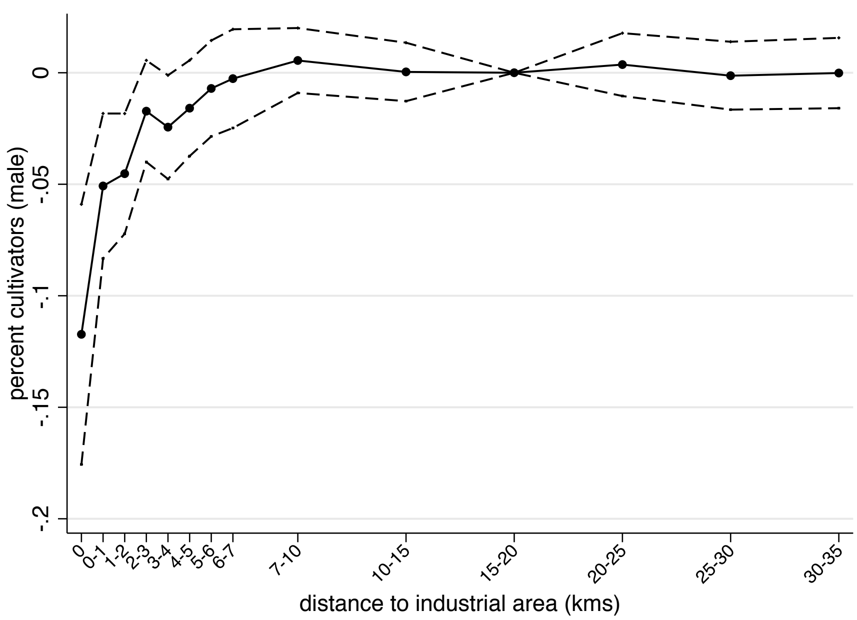
B2.2: Workers: Male Agriculture

Notes: Figure B2 plots the coefficients of the distance-post interaction terms from the difference-in-differences regression given in Specification (2). In Figure B2.1 the outcome variable is the number of male workers employed in non-agricultural wage labor, and in Figure B2.2 the number of male workers in agriculture. The x-axis measures the distance (in kms) of the village from the IA, where "0" refers to villages whose boundaries overlap those of the IA, and the omitted category is villages 15–20 kms from the IA. The dashed lines indicate the 95% confidence interval.

Figure B3: Effects of IAs on the Agriculture Workers



B3.1: Workers: Male Agriculture



B3.2: Workers: Male Cultivation

Notes: Figure B3 plots the coefficients of the distance-post interaction terms from the difference-in-differences regression given in Specification (2). In Figure B3.1 the outcome variable is the percent of male workers employed as agricultural laborers, and in Figure B3.2 the percent of male workers cultivating their own land. The x-axis measures the distance (in kms) of the village from the IA, where "0" refers to villages whose boundaries overlap those of the IA, and the omitted category is villages 15–20 kms from the IA. The dashed lines indicate the 95% confidence interval.

Table B1: Effect of IAs on Firms and Workers

	firms					
	coarsened match, <15kms from IA			coarsened match, >10kms from town		
	log workers	log firms	sample size	log workers	log firms	sample size
	(1)	(2)	(3)	(4)	(5)	(6)
within IA	0.725***	0.394**	2612	1.439***	0.776***	4302
	(0.228)	(0.169)		(0.362)	(0.236)	
0-1 kms	0.084	-0.003	4654	0.395**	0.127	8000
	(0.129)	(0.106)		(0.192)	(0.144)	
1-2 kms	0.283***	0.305***	5890	0.506***	0.368***	11190
	(0.102)	(0.088)		(0.123)	(0.098)	
2-3 kms	0.130	0.130**	6654	0.223**	0.151*	12512
	(0.085)	(0.066)		(0.109)	(0.080)	
3-4 kms	0.070	0.086	6874	0.327***	0.265***	13504
	(0.085)	(0.070)		(0.095)	(0.080)	

Note: Regression results are for the post-distance interaction terms using specifications (1). The outcome variables are (log) number of firms and (log) number of workers. A vector of time-interacted controls is included for characteristics determining site selection or correlated with potential growth. Village fixed effects are included. Robust standard errors (clustered at village level) are shown in parentheses. *** p<0.01, ** p<0.05, and * p<0.1. All specifications use the coarsened exact matching (CEM) method, and use all villages within the state to determine the best match. In columns (1) and (2) the sample is limited to villages within 15 kms of the IA. In columns (4) and (5) the sample is limited to villages more than 10 kms from the nearest town. Separate regressions are run for each distance interval, with the sample restricted to villages within the indicated interval and those more than 4 kms from the nearest IA. The adjacent column gives the respective sample size for these regressions. (See Section A2 in Appendix A for more details.)

