Firm Presence, Pollution, and Agglomeration: Evidence from a Randomized Environmental Place-Based Policy

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Abstract

Firm location decisions are a key managerial choice, optimizing factors such as proximity to customers or suppliers. These decisions also impose externalities on other firms due to competitive or agglomerative forces, and on the environment. The inherent endogeneity of these decisions makes estimating the impact of firm presence difficult. In this paper, we study an environmental place-based policy that randomly moved over 20,000 small firms operating in New Delhi to industrial areas outside the city over several years. We find that a reduction in firm presence improves air quality but is costly for firms: relocated firms have a high rate of exit, which increases in the distance relocated. We combine the exogenous assignment of firms to industrial plots with a model of firms playing a static game of incomplete information to estimate spillovers of neighboring firms on firm survival. We find that the impacts on firm survival due to relocation could have been mitigated by allocating firms to plots in the industrial area while taking into account their spillovers on neighboring firms. These results provide causal evidence on the trade-offs between firm presence and environmental quality, and show that firm spillovers can be a useful force to minimize the costs on regulated firms.

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1 Introduction

Firm location decisions are one of the most important choices managers make, optimizing factors such as proximity to customers, suppliers, and useful information. At the same time, these decisions may have spillovers on local neighborhoods, by impacting environmental quality and contributing to local economic activity. For this reason, numerous policies attempt to change location choices of firms, for instance, place-based policies that incentivize firms to locate in particular areas, or zoning regulations that restrict their location choices. Location restrictions that seek to limit pollution exposure in particular also have a long history, starting with the first zoning laws introduced in the early 20th century in New York, in part to improve environmental quality (Wilson et al., 2008). The inherent endogeneity of firm location decisions renders estimating the impact of firm presence on the local economy difficult. Policies that shock firm location decisions can help overcome this, but in many cases, may be bundled with other features – for instance, place-based policies that incentivize firms to locate in certain areas often provide local infrastructure or tax benefits.

In this paper, we study a policy tool that has commonly been deployed in developing countries for decades to impact firms' location choices, namely firm relocation. Such policies usually involve the mandated movement of existing firms operating in high-density areas to more remote locations, often, though not always, for environmental reasons. Firm relocation has been used in many parts of Asia, including China, India, Japan, and South Korea, but little is known about the impacts on relocated firms, and whether such policies achieve their environmental goals. Like many place-based policies, they are often bundled with other policy initiatives, making it difficult to understand their causal impact.

We study a large-scale environmental relocation policy in New Delhi, which moved over 20,000 firms to industrial areas outside the city over several years. A unique feature of this policy is that due to a shortage of industrial plots when relocation began, plot allotment was done via a series of lotteries between 2000 and 2005, with firms actually moving between 2006 and 2010. This generates random variation in firm presence over the time period, between neighborhoods with a greater number of firms receiving a plot earlier in the process, and those with a greater number of firms receiving a plot later in the process (conditional on the total number of firms relocated from a neighborhood). It also generates random variation within the industrial area on who a firm's neighbors are since, conditional on plot size and lottery year, the allocation of firms to plots was also random. This size of firm, namely, small and medium manufacturing, predominates in developing countries so understanding their emission profile is key to informing policymakers on the

potential effects of policies targeting them.

In the first part of the study, we use the random timing of firm removal to estimate the causal impact of firm presence on neighborhood environmental quality i.e. air pollution (our measure of neighborhood is a 1km by 1km grid-cell, which is the level at which our air pollution data is measured). This allows us to test whether such policies achieve their environmental objectives. Note that this is not ex-ante obvious because most developing countries have severely limited regulatory capacity. These firms might move back, be replaced by other polluting firms, or pollution may increase due to other causes such as growing vehicular emissions. We combine several data sources with administrative data on the policy for this estimation. Controlling for the total number of firms that were relocated in a neighborhood, we compare neighborhoods that on average relocated a higher number of these firms earlier vs. later, with the timing randomly generated by the allotment of plots to firms via lottery.

The results show that the relocation lottery timing has a strong first-stage in predicting a firm taking possession of their plot in the industrial area. This randomized timing of relocation is what we use to identify the impact of firm presence from sending regions on air pollution. We find that the average neighborhood impacted by the relocation experiences a 1.7 $\mu g/m^3$ drop in PM levels, i.e. by about 1.6 % of the mean fine PM concentration for the average neighborhood. Since industrial pollution contributes about 20% to Delhi's PM 2.5 (Sharma et al., 2018), relocation reduces industrial pollution in Delhi by 8%.

We conduct several robustness checks on this result, some of which we mention here. First, we show that the latitude and longitude of sending regions with early vs. late relocation are similar i.e., neighborhoods' location does not predict early vs. later relocation, as we would expect given that the timing is decided randomly. Second, we address possible violations in the integrity of lotteries by performing randomization inference, testing the sharp null hypothesis that the actual allocation had no effects. These p-values are similar to their unadjusted counterparts, indicating the violations of the lottery are not driving our results. Third, we conduct a placebo test using firms that had applied for but been deemed ineligible for relocation, and show that their presence in a neighborhood does not predict air pollution changes post the relocation policy. This indicates that our results are not driven by neighborhoods with more economic activity undertaking other regulations to reduce pollution concurrently.

In the second part of the paper, we take advantage of the random assignment of firms to plots (conditional on plot size) to identify the impact of neighboring firms on firm survival. The largest industrial area, which contained about 15,000 firms had 74 clusters of 150-300 firms within it, and we use within-cluster variation in the proportion of upstream,

downstream and own product firms to study how this proximity impacts firm survival. This allows us to causally estimate the direction and magnitude of firm spillovers at a micro-level, sidestepping the omitted variable bias that usually incentivizes firms of certain types to co-locate. Indeed, the results show that presence of a particular industry can generate in some instances positive and in other instances negative impacts on firms in other industries. [1]

We then model firms' exit decisions as the outcomes of a static game of incomplete information played in each neighborhood of the industrial area, using our causal spillover effect estimates to approximate conditional choice probabilities. We leverage the structure of the model to generate counterfactual exit rates under alternative assignments of firms to plots. Compared to the lottery policy's uniform assignment of industries to clusters, we find an alternative assignment which groups industries with positive spillovers would have reduced aggregate exit by 15 percentage points.

Finally, we conduct a back of the envelope cost-benefit exercise for the policy. Relocation reduces air pollution in the sending regions, but is costly for the relocated firms. 75% of firms in the largest industrial area comprising about 15,000 firms had exited by 2018. To estimate survival probabilities for relocated firms that were caused by the policy (rather than a "natural" rate of exit), we use the distance firms are relocated. Every kilometer relocated increases the probability of exit by 0.4-1 p.p, indicating the importance of endogenous location choices and the costs of being moved from that location. Using this elasticity, we find that relocation caused an increase in relocated firms' exit rate between 18 and 32 percentage points. A back of the envelope cost-benefit analysis, which converts the reduction in PM levels to the statistical value of lives lost and compares this to costs associated with firm death, finds that the benefits outweigh the costs. Notably, our alternative assignment would reduce the effect of relocation on firm exit by by 47 to 83%.

The paper builds on several literatures, and lies at the intersection of the impact of environmental policies on firms as well as the returns to agglomeration. First, we contribute to the literature on the impact of environmental regulation targeting firms (Blackman et al., 2010; Chen et al., 2021; De Simone et al., 2024; Do et al., 2018; Fan et al., 2019; Fenske et al., 2023; Foster and Kumar, 2011; Greenstone and Hanna, 2014; Harrison et al., 2015; He et al., 2020; Karplus et al., 2018; Muller and Mendelsohn, 2009; Ryan, 2012; Shapiro and Walker, 2020; Song et al., 2022).[2] Most of these studies focus on natural experiments

[1] This is in contrast to more aggregated agglomeration analyses which are typically unable to differentiate between positive and negative spillovers (e.g. Ahlfeldt et al. (2015)). We find that a firm's position in the input-output matrix relative to its neighbors explain the large majority of spillover effects it experiences.

[2] Also related is recent experimental work that randomizes particular aspects of environmental regula-

that evaluate a bundle of pollution reduction measures on environmental quality, and in some instances, firm outcomes. We study a unique experiment allowing us to identify the effect of a particular type of environmental regulation, one that forces polluting firms to move out of populated neighborhoods. Such policies are common in low state capacity settings, but relatively little is known about their impacts. Using the randomized timing of removal for identification allows us to estimate the casual impact of firm presence on environmental quality, as well as test how changing firms' location for environmental reasons impacts these firms. Furthermore, we study how firms' spillovers on each other can be used to reduce the costs of environmental policies on regulated firms. A related but distinct literature studies how environmental regulation that does not explicitly target firms' location decisions nevertheless impacts entry and exit decisions (Henderson, 1995; Levinson, 1996; List et al., 2003). These include tests of the pollution haven hypothesis, which posits that firms move to areas with lower environmental standards (Brunnermeier and Levinson, 2004; Choi et al., 2023; Jaffe et al., 1995; Millimet and Roy, 2016; Tanaka et al., 2022). In contrast, we study how environmental policies that target firm location impact environmental quality and costs for firms.

Secondly, we are part of a growing literature investigating the nature of agglomeration economies for firms (the classical foundation of this literature being Rosenstein-Rodan (1943) and Murphy et al. (2000), also see Rosenthal and Strange (2004), Rosenthal and Strange (2020), and Duranton and Puga (2020) for excellent reviews on empirical applications in this literature), which focuses on measuring the magnitude of such effects (Baum-Snow et al., 2023; Combes et al., 2012; Ellison et al., 2010; Gechter and Tsivanidis, 2020; Greenstone et al., 2010; Kline and Moretti, 2014; Leonardi and Moretti, 2023; Tsivanidis, 2023; Vitali, 2022). This literature is largely (though not exclusively) focused on developed countries, though the nature and magnitude of such effects might vary in developing countries due to differences in firm size, market frictions, and other government policies. Furthermore, in this literature, experimental variation is (unsurprisingly) almost entirely absent. Nakajima and Teshima (2017) is an exception, using random assignment of firms within a fish market in Tokyo to investigate the specific channel of shopping externalities. The relocation policy we study affects firms in a variety of manufacturing industries in Delhi, and the random assignment of firms to specific plots in the industrial area allows us to separately identify the effects of these industries on each other's profitability (for instance, upstream vs. downstream relationships), similar to Ellison et al. (2010) but with the benefit of experimental variation. Moreover, we also estimate how

tion such as auditor discretion Duflo et al. (2018) or emissions trading (Greenstone et al., 2022).

firm presence impacts environmental quality. [3]

The rest of the paper is organized as follows. Section 2 describes the context and Delhi's relocation policy. Section 3 details the data used. Section 4 describes the empirical strategy and results for impacts of the relocation policy on the neighborhoods firms left and the firms themselves. In Section 5 we discuss our results on the effect of industrial neighborhood composition on firm exit and use these results to allocate firms to neighborhoods. Section 7 concludes.

2 Context and Relocation Policy

2.1 Air Pollution in India: Impacts and Related Policies

Air pollution is the second leading risk factor for death, accounting for over 8 million deaths in 2021(HEI, 2021). It is a significant public health concern in India, where 100% of the population lives in areas where annual fine PM concentrations exceed WHO recommendations (Greenstone and Fan, 2018). About 1.6 million deaths, 17% of all deaths in India, were attributable to air pollution in 2019 (Pandey et al., 2021), indicating the significant health impacts of persistent and high pollution exposure.

India has several comprehensive environmental laws, including the Water Act of 1974 and Air Act of 1981. Beginning in the 1980s and 1990s, several pollution reduction policies were initiated, a primary one being the Supreme Court Action Plans (Greenstone and Hanna, 2014) (SCAPs). These plans were comprehensive measures that 17 polluted cities were directed to take by the Supreme Court, and comprised bundles of pollution reduction measures such as fuel switching or firm closures and relocation. A primary means to reduce industrial pollution mentioned in these action plans was mandates regarding the location of polluting industries– for instance, 13 of 17 Action Plans mention environmentally driven location mandates like closure or industrial relocation (Harrison et al., 2015). This focus on regulating firms' location choices to reduce industrial pollution continues to the present- the National Clean Air Programme (NCAP) policy is currently the flagship air pollution reduction policy initiative by the central government, which calls for

[3] A second direction of this literature evaluates whether place-based policies such as industrial areas and enterprise zones truly improve firm outcomes, or only displace economic activity from regions not covered by the place-policy to regions covered by the place-based policy (see Glaeser and Gottlieb (2008) and Neumark and Simpson (2015) for excellent reviews of this literature; other related work includes studying place-based policies in developed (Busso et al., 2013; Criscuolo et al., 2019; Greenbaum and Engberg, 2004; Hyman et al., 2022; Neumark and Kolko, 2010; O'keefe, 2004) and developing economies (Betcherman et al., 2010; Chaurey et al., 2023; Hasan et al., 2021; Lu et al., 2019)). Our estimates of firm spillovers do not have this concern of displacement causing an upward bias in any firm spillover estimates, since we make use of a large and known set of firms that were moved and co-located.

city-specific abatement plans to reduce air pollution. Relocation of polluting industries continues to be a commonly used tool in these plans.[4]

2.2 Relocation Policy In Delhi

In 1999, the Supreme Court mandated the relocation of manufacturing firms in Delhi that were operating in residential areas (there were exemptions for certain types of household industries). The Government started developing three industrial areas on the edges of the city to house these firms (a very small fraction of firms, about 2.5%, were given plots in other industrial areas around Delhi). Firms were asked to apply to the program to be allotted a plot in one of these areas– only firms that had been registered before 1999, were in a residential neighborhood, and were in an industry that was to be relocated, were eligible.[5] These firms comprised a large range of small manufacturing firms, including automobile parts, food processing, and rubber and plastics products.