Table B2: Effect of IAs on Male Non-Agricultural Wage Employment

	coarsened exact matching			
	all-state match		within-district match	
	treatment effect	sample size	treatment effect	sample size
	(1)	(2)	(3)	(4)
Panel A: log number non-agr wage labor				
within IA	0.472***	11510	0.538***	1084
	(0.163)		(0.189)	
0-1 kms	0.287***	21166	0.270***	2662
	(0.085)		(0.104)	
1-2 kms	0.190***	25454	0.168**	4362
	(0.071)		(0.084)	
2-3 kms	0.232***	27236	0.138**	6108
	(0.056)		(0.067)	
3-4 kms	0.186***	28120	0.174**	6532
	(0.055)		(0.070)	
Panel B: pct non-agr wage labor				
within IA	0.121***	11868	0.111***	1114
	(0.028)		(0.029)	
0-1 kms	0.053***	22424	0.053***	2828
	(0.016)		(0.017)	
1-2 kms	0.040***	26954	0.024*	4630
	(0.011)		(0.013)	
2-3 kms	0.045***	29078	0.019*	6498
	(0.009)		(0.011)	
3-4 kms	0.019**	29912	0.014	6940
	(0.009)		(0.011)	

Note: Regression results are for the post-distance interaction terms using specifications (1) and (2) for direct and spillover effects, respectively. The outcome variables are the (log) number and share of male workers in non-agricultural wage labor. A vector of time-interacted controls is included for characteristics determining site selection or correlated with potential growth. Village fixed effects are included. Robust standard errors (clustered at village level) are shown in parentheses. *** p<0.01, ** p<0.05, and * p<0.1. Columns (1) and (3) give the results using the coarsened exact matching (CEM). Method is as described in Note for Table 2.

Table B3: Effect of IAs on Labor by Agricultural Occupation

	percent agriculture					
	male			female		
	all	cultivator	ag labor	all	cultivator	ag labor
	(1)	(2)	(3)	(4)	(5)	(6)
within IA	-0.150***	-0.122***	-0.028	-0.065	-0.049	-0.016
	(0.025)	(0.029)	(0.025)	(0.058)	(0.038)	(0.046)
0-1 kms	-0.065***	-0.050***	-0.015	-0.023	0.021	-0.045*
	(0.016)	(0.016)	(0.015)	(0.033)	(0.025)	(0.026)
1-2 kms	-0.052***	-0.037***	-0.015	0.008	0.032	-0.024
	(0.012)	(0.013)	(0.012)	(0.026)	(0.020)	(0.020)
2-3 kms	-0.034***	-0.014	-0.020**	0.029	0.048***	-0.019
	(0.010)	(0.011)	(0.009)	(0.022)	(0.018)	(0.016)
3-4 kms	-0.024**	-0.025**	0.001	0.016	0.012	0.005
	(0.011)	(0.011)	(0.009)	(0.020)	(0.017)	(0.016)
R-squared	0.767	0.763	0.659	0.588	0.600	0.634
N	40832	40832	40832	40114	40114	40114

Note: Regression results are for the post-distance interaction terms using specification (2). The outcome variables are the percent of workers in different types of agricultural employment, disaggregated by gender. A vector of time-interacted controls is included for characteristics determining site selection or correlated with potential growth. Village fixed effects are included. Robust standard errors (clustered at village level) are shown in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.

Table B4: Effects of IAs by Firm Size

	number of firms with:									
	1 wrkr	2 wrkrs	3 wrkrs	4 wrkrs	5 wrkrs	6 wrkrs	7 wrkrs	8 wrkrs	9 wrkrs	10 wrkrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
within IA	14.411*	6.868*	2.227*	0.900	0.800**	0.509	0.504	-0.312	0.167	0.186
	(8.280)	(3.521)	(1.248)	(0.812)	(0.403)	(0.490)	(0.496)	(0.316)	(0.195)	(0.198)
0-1 kms	10.541*	2.113	1.098*	0.385	0.210	0.138	-0.102	0.105	0.101*	0.111**
	(5.725)	(2.257)	(0.605)	(0.365)	(0.247)	(0.142)	(0.128)	(0.066)	(0.056)	(0.051)
1-2 kms	9.871***	8.702***	1.273**	0.902**	0.187	0.289	0.031	0.100	0.011	0.070
	(3.759)	(2.404)	(0.640)	(0.392)	(0.230)	(0.299)	(0.107)	(0.081)	(0.068)	(0.061)
2-3 kms	5.782**	0.453	0.766*	0.644**	0.820***	0.264	0.210	0.075	0.069*	0.066*
	(2.634)	(1.402)	(0.417)	(0.318)	(0.316)	(0.214)	(0.164)	(0.056)	(0.041)	(0.039)
3-4 kms	0.510	3.237**	0.569	0.001	0.014	-0.104	0.305	-0.069	0.046	0.017
	(2.230)	(1.468)	(0.440)	(0.264)	(0.198)	(0.209)	(0.392)	(0.084)	(0.041)	(0.042)
R-squared	0.679	0.639	0.619	0.578	0.543	0.535	0.525	0.540	0.530	0.529
N	35448	35448	35448	35448	35448	35448	35448	35448	35448	35448

Note: Regression results are for the post-distance interaction terms using specification (2). The outcome variables are the number of firms employing the number of workers indicated in the column head. A vector of time-interacted controls is included for characteristics determining site selection or correlated with potential growth. Village fixed effects are included. Robust standard errors (clustered at village level) are shown in parentheses. *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Table B5: Effect of IAs on Assets

	share of households owning asset				
	tv	radio	scooter	bicycle	mobile
	(1)	(2)	(3)	(4)	(5)
Panel A: full sample					
within IA	7.227***	-2.294	1.539	-2.833	5.830**
	(1.695)	(1.490)	(1.364)	(1.939)	(2.367)
0-1 kms	3.725***	-0.547	-0.586	-1.818	2.921**
	(1.213)	(1.285)	(0.890)	(1.344)	(1.369)
1-2 kms	2.165**	1.280	-1.213*	-1.503	0.771
	(0.899)	(1.033)	(0.695)	(1.051)	(1.155)
2-3 kms	1.551*	2.613***	-1.306**	-2.016**	-0.267
	(0.801)	(0.915)	(0.597)	(0.890)	(0.937)
3-4 kms	1.950***	0.713	-0.897	-2.012**	1.098
	(0.736)	(0.787)	(0.582)	(0.825)	(0.952)
R-squared	0.347	0.100	0.209	0.058	0.099
N	20149	20149	20149	20149	20149
Panel B: sample < 15kms					
within IA	6.625***	-2.732**	4.638***	3.592**	3.706
	(1.441)	(1.292)	(1.353)	(1.586)	(2.380)
0-1 kms	2.951***	-0.251	2.119***	2.766**	1.155
	(1.090)	(1.122)	(0.811)	(1.088)	(1.398)
1-2 kms	1.717**	1.191	1.159*	2.695***	-0.891
	(0.817)	(0.984)	(0.639)	(0.932)	(1.097)
2-3 kms	1.785**	2.322***	1.088**	2.536***	-1.628*
	(0.742)	(0.874)	(0.536)	(0.787)	(0.927)
3-4 kms	1.430**	-0.451	0.580	1.636**	-0.192
	(0.669)	(0.729)	(0.501)	(0.734)	(0.882)
R-squared	0.586	0.329	0.460	0.368	0.274
N	7047	7047	7047	7047	7047

Note: Regression results are based on Specification 2 using Demographic Census (DC) 1991 and 2011 data. Robust standard errors (clustered at village level) are shown in parentheses. *** p<0.01, ** p<0.05, and * p<0.1. Note: Regression coefficients are for the indicated distance terms running specification (2) as a cross-sectional regression, and omitting time interactions. The outcome variables are the percentage of households owning the assets indicated in the column head. A vector of controls is included for characteristics determining site selection or correlated with potential growth. District fixed effects are included. Panel A uses the full sample of villages, and Panel B limits the sample to villages within 15 kms of the nearest industrial area. Robust standard errors (clustered at village level) are shown in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.