There was some initial confusion about eligibility for relocation, and 50,000 firms applied to the program. The government deemed that about 21,000 were actually eligible for relocation and should be assigned land in the industrial areas (we use firms that applied to the program but were not relocated in a placebo check, which we detail in Section 4). Our primary analysis focuses on randomization within the 21,000 firms, and so is internally valid over the relevant sample of relocation-eligible firms. However, since the number of industrial plots was limited (more were developed over time), plots were allocated via a series of lotteries. The plot assignment lotteries were simple lotteries conditional on the year and plot size category from the pool of eligible firms. For instance, the first lottery assigned plots to about 11,000 firms in the first industrial area in the year 2000 in one of four size categories (100 m^2, 150 m^2, 200 m^2, and 250 m^2). The next large lottery, in 2003, assigned plots to 3,687 firms that had not yet been assigned a plot, and so on. In total, there were 4 large lotteries (with over 2,000 firms each relocated), and many small ones between 2001 and 2015. Most firms assigned a plot by lottery before 2004 were assigned to two industrial areas. In 2005, a third industrial area became operational, and the majority of firms assigned a plot in 2005 or later were assigned to this third area. This difference caused a significant delay in a firm moving however- the average year in which a firm relocated early (before 2004) took possession of their plot in the industrial area is

[4]Firms also have to demonstrate compliance with environmental regulation before getting a permit from their state's pollution control board, which is renewed periodically (Ghosh, 2015). Furthermore, firms in highly polluting sectors (a classification made by the Central Pollution Control Board) are audited regularly to ensure they continue to be in regulatory compliance (Duflo et al., 2013).

[5]Some neighborhoods were deemed to be exempt from relocation, since they were not adequately residential.

in 2005, while the average year in which a firm relocated later (after 2004) received a lease was 2014, a nine-year delay.

Firms that were not allotted an industrial plot in the earlier lotteries could continue operating while they waited for a plot, and once allotted a plot had to move their operations within 3 years. In 2005 however, the Supreme Court directed the government to increase the pace of relocation, and so leases began to be given for the industrial areas in 2006. We will show that firms that "won" the lottery earlier also were able to take possession of their plot earlier, generating exogenous variation in the timing of their departure from their original location. Given the random timing of the lottery, this generates random variation in firm presence that we use to estimate impacts on pollution (more details are provided in Section 4).

The majority of relocation lotteries were done by 2005, and only about 500-600 firms received an assignment 2010 or later. Each firm was allotted an industrial plot ranging from 28 m^2 (which was a spot in a building housing several small firms) to standalone plots of 250 m^2 - the average plot size was between 100 and 150 m^2. Firms were given concessional loans to allow them to build their factories in the allotted plots, and were given leases for these plots. They were not allowed to sell or rent them, and were technically supposed to continue producing the same products they had done while located within Delhi.

Of the three industrial areas, the largest one (Bawana) housed the majority of relocated firms (over 15,000), and included plots of four size categories (100 m^2, 150 m^2, 200 m^2, and 250 m^2, comprising 50.9%, 26.3%, 5.1% and 17.69% of the data, respectively). Using data from this industrial area regarding a firm's final allotted plot location and from geocoding their original address, we estimate how far firms were moved. We find that the average firm relocated to Bawana was moved 20.2 km (12.5 miles) from its original location– the 25th percentile is 16.2km (10.1 miles), while the 75th percentile is 27.3km (17 miles).

All the industrial areas were developed by the government body charged with implementing the relocation policy, and within the industrial area, conditional on a year and plot size category, the plot allocation was random as well (e.g. amongst firms to be assigned a plot of 100 sq m in 2000). Figures A1, A2, and A3 show Google Maps images of the largest industrial area where over 15,000 of these firms were relocated for the years 2000, 2001, and 2010, respectively. These show that the area that was developed into the industrial area was undeveloped when first acquired in 2000. By 2001 plots had been delineated but no development had occurred and by 2010 there was significant development of the industrial area with many firms operating in the area.

3 Data

3.1 Air Pollution

To estimate impacts on pollution, we need high-resolution data on pollution before the relocation began (in 2000) as well as after. This is challenging, since pollution monitors were relatively sparse for Delhi for this time period, with only one air quality monitor reliably reporting data for this period. We use data on fine particulate matter (PM 2.5) created by van Donkelaar et al. (2016). These data are constructed by combining satellite retrievals of aerosol optical depth, chemical transport modeling, and ground-based measurements (for more details, please refer to Van Donkelaar et al. (2021)).

These data have several advantages for our analysis. First, they are available monthly at the 1km by 1km resolution, providing data at a fine spatial resolution and starting before the policy began to be implemented. Second, they cover fine PM, which is an important air pollutant, responsible for large damages to human health globally (McDuffie et al., 2021). We use the 1km by 1km grid cells as our definition of neighborhood, since this is the finest level for which pollution data is available, and create annual measures which is our outcome variable for environmental quality.

3.1.1 Latitude and Longitude of Sending and Receiving Addresses

Geocoding the original addresses using Google's API, we assign a firm to a neighborhood. Combining this information with the timing of when a firm was given a plot, we create a neighborhood-level dataset of the number of firms that were allotted a plot via lottery each year between 2000 and 2005 (95% of firms were assigned a plot via lottery by then), as well as the number of firms whose lease began in each year between 2006 and 2010. Figure 1 presents the cumulative probability of having won a plot lottery by a given year as well as the probability of having taken possession of the industrial plot by year, showing a positive relationship between the two measures. We present formal first stage results in the next section. We identify the longitude and latitude of plots within the industrial area by digitizing maps we acquired from industrial associations, cross-referencing street names in these stylized maps (see Figure A4 for a photograph of one cluster) with Google Earth.

3.2 Administrative Data on Relocation Policy

The administrative data on the relocation policy is available from the government body that was responsible for the relocation, the Delhi State Industrial and Infrastructure Development Corporation Ltd. (DSIIDC). The data include firm name, original address from where they were relocated, details such as applicant name, date of the lottery when they were allotted a plot, a free text description of the firm's products entered by the owner, as well as the ID of the plot they were allocated in the industrial area. It also includes details on the timing of the dates when the firm took possession of the industrial area plot and when the firm's lease began.

While about 25,000 firms were deemed eligible for relocation, only 21,748 received a plot assignment in the industrial area and 21,174 have non-missing information on the lottery year of the firm. In Table A1, we show that the availability of lottery year information is not correlated with neighborhood latitude and longitude i.e. is uncorrelated with firms' starting geography.

3.2.1 Firm Survival Census in 2018: Bawana Industrial Area

In 2018, DSIIDC conducted a census of all plots in the Bawana industrial area, to determine whether the firm assigned to a plot was still operating there. We classify an assigned firm as having exited the market if it was found to be closed in this census, or to have (illegally) rented or sold its plot to another firm.

3.2.2 Product Classification

The firm application data include free text information of what firms produce. We determine the 3-digit Annual Survey of Industries Classfication Code (ASICC) to assign to each firm a product code through a combination of human judgment and a custom GPT-4 pipeline. We discuss the full details and tailored prompts used in Appendix B.

From this exercise, we were able to get 3-digit assignments for 9,200 of about 15,800 firms in Bawana. For each firm, we create a measure of what proportion of other firms in their assigned cluster in the industrial area are producing the same product. To understand upstream and downstream linkages, we use the 2010 Annual Survey of Industries (ASI) data. From the 2010 ASI, we first retain only firms producing a single product (to avoid the issue of assigning inputs to multiple outputs, which, like other firm panel datasets, is not available in the ASI), and only keep 3-digit products that have at least five firms producing them. We create a product-level expenditure on each input, and generate the proportion of input expenditure for each input.

We call a product x upstream of product y if the input expenditure y spends on x is above the median amount y spends on any input in the 2010 ASI data. For each firm, we create a measure of what proportion of other firms in their assigned cluster in the industrial area are upstream of them. Similarly, we use product-level revenues from other products to generate measure of downstreamness. We call a product x downstream of product y if y's revenues from selling to x are above the median of y's revenues from selling to any other type of producer. For each firm, we create a measure of what proportion of other firms in their assigned cluster in the industrial area are downstream of them (total revenue of each product is taken from the output module, since products could be sold to firms producing other products or directly to customers). The sum of proportion upstream and proportion downstream give us the proportion of firms in the industrial area that have any input-output linkage with each firm.[6]

3.3 Primary Data Collection

3.3.1 Surveyor Visits to Baseline Addresses of Relocated Firms

To ensure that any geocoding measurement error on assigning firms to neighborhoods is independent of lottery timing, we collected data for about 15,000 firms which were geocoded in-person by surveyors (about 71.4% of the total relocated sample).[7] Of these, Google and the surveyors place an address in the same administrative area of the state (ward) about 73% of the time (9,883 of 13,511). The probability that the ward is not the same according to Google and the surveyors is not correlated with the year of the lottery (see Table A6), nor is the probability that geocodes are missing from either of these sources. Furthermore, our neighborhood level measure of early relocation, which is the number of firms assigned a plot by lottery by 2004 according to Google maps and the surveyors are highly correlated, with a correlation of 0.97.

[6] Our results are robust to alternative definitions of upstream and downstream, including replacing the median with the 75th percentile, and specifying absolute thresholds of fraction of spending on inputs and fraction of revenue for defining upstream and downstream respectively.

[7] We sent surveyors to about 15,811 firms but could not find about 1,328 addresses.

4 Impact of Firm Presence on Environmental Quality: Empirical Strategy and Results

4.1 Balance Tests: Firm Original Location

Our use of the distribution of lottery winning times as an exogenous factor in determining the level of firm presence in a neighborhood depends on the fact that lottery winning is truly independent of neighborhood characteristics. To test whether lottery winning time is uncorrelated with firms' starting geography, we run the following pair of regressions at the firm level.

$$\begin{aligned} \text{Initial Longitude}_j &= \alpha + \kappa \text{Year of Lottery Win}_j + \epsilon_j \\ \text{Initial Latitude}_j &= \tilde{\alpha} + \tilde{\kappa} \text{Year of Lottery Win}_j \leq 2004\}_j + \tilde{\epsilon}_j \end{aligned} \tag{1}$$

If lottery winning time is unrelated to firm j's original address, κ and $\tilde{\kappa}$ should be estimated as precise zeros.

The results from estimating Equations (1) are given in Table 1. The coefficient estimates are in degrees, and as expected are very small and imprecisely estimated. This indicates that the winners of specific lotteries were not, as expected geographically clustered.

4.2 The Impact of Lottery Timing on Movement to the Industrial Area

This section discusses first stage estimation at the firm-level, to test that the timing of receiving a plot in the industrial area in the lottery process drove the time of moving to the industrial area. We estimate the following equation for timing outcomes related to movement to the industrial area, analogous to the balance equation (1):

$$Y_j = \alpha + \mu \text{Year of Lottery Win}_j + \epsilon_j \tag{2}$$

where Y_j is the year in which the firm took possession of the industrial plot. This action is the first one that firms undertake to begin construction on their assigned plots, and move to the industrial area. The coefficient of interest is μ, which measures the marginal impact of a one-year delay in "winning" the lottery for firm j.

Results from estimating Equation 2 are presented in Table 2. The first two columns show that a year one delay in getting a plot assignment in a lottery causes just over a year's delay in the firm taking possession of the plot. Column 1 presents the results for

all firms, and column 2 for firms that had received a plot assignment by 2005 (96% of the data). Columns 3 and 4 show the results using a dummy variable for whether the firm received a plot by 2004 or earlier, with the same samples as in columns 1 and 2, respectively. If a firm did not receive a plot in the earlier lotteries, this delayed it taking posession of the plot by 9 years, indicating a large gap between firm removal for firms that received a plot in an early vs. late (in 2005) lottery. Thus, these results indicate that the lottery timing generated variation in the timing of firm removal from a neighborhood, allowing us to estimate the causal impacts of firm presence on environmental quality.[8]

4.3 Air Pollution

At the neighborhood level, our primary outcome of interest is air pollution i.e. fine particulate matter concentrations. We begin by estimating the following specification:

$$\text{Fine PM}_{it} = \alpha + \beta \text{Log(Firms Remaining)}_{it} + \psi_i + \tau_t + \epsilon_{it},$$

where i denotes a 1 km by 1km grid cell and t the year of measurement. Fine PM is the annual concentration of fine particular matter in μg/m^3 at the neighborhood -year level. Firms Remaining is the difference between the total number of firms relocated in a neighborhood and the number of firms that have taken possession of their plots in the industrial area in neighborhood i in year t. The main coefficient of interest is β, which measures the marginal impact of firm presence, namely, of firms who have not yet moved to the industrial area. This does not explicitly use the randomized removal (which we do in the next section), though as we showed in the previous section, lottery timing strongly predicts firms taking possession of the plot in the industrial area. We expect β to be positive since we expect firm presence to increase air pollution. We include neighborhood and year fixed effects, and cluster standard errors at the neighborhood level.

Results are presented in Table 3. Column 1 includes all neighborhood-year observations, and column 2 only includes neighborhoods where at least one firm has taken possession of their industrial plot, and therefore restricts it to neighborhoods where firm

[8] We also show first stage results at the neighborhood-level i.e. we estimate

$$\begin{aligned}\text{Log(Firms Taken Plot Possession)}_i = &\alpha + \beta \text{Log(Firms Winning a Lottery by 2004)}_i \\ &+ \nu \text{Log(Total Number of Firms Relocated)} + \epsilon_i\end{aligned}$$

, where i denotes the neighborhood. We estimate this equation for the year 2006, as well as nine years later when the third industrial area is open, in 2015. Results are presented in Table A5. It shows that a one percent increase in the number of firms winning a lottery early increases the number of firms who took plot possession by nearly one percent in 2006, so an almost one-for-one increase. Nine years later, in 2015, the first stage estimate is about half that, as firms continue to be moved to the industrial areas over time.

removal has begun. The results are quite similar, showing that a one percent increase in firm presence increases pollution by about 0.33 $\mu g/m^3$. The results are precisely estimated, and show that firm presence does indeed increase air pollution. Next, we present a specification that only uses the randomized removal for identification of firm removal on air pollution. We estimate the following specification for the event study:

$$\begin{aligned}\text{Fine PM}_{it} =&\alpha + \beta_t \text{Log(Firms Winning a Lottery by 2004)}_i + \psi_i + \tau_t \\ &+ \pi_t \text{Log(Total Number of Firms Relocated)} \times \mu_t + \epsilon_{it},\end{aligned}$$

where i denotes a neighborhood and t the year of measurement. The main coefficients of interest are the β_ts, which measure the marginal impact of a greater number of firms winning a lottery earlier in the process i.e. by 2004, in each year. The main coefficients of interest are β_t, which measure the marginal impact of a greater number of firms winning a lottery earlier in the process i.e. by 2004, in each year. This timing is plausibly exogenous due to the lottery governing the allotment of plots, and the fact that a delay in winning the lottery resulted in a delay in the beginning of a firm's presence in the industrial area on average (as shown in Table 2). Note that since β is measuring the impact of firm presence (rather than firm removal), we expect the coefficient to be negative if firm removal impacts air quality.

We control flexibly for the total firms relocated by including interactions of this variable with year fixed effects, and also include neighborhood and year fixed effects (ψ_i and δ_t, respectively). The average year in which firms who had received industrial plots prior to the last lottery in 2005 to take possession of their plots is 2005. Therefore, the interactions terms are omitted for the year 2005.

Event study estimates are presented in Figure 2. Neighborhoods with a greater number of firms winning lotteries by 2004 do not have differential pollution before 2005. However, they exhibit lower levels of pollution after, until locations with fewer lottery winners before 2005 catch up by 2012. As a robustness check, results from the same specification, but restricting to neighborhoods where surveyors found at least one origin address of a relocated firm are presented in Table A6, and are consistent with the main sample (Note that while surveyors were only assigned to 70% of the addresses, they were assigned randomly, which implies that these neighborhoods are likely those with more dense economic activity.).[9]

[9]The event study estimates show some evidence of reversion of treatment effects for the last three years, though this is less pronounced when considering neighborhoods with more density of relocated firms (Figure A6). This convergence could also be partially driven by the fact that the first stage is weaker across time, as shown by the neighborhood-level first stage estimates in Table A5-the coefficient in 2006 for log(firms

The analogous DID specification for the event study estimates is as follows:

$$\begin{aligned}\text{Fine PM}_{it} =& \alpha + \beta \text{Log(Firms Winning a Lottery by 2004)}_i \times 1\{t > 2005\} + \psi_i + \tau_t \\ &+ \text{Log(Total Firms Relocated)}_i \times 1\{t \geq 2005\} \times \mu + \epsilon_{it}\end{aligned}$$

where the variable definitions are the same as in the previous equation. $\{t \geq 2005\}$ is a binary variable that takes the value 1 if the year is 2006 or later, and 0 otherwise. As in the previous equation, standard errors are clustered at the neighborhood-level.

Finally, we also run an alternative specification that uses the firms that applied for relocation but were deemed ineligible as a placebo. We estimate the previous equation, and additionally include the interaction of the log of number of ineligible firms and the post-2005 dummy variable. We expect this coefficient to be statistically indistinguishable from zero, since the presence of these firms (which were not removed by the policy) should not systematically change air quality after 2005.

Results are presented in Table 4, with the odd numbered columns showing results from the main specification and even numbered columns additionally including the placebo interactions. The first two columns show results using all neighborhoods, including those with no relocated firms, and the next two columns show results using only neighborhoods with relocated firms. The results are quite consistent across these columns, showing that a one percent increase in firm removal reduces pollution by 0.5 to 0.6 $\mu g/m^3$. Since the mean number of firms relocated is 32.35, this implies a reduction of 0.5*(log(32.35)-log(1)), or 1.7 $\mu g/m^3$ as a result of relocation, or 1.6 percent of total PM concentrations for the average neighborhood. Industrial pollution contributes about 20% to Delhi's PM 2.5 (Sharma et al., 2018), which implies that relocation reduces industrial pollution in Delhi by 8%. Columns 5 and 6 report results restricting the sample to neighborhoods with surveyor-identified firms (the analogous DID estimation to the event study presented in Figure A6), with and without the placebo, respectively. Results are consistent with the main specification, although somewhat larger, with a point estimate for β of 1.13 $\mu g/m^3$.

In addition to the clustered OLS results, we also present randomization inference p-values for the main DID coefficient, β, we conducts 1,000 simulations with alternate allocations of the number of firms relocated early. The p-values test the sharp null hypothesis of the actual allocation having no treatment effects (so the p-value is the proportion of times the estimated treatment effect under the hypothetical allocation exceeds actual estimated treatment effect) and are also clustered at the neighborhood-level. These are similar to the OLS clustered results.

relocated by 2004) is nearly one in 2006 (0.997), and nearly half that (0.502) in 2015.

The placebo results are consistent with the hypothesis that the presence of ineligible firms should not change air quality differentially post-2005. The coefficients on the interaction of the log of the number of ineligible firms and the post-2005 dummy variable in Columns 2, 4, and 6 are, as expected, statistically indistinguishable from zero.

4.4 Additional Specification and Robustness

In this section, we consider an additional specification to estimate the impact of firm presence as well as present other robustness checks. This additional specification uses the fact that conditional on a baseline number of relocation-eligible firms, neighborhoods with a higher proportion of early plot assignments should see reductions in pollution relative to those with a lower proportion of early plot assignments.

This additional event-study specification is as follows:

$$\begin{aligned}\text{Fine PM}_{it} =& \alpha + \beta_t \left[\text{Bin}_i \times \text{Prop Firms Lottery by 2004}_i \times \mu_t\right] \\ &+ \pi_t \left[\text{Bin}_i \times \mu_t\right] + \psi_i + \tau_t \\ &+ \xi_t \left[\text{Prop Firms Lottery by 2004}_i \times \mu_t\right] + \epsilon_{it},\end{aligned}$$

where the Fine PM variable definition is the same as in the previous specification. Prop Firms Lottery by 2004 is the proportion of firms in neighborhood i that received a plot assignment by 2004. Bin takes on 1 of 4 values. It is 1 if the number of relocation-eligible firms is in the first quartile, 2 if it is in the second, and so on. We also report results from a version of this variable with 10 bins. The parameter of interest is β, the coefficient on the triple interaction. The analogous DID specification replaces the year dummies in the interaction terms with a post-dummy 2005, as in the main specification.

Event study estimates using 4 bins are presented in Figure A7, and the DID results in Column 1 of Table A2. The event study estimate does not show evidence of a pre-trend before 2005, and shows a negative impact after. The DID estimate shows that conditional on a baseline number of relocation-eligible firms, a marginal increase in the proportion of firms relocated early causes a 1.2 μg/m^3 reduction in fine PM. Normalizing by the standard deviation of proportion relocated early, this would imply that a one standard deviation increase in the proportion of firms relocated early causes a 0.51 μg/m^3 reduction in fine PM. Event study estimates using 10 bins are presented in Figure A8, and the DID results in Column 2 of Table A2. These are consistent with the specification using 4 bins, showing a negative coefficient on the triple interaction that is precisely estimated.

We also show results for the main DID specification without neighborhood and year

fixed effects, using the conventional DID specification. These results are presented in Table A4, and are nearly identical to the main results. Finally, as an additional robustness check for the specification that only uses the randomized removal for identification, we test for how spatial correlation may impact the analysis, by clustering at a larger geographic level (2km by km) instead of at the neighborhood-level. Results are presented in Table A3, and are consistent with the main results.

5 Agglomeration and Industrial Area Design

Random assignment of individual plots to firms means that a firm's neighbors are also random, generating independent variation in neighbor characteristics and allowing us to determine how each neighbor characteristic impacts economic performance. We investigate how the industrial composition of firm i's block in its industrial area affects its probability of exit.

5.1 Heterogeneous Spillovers by Input-Output Position

We are interested in the parameters $\alpha_{upstream}, \alpha_{downstream}$, and α_{own} in the following partially-linear model:

$$
\begin{aligned}
&Active_{ik} = \\
&\alpha_{upstream}\overline{1\{product_j \rightarrow product_i\}}_k + \alpha_{downstream}\overline{1\{product_j \leftarrow product_i\}}_k + \alpha_{own}\overline{1\{product_j = product_i\}}_k \\
&+ g\left(\{1\{product_i = m\}\}_{m=1}^{M-1}, \overline{1\{missing(product_j)\}}_k\right) + \epsilon_{ik}. \qquad (3)
\end{aligned}
$$

$Active_{ik}$ is an indicator for firm i assigned to block k's being present in the largest industrial area in 2018. $\overline{1\{product_j \rightarrow product_i\}}_k$ is the share of block k's assigned firms upstream of i's product. $\overline{1\{product_j \leftarrow product_i\}}_k$ is the share of block k's assigned firms downstream of i's product. $\overline{1\{product_j = product_i\}}_k$ is the share of block k's assigned firms producing the same product as i. $\{1\{product_i = m\}\}_{m=1}^{M}\}$ is a vector of product indicators, with M being the total number of products. $\overline{1\{missing(product_j)\}}_k$ is the share of firms assigned to block k for which a product code could not be assigned.

Each of the $M \times K$ values of $\overline{1\{product_j \rightarrow m\}}_k$, $\overline{1\{product_j \leftarrow m\}}_k$, $\overline{1\{product_j = m\}}_k$ depends on the product indicators and the share of firms without a product code as-

signed. For instance

$$\overline{1\{product_j \to m\}}_k = m_{upstream}\left(\{1\{product_i = m\}\}_{m=1}^{M-1}, \overline{1\{missing(product_j)\}}_k\right) + \nu_{mk}. \tag{4}$$

We linearly approximate Equations (3), (4), and Equation (4)'s downstream- and own-counterparts:

$$\begin{aligned}
&Active_{ik} = \\
&\alpha_{upstream}\overline{1\{product_j \to product_i\}}_k + \alpha_{downstream}\overline{1\{product_j \leftarrow product_i\}}_k + \alpha_{own}\overline{1\{product_j = product_i\}}_k \\
&+ \sum_{m=1}^{M-1}\gamma_{active,m}1\{product_i = m\} + \psi_{active}\overline{1\{missing(product_j)\}}_k + r_{active,i} + \epsilon_{ik} \\
&\overline{1\{product_j \to m\}}_k = \gamma_{upstream,m} + \psi_{upstream}\overline{1\{missing(product_j)\}}_k + r_{upstream,mk} + \nu_{mk} \\
&\overline{1\{product_j \leftarrow m\}}_k = \gamma_{downstream,m} + \psi_{downstream}\overline{1\{missing(product_j)\}}_k + r_{downstream,mk} + \nu_{mk} \\
&\overline{1\{product_j = m\}}_k = \gamma_{own,m} + \psi_{own}\overline{1\{missing(product_j)\}}_k + r_{own,mk} + \nu_{mk}.
\end{aligned}$$

$(r_{active,i}, r_{upstream,mk}, r_{downstream,mk}, r_{own,mk})$ represent approximation errors. Following Belloni et al. (2013), we assume the approximation errors are small relative to estimation error:

$$\bar{E}[r_{active,i}^2]^{1/2} \leq c\sqrt{s/N} \text{ and } \bar{E}[r_{upstream,mk}^2]^{1/2}, \bar{E}[r_{downstream,mk}^2]^{1/2}, \bar{E}[r_{own,mk}^2]^{1/2} \leq c\sqrt{s/MK}$$

where s is the maximum number of non-zero elements across the four equations and c is a constant. This allows us to use Belloni et al. (2013)'s post-double-selection methodology. Specifically, we estimate a LASSO regression of $Active_{ik}$ on the product and block indicators, and LASSO regressions of the block-level upstream, downstream, and own means on the block indicators. The LASSO regressors include product fixed effects as well as dummmy variables for each of the four size categories, and controls for the proportion of plots that did not get a 3-digit assignment in the process of mapping firms' outputs to ASI product codes. We then estimate an OLS regression of $Active_{ik}$ on the upstream, downstream, and own-block-level means and the union of selected indicators from the previous step.

Results are presented in Table 6. Column 1 shows that a one standard deviation increase in the proportion of firms with any input-output linkage in a pocket increases the probability of firm survival by 4 p.p., about 15% relative to the mean survival rate. In contrast, a one standard deviation increase in the proportion of firms producing the same

product has a small, negative, and imprecisely estimated impact on survival. The second column shows the impact of input linkages and output linkages separately. Both upstream and downstream linkages matter, but the point estimate on upstream linkages is bigger, about 5 p.p, or 20% relative to mean survival rate (however, we cannot reject that these two coefficients are equal). We are able to reject that upstream linkages have the same effect as own product firms, and the coefficient on own product firms is, as in Column 1, small and positively impacts firm survival. These results show the significant impact that input-output linkages can have in improving firm survival.

5.2 Balance Tests for Assignment of Plots in the Industrial Area

In this section, we test whether the plot assignments by firm product are indeed randomly allocated. For each year of the lottery and plot size category, we randomly pick firms (each lottery randomly picks the number of firms by size category) and randomly assign them to available plots of that size category (for instance, if x firms were assigned 100 m^2 plots in 2000, we randomly pick x of all the 100 m^2 firms and randomly assign them to the 100 m^2 plots that were assigned in 2000). This generates actual and simulated data on the proportion of firms producing a product in each of 74 the industrial clusters in Bawana. We present the actual and simulated data in Figure 3. The two distributions are extremely similar, and the Kolmogorov–Smirnov test for equality of distribution functions fails to reject that the two are equal (p-value=0.86). As an additional robustness check, we present results using the total number of firms in a cluster producing a product (rather than the proportion). The results are shown in Figure A5 and also show that the distributions are very similar (The Kolmogorov–Smirnov test for equality of distribution functions has a p-value of 0.92).

5.3 Exit-Reducing Assignment

5.3.1 Static Model of Firm Entry Decisions

These results imply a matrix of effects of the share of every product in a firm's block on the survival of any type of producer. We can use this matrix to evaluate the aggregate effect of alternatives to the uniform distribution of firms to plots in the largest industrial area To do so, we model firms' decision to remain active in the industrial area as a static game of incomplete information within each block k, as in a single time period version of the dynamic game analyzed in Benkard et al. (2020). Since firm characteristics, including size, do not vary much within industries, we model each firm in an industry as identical

except for a firm-specific profit shock ν_{ik}, which is unobserved to us as researchers and to the other firms. The initially-assigned vector of industry shares for neighborhood k is denoted $s_k \in \Delta^{M-1}$, where Δ^{M-1} is the $(M-1)$-dimensional simplex. This vector of shares constitutes the state variable in the model summarizing conditions following entry of the assigned firms in neighborhood k. Given s_{rk}, firms choose whether to remain in operation or exit. Before making this decision, firms receive the profit shock ν_{ik} from a common distribution $G(\nu|s_{rk})$ with support $\mathcal{V}$.

We assume the set of firm exit strategies in a neighborhood form a Bayes Nash Equilibrium (BNE). The strategy for firm i is the function $\sigma_i : \Delta^{M-1} \times \{0,1\}^R \times \mathcal{V} \to \{0,1\}$, where 1 represents the choice to exit and 0 the choice to stay active. A profile of strategies is a mapping $\sigma : \Delta^{M-1} \times \{0,1\}^R \times \mathcal{V}^N : \{0,1\}^N$.We assume that a BNE exists. Under this setup

$$P(Exit_{ikr} = 1|s_{kr}, m_{ikr}) = \int \{\nu : \sigma_i(s_{kr}, \nu) = 1\} dG(\nu|s_{kr}, m_{ikr}),$$

the measure of the set of ν values such that firm i chooses to exit, where m_{ikr} indexes the product firm i manufactures. Random assignment of firms to neighborhoods assures us that $G(\nu|s_{kr}, m_{ikr})$ does not depend on the identity of the firm or neighborhood, only on their characteristics. We can therefore arrive at counterfactual exit rates by varying the values of the conditioning variables in estimates of $P(Exit_{ikr} = 1|s_{kr}, m_{ikr})$. Our estimates from Table 6 yield linear approximations to these conditional probabilities.

5.3.2 Counterfactual Assignment

To arrive at an alternative to uniform assignment across pockets, we formulate the following optimization program:

$$\min_{s \in [0,1]^{(M-1)\times K}} s' \left(\begin{bmatrix} \frac{1}{p_1} & 0 & 0 & \cdots & 0 \\ 0 & \frac{1}{p_2} & 0 & \cdots & 0 \\ 0 & 0 & \frac{1}{p_3} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \frac{1}{p_K} \end{bmatrix} \otimes \delta \right) s \tag{5}$$

subject to

$$\sum_{m=1}^{M-1} s_{mk} \leq p_k \; \forall k$$

$$\sum_{k} s_{mk} = S_m \; \forall m.$$

p_k is the fraction of plots in block k, S_m the total share of firms of industry m, and s_{mk} the share of industry/product m in block k times p_k. δ is the matrix of effects of producer shares on the exit of firms producing each product, with rows identifying the product the affected firm manufactures and columns the share of each product. For aggregate exit, only the average pairwise spillover effect matters so that we can set $\delta_{nm} = \delta_{mn} = 1/2(\delta_{mn} + \delta_{nm})$.

We work with all 3-digit product codes with 50 or more firms assigned, which together make up 84% of all firms assigned a 3-digit code, and an "other" category. Figure 5 plots the matrix of net spillover effects across these product codes, based on flipping the signs of the results in Table 6 so that we can minimize exit. Figure 6 illustrates our alternative assignment obtained by solving a mixed integer reformulation of problem (5) in GUROBI. The reformulation specifies a relatively small number of clusters per industry with nonzero shares to make the solution space more tractable; this is the integer (binary) part of the problem. The shares assigned indicated by the color of each cell in the figure add up to 1 across rows, which represent industries. The columns represent the 74 clusters of the largest industrial area. Comparing with Figure 5, we see that products with input-output linkages implying a net negative cross-industry effect on exit tend to be grouped together in clusters. For instance, product codes 421 and 422, whose net spillover implies a strong negative effect on exit, are most often in the same cluster.

Figure 7, by contrast, shows the uniform assignment of products to blocks in Bawana (note the different scales in the legend). The identical shares by industry illustrate the relative size of the pockets in our sample. Relative to uniform assignment, the exit-reducing assignment illustrated in Figure 6 decreases aggregate exit by 15 percentage points. This is result to alternative definitions of upstream and downstream. If we call a product x downstream of product y if y's revenues from selling to x are above the 75th percentile of y's revenues from selling to any other type of producer, instead of the median, and do the same for the definition of upstream, our assignment reduces aggregate exit by 14 percentage points. This once again shows that leveraging firm spillovers can mitigate a substantial amount of the destructive effects of industrial relocation.

6 Back of the Envelope Cost-Benefit Analysis

6.1 Benefits

In this section, we construct a back-of-the-envelope estimate of the impacts of firm removal. To estimate the benefits of the program, we consider benefits from avoided mor-

tality as a result of reduced pollution exposure. These are a function of three factors. The first is the impact of firm removal on air pollution, which we have already estimated. We use the most conservative coefficient for Log (firms receiving a plot assignment by 2004) of 0.5 μg/m^3 from Table 4, and assign each neighborhood a pollution reduction of Log(Total Firms Removed) times 0.5 (since it is a pollution change of (log (total firms removed)-log(1))*0.5 μg/m^3). This has the benefit that neighborhoods that removed more firms experience a greater increase in the health benefits. The second factor is the population exposed. We assign each neighborhood the 2011 Population Census population density of the Census ward it lies in- the average density for neighborhoods with any relocated firms is 19,677.16 people per sq km, which reflects the large numbers of people exposed to pollution in Delhi. The third factor is how to map the change in exposure to mortality risk. To translate the change in exposure to reduction in mortality risk, we use estimates from prior work (Pope III et al., 2020). Pope III et al. (2020) conduct a meta-analysis, and across all studies they include from Asia, show that a 10 $\mu g/m^3$ reduction in exposure to fine PM reduces all-cause mortality risk by 5% (1.05 hazard ratio). Scaling that linearly gives a mortality reduction estimate of 0.5% per μg/m^3. Aggregating up the reduced mortality risk in each grid square by multiplying these three factors yields an estimate of 82,823.47 lives saved annually. Using a $700,000 Value of Statistical Life (VSL) (Majumder et al., 2018), the mortality benefits of the policy are about $57.98 billion.

How do these estimates change once we account for the increase in pollution in the Bawana area? If we assign all the firms to Bawana, using the estimated reduction in pollution from firm removal would imply that air quality worsened by 0.5*(log(21,000)-log(1)), or 4.98 $\mu g/m^3$. The population of Bawana in 2011 was about 73,000, and applying the mortality reduction estimate above gives an impact of 1,754.89 lives lost. This reduces the benefits of the policy to fall to 81,068.58 lives ($56.75 billion). Thus, while the benefits of the policy are still substantial, the distributional effects are also significant due to the increased pollution burden in Bawana.

6.2 Costs: Impact on Relocated Firms

In this section, we consider how the relocation impacted firms that were moved outside the city. First, we use exit from the industrial area to show that the probability firms survived in the industrial area in the long run is strongly decreasing in the distance they were moved, highlighting that location choice is a consequential endogenously chosen parameter by firms. Second, we consider two different types of counterfactual death rates for the firm to understand how the policy led to a lower firm survival probability.

We use data on firm survival in 2018 from the Bawana firm census. The data includes information on whether each of the 15,849 firms that were allotted a plot this area (the remainder of the relocated firms were allocated plots in two much smaller industrial areas) were still operating out of the industrial area. The data indicate that the vast majority of firms did not survive the move, with only about 26% of firms still present and functioning in the industrial area by 2018. While this is a large number, firms in developing countries have high exit rates on average, and so all of these exits cannot be attributed to the policy. To estimate a counterfactual death rate for these firms, we take two approaches - the first is estimate how the death rate varies as a function of the distance which the firm was moved. In Figure 4, we present evidence that the further a firm was moved, the more likely it is to exit, and Table 7 presents regression results for this relationship. Column 2 of Table 7 includes neighborhood fixed effects, comparing firms from nearby baseline locations. Each kilometer relocated increases the probability of firm exit by between 0.4 and 1.4 percentage points- the latter estimate includes neighborhood fixed effects, while the former does not. This implies that the average firm, which was relocated 20.37 kilometers, the increase in the probability of firm exit is 28.42 percentage points higher than a firm that was not relocated at all (using the second estimate). This is a substantial increase in the risk of firm exit, although much lower than the average rate of 74%.

A second approach compares these exit rates to those estimated for Indian firms more broadly - for instance, Sengupta and Singh (2019) find that the probability of firm survival in India over 20 years for registered firms is about 50%, about a risk of 2.5% each year. Therefore, seventeen years after the policy, about 42.5% of these firms should have exited, yielding a treatment effect on firm death of 31.5%, which is quite close to our estimate using distance relocated with the neighborhood fixed effects.

Next, we use the larger firm exit estimate of attributing 28 percentage points greater exit probability to the policy to estimate the costs on firms. This occurred over 12 years (the average firm takes possession of the plot in 2006, and the exit data was collected in 2018), yielding an annual probability of 2.3% greater risk of exit due to the policy. We use panel data from Center of Monitoring the Indian Economy (CMIE) to impute firm sales and salaries (this is likely an overestimate, since CMIE is more likely to include larger firms). Restricting the sample to the state of Delhi and to the year 2006 when the average firm took posession of their industrial plot, the median firm has $2.9 million in sales, and pays $87,700 in wages annually. This implies that the policy caused $ 1.44 billion in lost sales and wages per year.

6.3 Comparison of Benefits and Costs

Compared to the benefits of reduced mortality, the benefits are 39.3 times higher than the costs to firms. Thus, while the relocation policy caused firms to exit at a faster rate and consequently led to lost sales and wages, the benefits of improved air quality were substantially higher.

How do these cost-benefit estimates compare with other pollution reduction possibilities in India? First, let us consider mitigating damages from coal-fired power plants, which claim 84,650 lives in India each year. Installing scrubbers avoids 72% of deaths in the first year (Cropper et al., 2019), saving 60,948 lives. India has 204 GW of coal capacity (Ministry of Power, 2022); therefore, on average, scrubbers in a 500 MW plant would save 150 lives per year, at a cost of $1.2 billion over 20 years, or 60 million per year. These estimates imply that the cost per life saved is around $400,000. Another pollution reduction possibility is crop residue burning in India, which causes 86,000 premature deaths in India annually (Lan et al., 2022). Jack et al. (2022) find that payment for ecosystem services to incentivize farmers to not burn residue is effective in reducing burning, and applying those treatment effects leads to a cost of life saved of $2,930. Firm removal is in the middle of these policies in terms of cost-effectiveness, saving 81,068.58 lives per year at a cost of 1.44 billion, which yields a cost of life saved estimate of $17,269.33.

Taking firm spillovers into account with our exit-reducing assignment cuts the effect of firm relocation on exit roughly in half. This brings the cost per life saved down to $ 8,884.67.

7 Conclusion

Firm location decisions have important spillovers to the neighborhoods they locate in. These spillovers can be positive, generating employment and knowledge flows, or negative, such as increasing pollution exposure. We find that the presence of the polluting firms studied in this paper negatively impacts neighborhood-level ambient environmental quality in New Delhi. The removal, however, also impacts the relocated firms, substantially decreasing their survival probabilities. These survival probabilities could have been increased by relocating firms taking into account firm spillovers in the relocated industrial areas, indicating that such spillovers can be a powerful force to reduce costs on relocated firms.

Did this firm removal persist in the longer-term? In 2021-2022, we sent surveyors to original addresses of relocated firms (details of this data collection are in Section 3.3.1),

where they identified what was present at the original address. Results are summarized in Table 8, and show that *any* firm was present in less than 10% of the locations. We also asked the surveyors to collect information on whether the firm could possibly be the same as the relocated firm, using firm name and other characteristics to identify this. This happened for less than a third of all firms, or about 3% of all observations. The largest category of land use was residential buildings (in 45% of locations), followed by mixed use residential with retail shops and retail shops alone (21% of locations). The rest were split between construction or empty lots (2.7%), warehouses (4%), or were locked during multiple visits (7.7%).[10] Overall, firm removal seems permanent, leading the way for largely residential and retail uses to replace these firms.

Removal of firms may have important equity implications, by increasing commuting costs or moving costs for workers, as well as impacting the affordability of a neighborhood. Furthermore, Which types of industries should be relocated to provide the maximum environmental benefits and minimize costs to firms and workers, and whether lump sum transfers instead of allocating them land in a fixed place is better for firms' survival, remain interesting questions for future work.

[10]Surveyors were unable to locate about 10% of locations.

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Figure 1: Timing of Plot Lottery and Beginning of the Lease

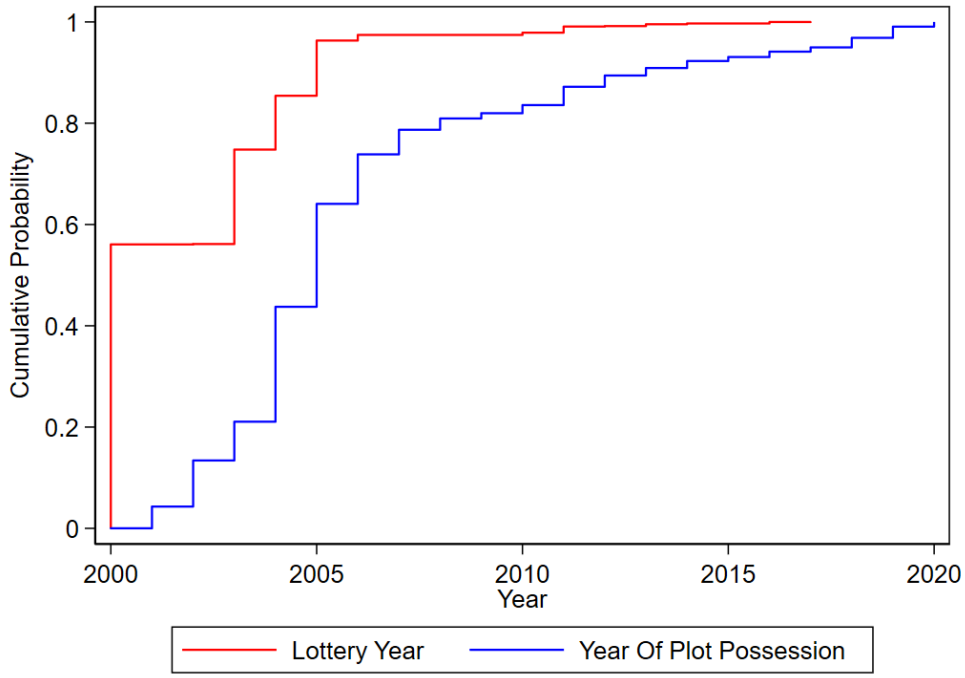
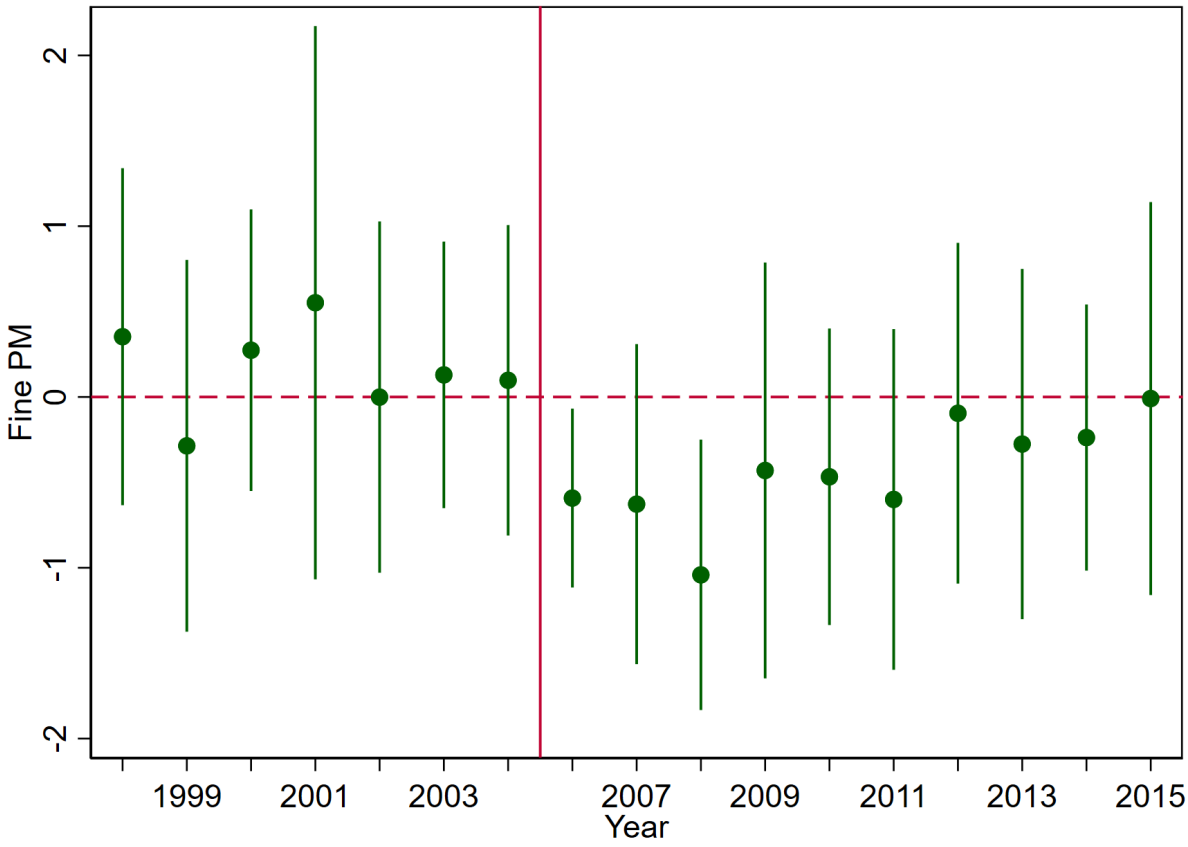


Figure 2: Effect of Firm Removal on Air Pollution (Fine PM, $\mu g/m^3$)



Notes: Interactions of year fixed effects with Log(firms relocated by 2004) shown in the figure. 2005 is Omitted. Grid ID and year fixed effects, as well as interactions of year fixed effects with the log of total firms relocated included. Bars represent 90% confidence intervals.

Figure 3: Actual vs. Simulated Plot Assignments in the Industrial Area

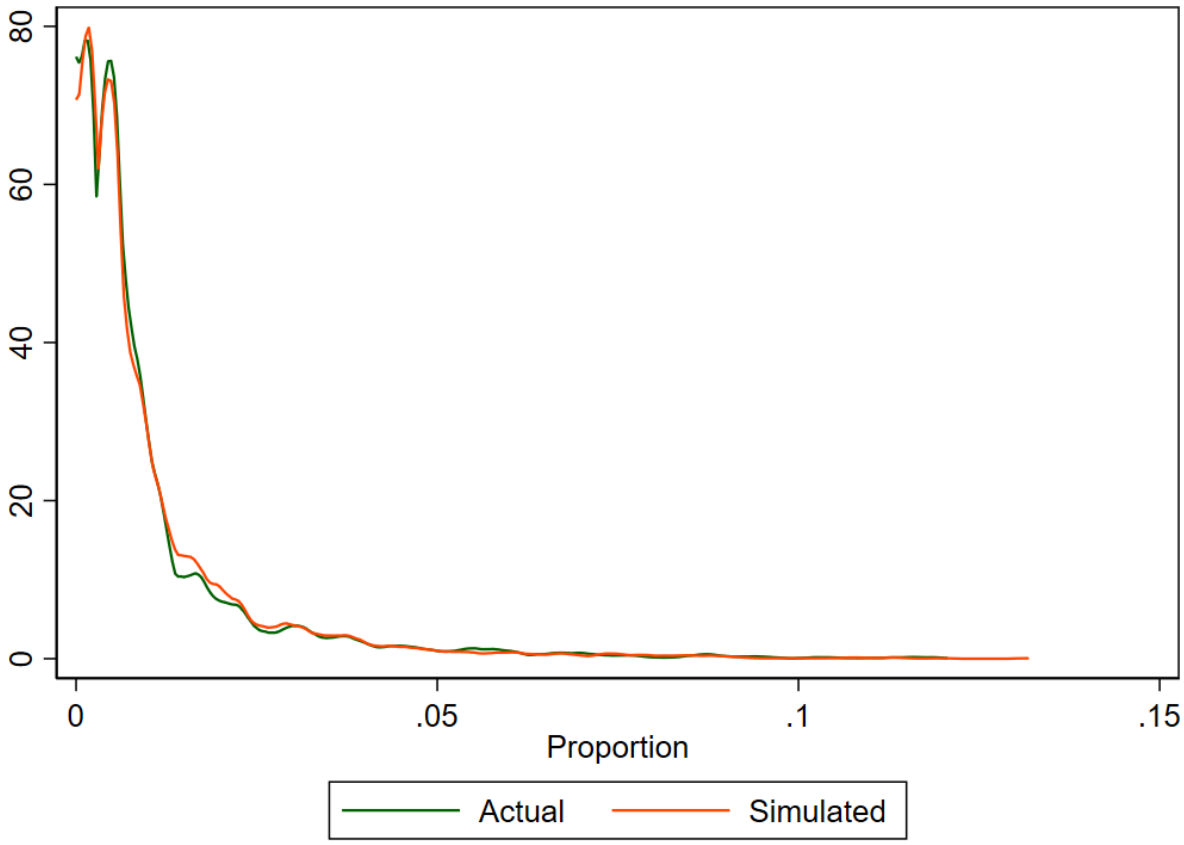


Figure 4: Distance Relocated and Firm Exit

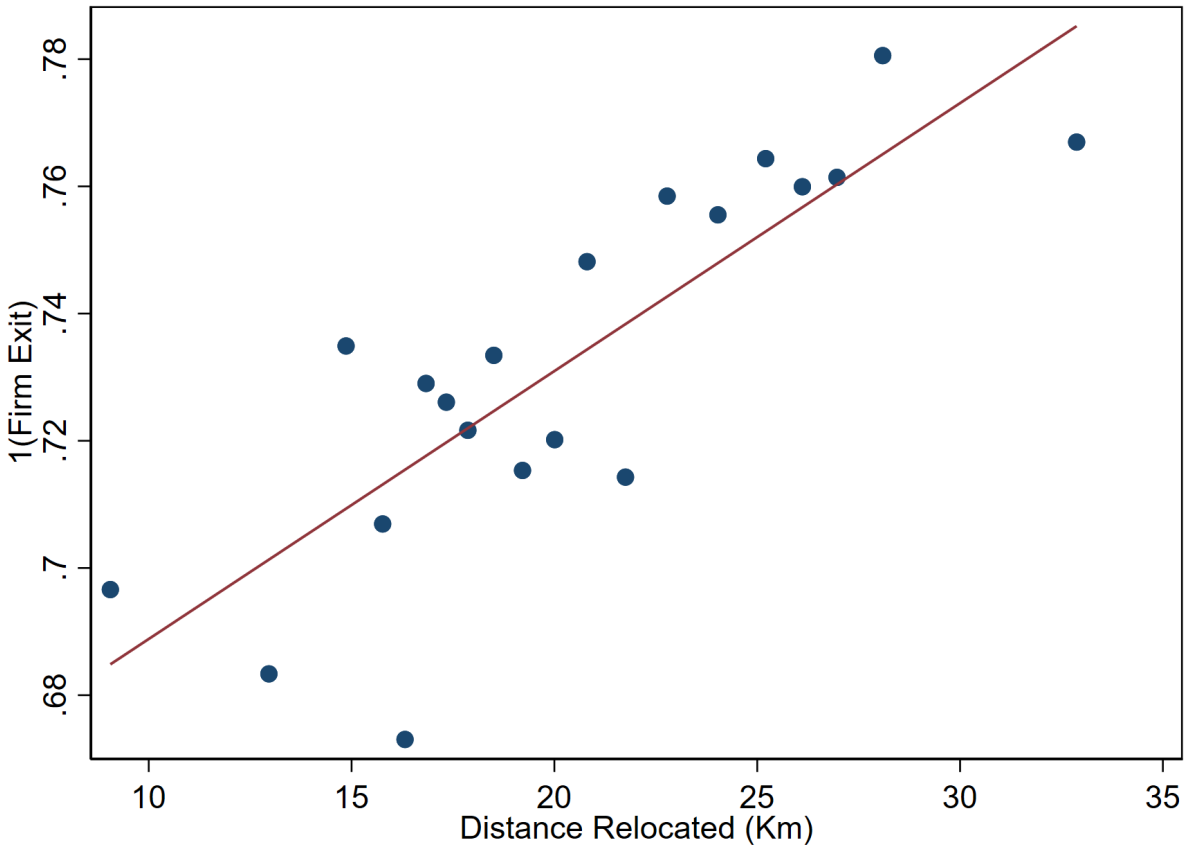


Figure 5: Effect of the Neighborhood Share of Each Industry on the Exit of a Firm by Own-Industry, Symmetrized

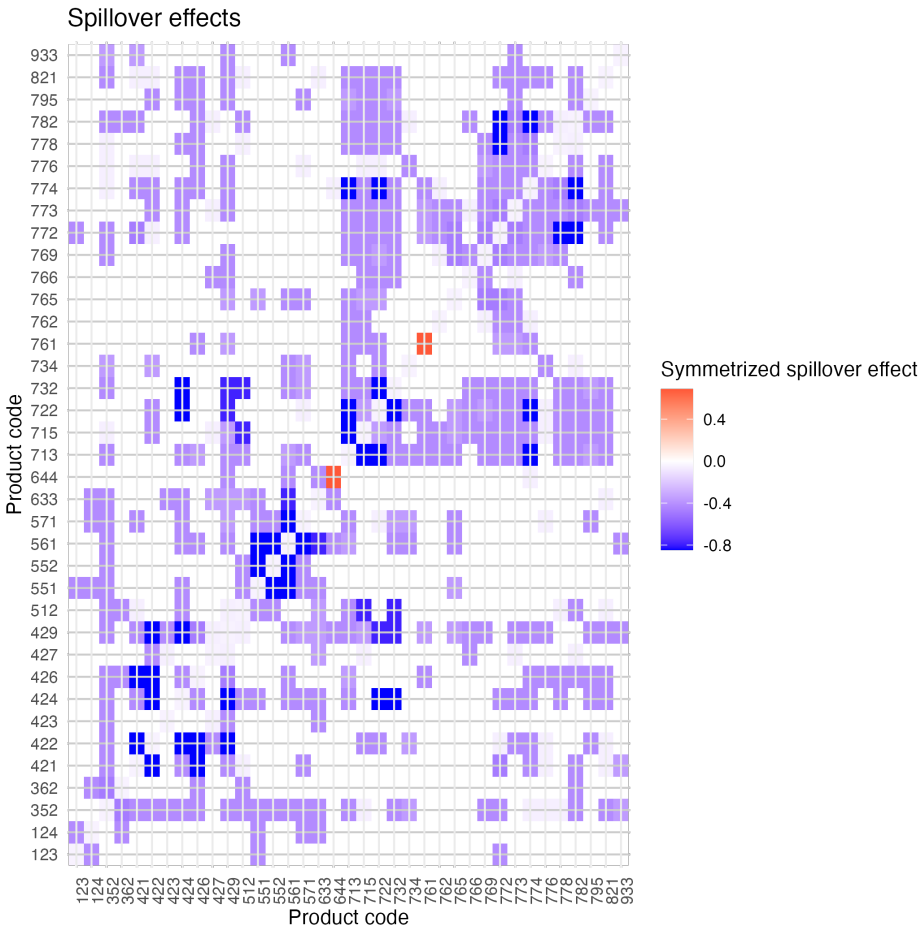


Figure 6: Exit-Reducing Product Composition of Clusters (Pockets) in the Industrial Area

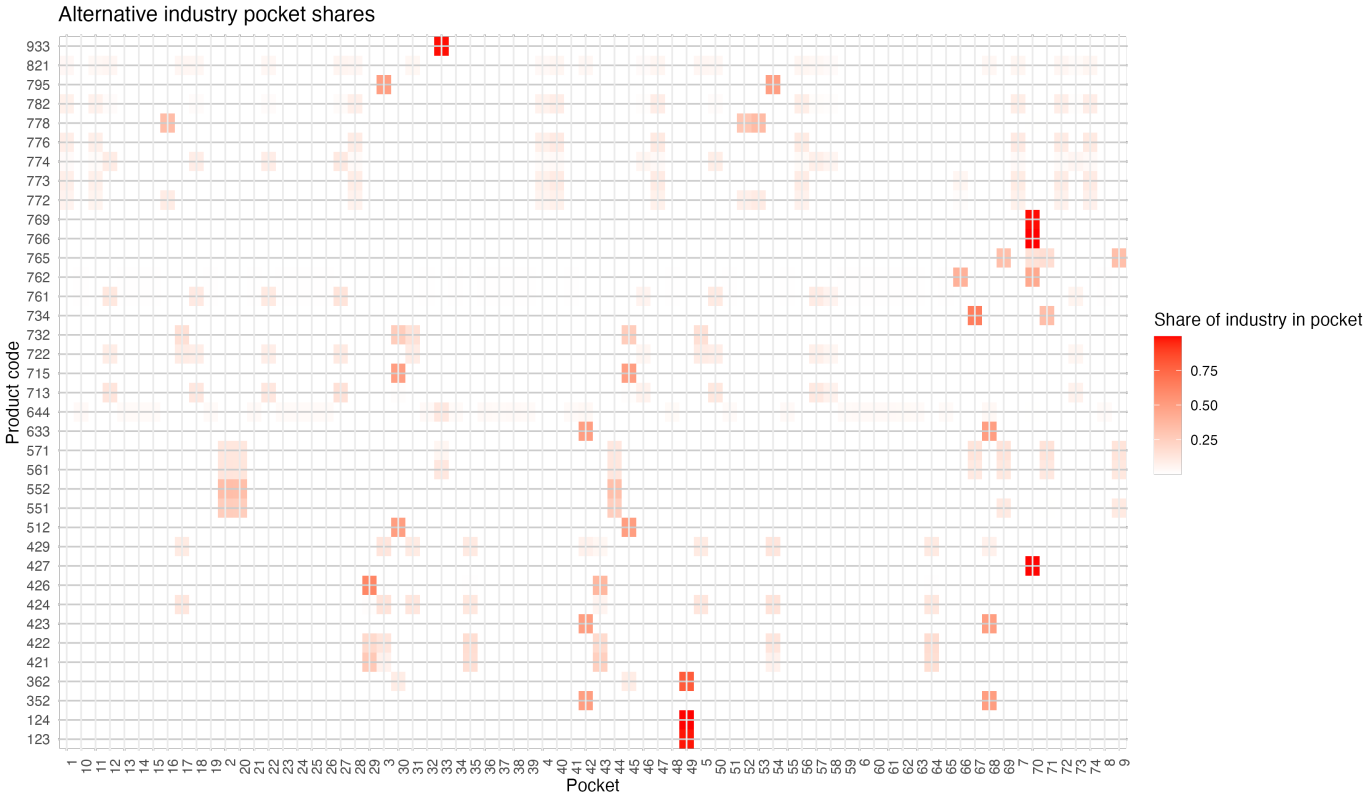


Figure 7: Product Composition of Blocks (Pockets) in the Industrial Area, Uniform Assignment

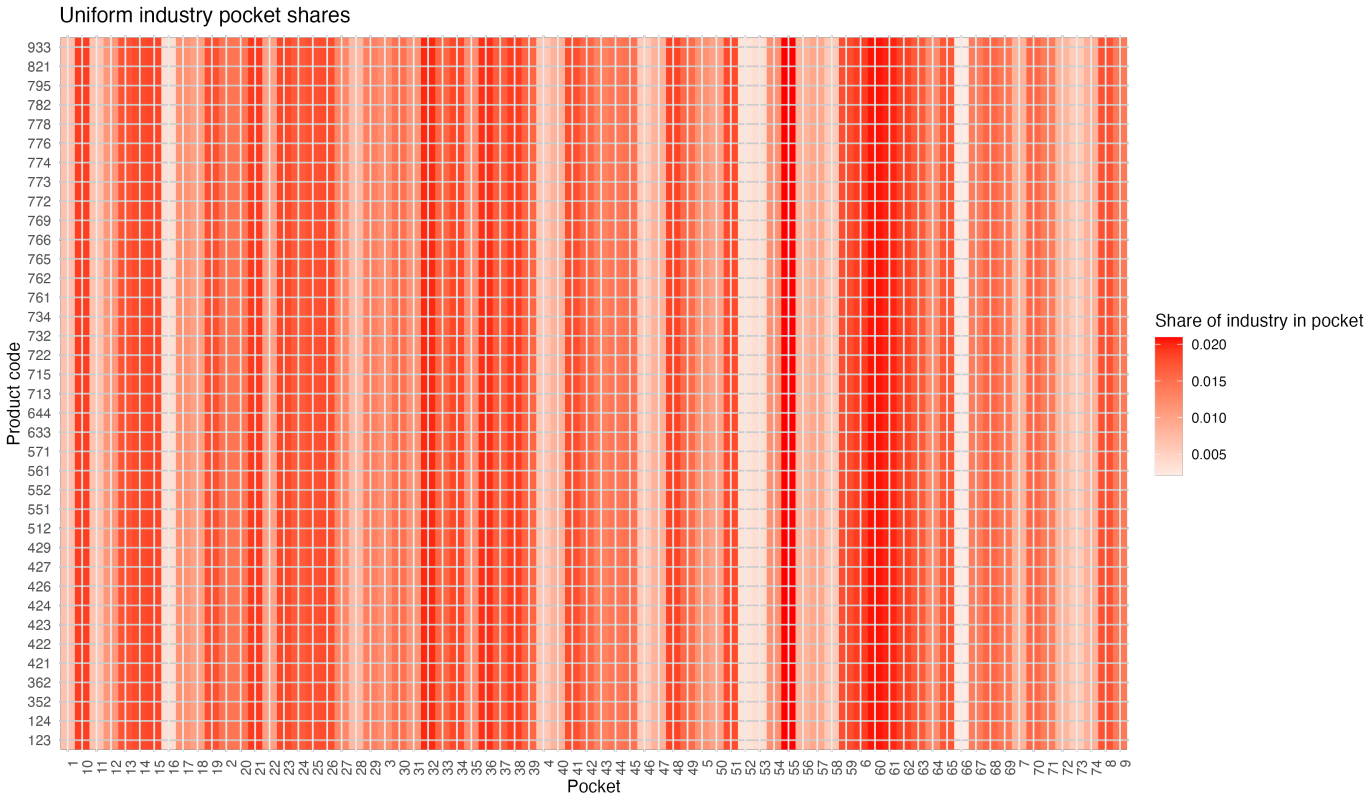


Table 1: Balance by Year of Lottery: Longitude and Latitude

	(1) Latitude	(2) Longitude	(3) Latitude	(4) Longitude
Lottery Year	0.0000629	-0.00370	0.0000932	-0.000906
	(0.000671)	(0.00318)	(0.000326)	(0.00148)
Constant	28.54****	84.60****	28.48****	79.00****
	(1.343)	(6.367)	(0.652)	(2.960)
Lottery Year	≤ 2005	≤ 2005	All	All
Mean of Dependent Variable	28.66	77.19	28.66	77.19
R-Squared	0.0000	0.0002	0.0000	0.0000
N	18581	18581	19508	19508

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, ****. Latitude and longitude are the latitude and longitude of the firm's origin address as provided by Google Maps. Lottery Year is the year in which a firm received their plot assignment.

Table 2: First Stage of Lottery Year Impacting Firm Movement to Industrial Area

	Year of Plot Posession			
	(1)	(2)	(3)	(4)
Lottery Year	1.310****	1.150****		
	(0.0150)	(0.0110)		
Lottery Year $\geq$ 2005			9.929****	9.942****
			(0.0801)	(0.0693)
Constant	-617.1****	-295.2****	2004.7****	2004.7****
	(29.95)	(22.02)	(0.0186)	(0.0186)
Lottery Year	$\leq$ 2005	All	$\leq$ 2005	
Mean of Dependent Variable	2005.84	2006.16	2005.84	2006.16
R-Squared	0.3971	0.4577	0.5999	0.6443
N	18848	19568	18848	19568

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, ****. Year of Plot Posession is the year in which the firm took possession of the plot in the industrial area. Lottery Year is the year in which a firm received their plot assignment.

Table 3: Impact of Firm Presence on Air Pollution (Fine PM, μg/m^3)

	Fine PM (μg/m^3)	
	(1)	(2)
Log(Firms Remaining)	0.345****	0.353**
	(0.0463)	(0.171)
Constant	106.5****	111.8****
	(0.0560)	(0.257)
Sample	All	Any Firm Has Taken Posession
Mean of Dependent Variable	107	112
R-Squared	0.9768	0.9665
N	10692	7585

Notes: Standard errors clustered at the neighborhood (1km by 1km grid cell) level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, ****. Fine PM is the annual concentration of fine particular matter in μg/m^3 at the neighborhood -year level. Firms Remaining is the difference between the total number of firms relocated in a neighborhood and the number of firms that have taken possession of their plots in the industrial area.

Table 4: Impact of Random Firm Removal on Air Pollution (Fine PM, $\mu g/m^3$)

	Fine PM ($\mu g/m^3$)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Firms Relocated Per by 2004) $\times$ $\mathbb{1}$(Year>2005)	-0.662**	-0.589*	-0.577*	-0.563*	-1.132***	-1.137***
	(0.306)	(0.314)	(0.321)	(0.325)	(0.381)	(0.408)
Log(Ineligible Firms) $\times$ $\mathbb{1}$(Year>2005)		0.157		0.0585		-0.00986
		(0.0999)		(0.115)		(0.164)
Constant	105.8****	105.7****	106.9****	106.9****	106.7****	106.7****
	(0.0152)	(0.0173)	(0.0494)	(0.0548)	(0.0692)	(0.0782)
Neighborhoods	All		With Relocated Firms		With Surveyor Identified Relocated Firms	
Randomization Inference P-Value	0.06	0.11	0.05	0.00	0.00	
Mean of Dependent Variable	106	106	107	107	107	107
R-Squared	0.9695	0.9695	0.9767	0.9767	0.9792	0.9792
N	24930	24930	10692	10692	7326	7326

Notes: Standard errors clustered at the neighborhood (1km by 1km grid cell) level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, ****. Fine PM is the annual concentration of fine particular matter in $\mu g/m^3$ at the neighborhood -year level. Firms Relocated by 2004 is the total number of firms in a neighborhood who have been assigned an industrial plot in a lottery by 2004. Ineligible Firms is the total number of firms in a neighborhood who applied for relocation, but were deemed to be ineligible for relocation by the government. Randomization Inference P-Value is the randomization inference p-value from randomly assigning Log (Firms Relocated by 2004) in 1,000 simulations.

Table 5: Most Common Products in the Largest Industrial Area

Product Name	Number of Firms
Motor vehicles (Passengers/goods transportation & special purpose vehicles)	1239
Printed books, newspaper, periodicals, notebooks, register etc. & other printed matters	770
Packing materials made of paper	614
Lamp, filament, electrodes, anodes/connectors, fittings & parts	487
Bags/boxes/panels/containers of plastic/pvc	401
tubes/pipes/basin & sanitary fittings of plastic/pvc	321
Film (non-sensitive/photographic)/foil/rolls/tape/rope of plastic/pvc & related materials	314
Articles, parts of plastic/pvc n.e.c	294
Copper and copper alloy, worked	266
Finished products of iron/steel	257
Wooden (incl plywood) furniture, boxes (incl packing box) and other wooden articles	248
Electrical motors, generators, transformer, power pack (this incl pump set fitted with electric motor)	226
Footwear plastic/pvc	210
Audio/video/sound apparatus & parts	182
Aluminium and aluminium alloys, worked	180

Notes: The product names are three digit ASICC codes (from 2010 product codes for the ASI). The second column shows the number of firms that produce products with the closest match with that ASICC code according to ChatGPT (please see appendix for details on the matching procedure).

Table 6: Reduced Form Impacts of Firm Spillovers

	Firm Survival	
	(1)	(2)
Proportion Upstream or Downstream (Std)	0.0403*	
	(0.0239)	
Proportion Own Type (Std)	-0.0211	-0.0203
	(0.0135)	(0.0135)
Proportion Upstream (Std)		0.0504**
		(0.0212)
Proportion Downstream (Std)		0.0251
		(0.0266)
P-Val: Any Linkage=Own	0.075*	
P-Val: Upstream=Own		0.019**
P-Val: Downstream=Own		0.178
P-Val: Upstream=Downstream		0.497
Mean of Dependent Variable	.26	.26
N	9184	9159

Notes: Robust standard errors clustered at the industrial area cluster-level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, ****. All dependent variables are standardized by dividing by their respective standard deviation.

Table 7: Impacts of Distance Relocated on Firm Exit

	(1)	(2)
	$\mathbb{1}$(Firm Exit)	
Distance Relocated	0.00421***	0.0141***
	(0.000672)	(0.00479)
Constant	0.647***	0.446***
	(0.0142)	(0.0974)
Mean of the Dependent Variable	0.733	0.732
N	13578	13431
R2	0.00289	0.0365

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, ****. Firm exit is a dummy variable that takes the value 1 if the firm is not operating in the industrial area (Bawana) in 2018, and 0 otherwise. Distance relocated is the distance in kilometers between the firm's original address and the plot it is assigned in the industrial area.

Table 8: Descriptive Evidence From Surveyor Visits in 2021/2022

What is Located at Original Address	Proportion
Residential	0.452
Commercial and Residential/Market	0.21
Firm	0.099
Locked building	0.077
Warehouse	0.04
Empty Plot/Under Construction	0.027

Notes: 15,756 addresses were visited in total by surveyors. Surveyors were asked to reach the origin address, and record what they found there e.g. a firm, residence etc. If there was a firm, they administered a short survey to elicit the firm's name, size, and products sold. 10% of addresses were not found by surveyors.

Appendices

A Appendix Figures and Tables

Figure A1: Bawana Industrial Area-2000

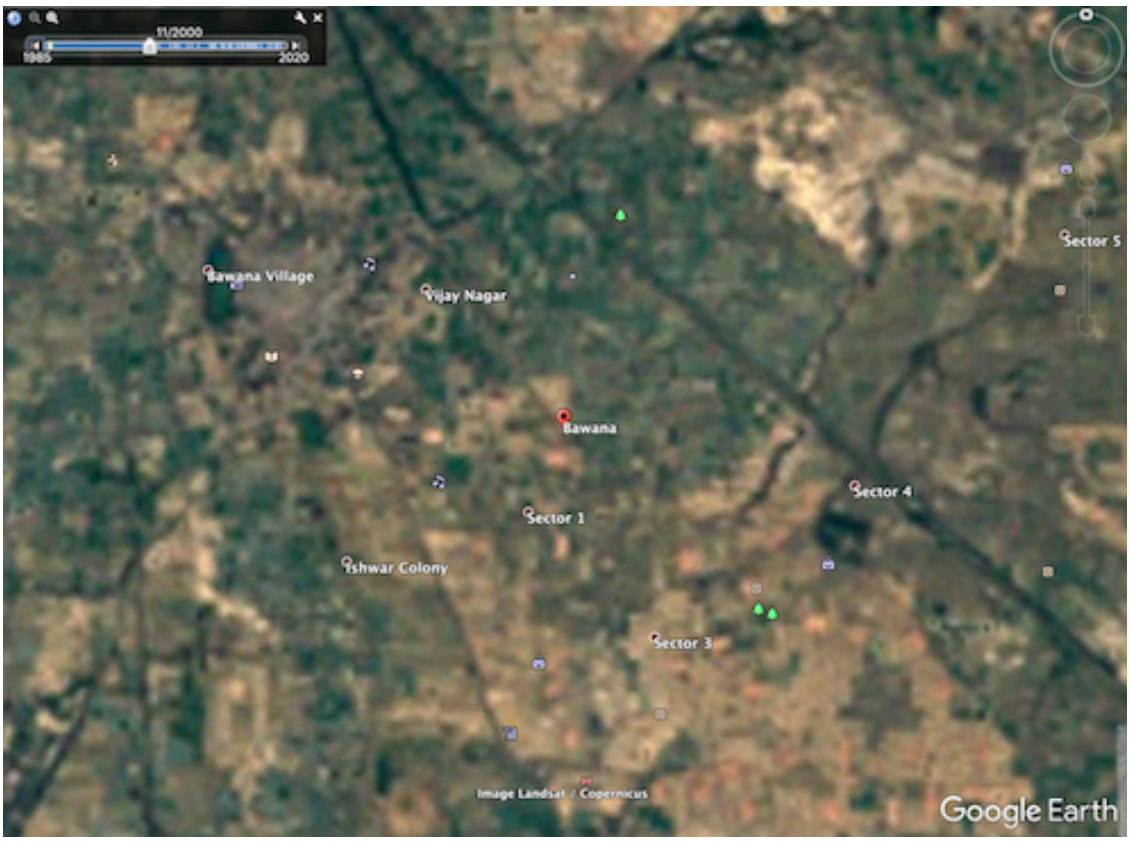


Figure A2: Bawana Industrial Area-2001



Figure A3: Bawana Industrial Area-2010



Figure A4: Map of an Industrial Area Cluster (Pocket)



Figure A5: Actual vs. Simulated Plot Assignments in the Industrial Area

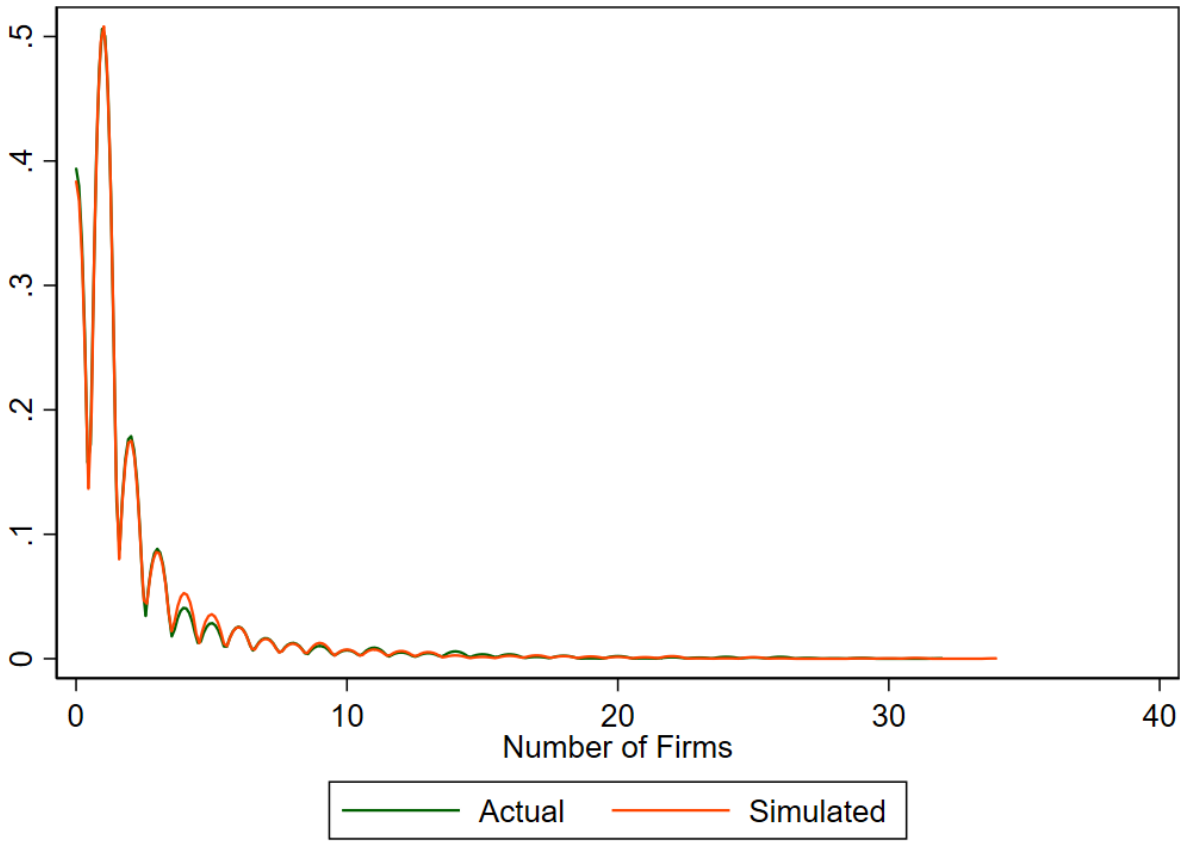
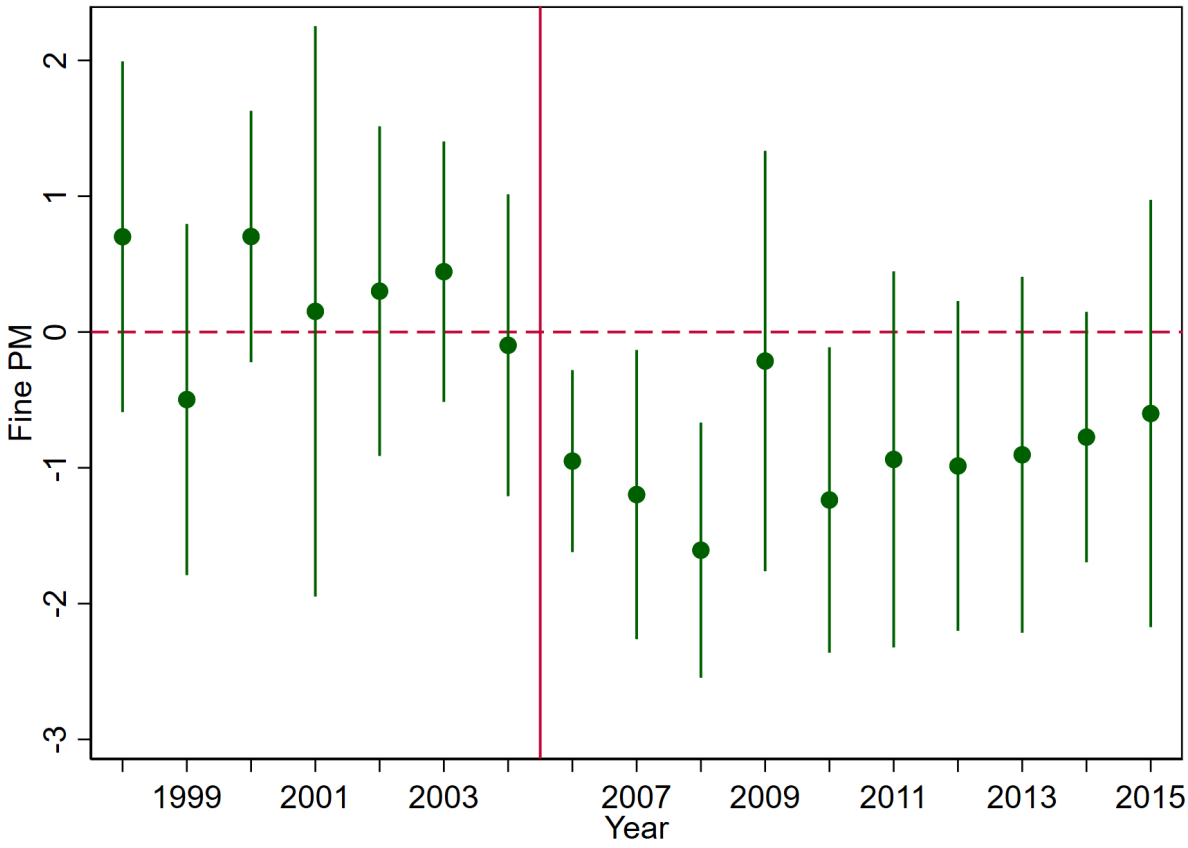
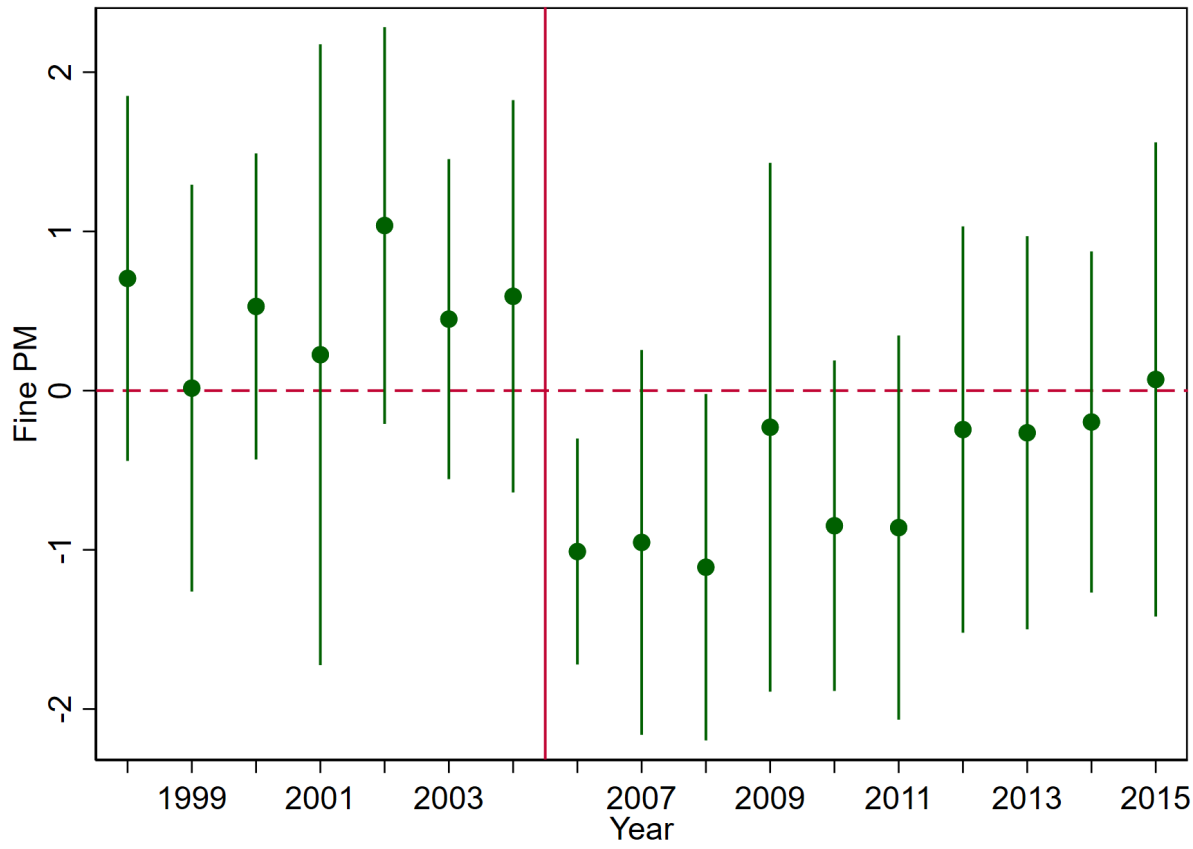


Figure A6: Effect of Firms Leaving on Air Pollution (Fine PM, $\mu g/m^3$): Neighborhoods with Surveyor-Indentified Firms



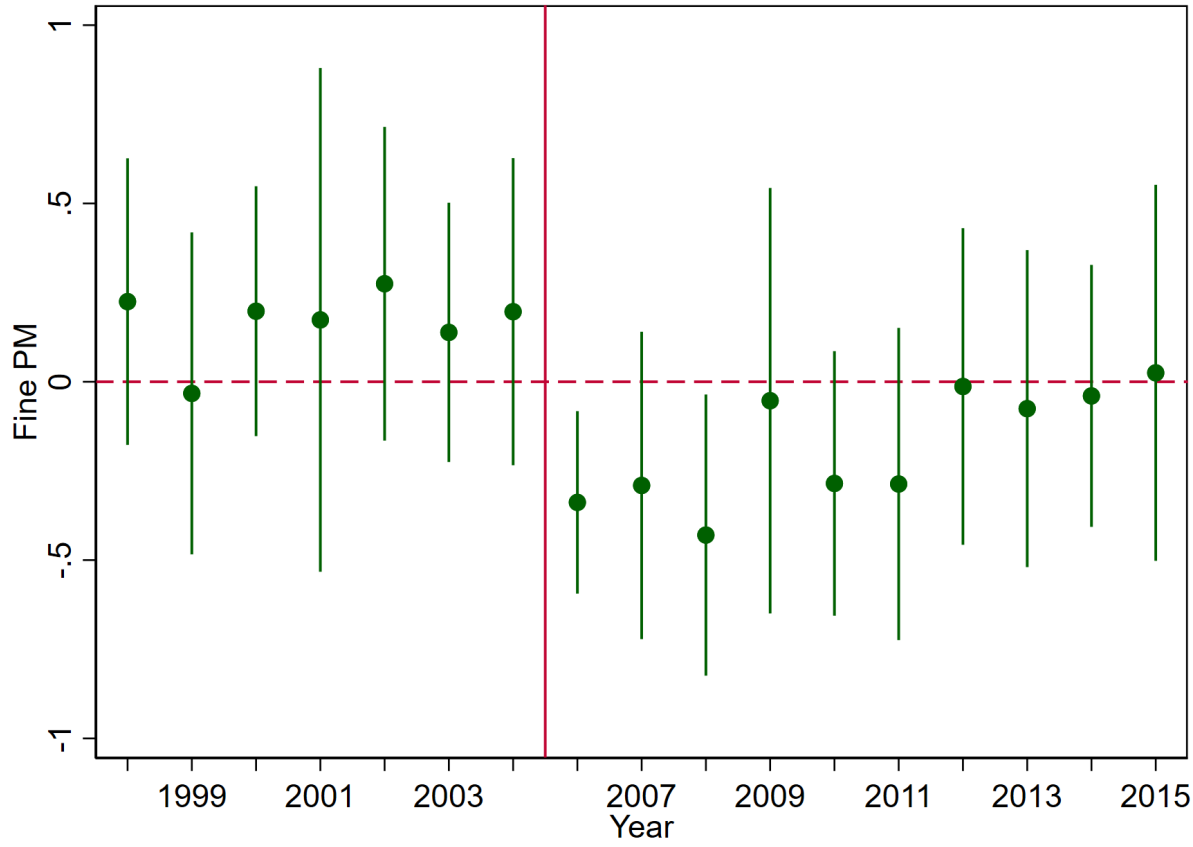
Notes: Interactions of year fixed effects with Log(firms relocated by 2004) shown in the figure. 2005 is Omitted. Grid ID and year fixed effects, as well as interactions of year fixed effects with the log of total firms relocated included. Bars represent 90% confidence intervals.

Figure A7: Impact of Random Firm Removal on Air Pollution (Fine PM, $\mu g/m^3$): Triple Interaction Between Baseline Number of Firms and Proportion Lotteried Early, 4 Bins



Notes: Triple interactions presented of three variables. The first is a variable that takes the value 1 if the baseline total number of firms relocated is in the first quartile, 2 if it is the second, and so on. The second is the proportion of firms in the neighborhood that had received an industrial plot by 2004. The third is a dummy variable that takes the value 1 if the year is 2006 or later. Grid ID and year fixed effects, as well as all double interactions included. Bars represent 90% confidence intervals.

Figure A8: Impact of Random Firm Removal on Air Pollution (Fine PM, $\mu g/m^3$): Triple Interaction Between Baseline Number of Firms and Proportion Lotteried Early, 10 Bins



Notes: Triple interactions presented of three variables. The first is a variable that takes the value 1 if the baseline total number of firms relocated is in the first decile, 2 if it is the second, and so on. The second is the proportion of firms in the neighborhood that had received an industrial plot by 2004. The third is a dummy variable that takes the value 1 if the year is 2006 or later. Grid ID and year fixed effects, as well as all double interactions included. Bars represent 90% confidence intervals.

Table A1: Balance by Whether Lottery Year is Missing: Longitude and Latitude

	(1) Latitude	(2) Longitude
1(Lottery Year Missing)	-0.000228	-0.00567
	(0.00546)	(0.0150)
Constant	28.66****	77.19****
	(0.000926)	(0.00405)
Mean of Dependent Variable	28.66	77.18
R-Squared	0.0000	0.0000
N	24373	24373

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, ****. Latitude and longitude are the latitude and longitude of the firm's origin address as provided by Google Maps. 1(Lottery Year Missing) is a binary variable that takes the value 1 if the year of the firm's assignment by lottery is missing, and 0 otherwise.

Table A2: Impact of Random Firm Removal on Air Pollution (Fine PM, $\mu g/m^3$): Triple Interaction Between Baseline Number of Firms and Proportion Lotteried Early

	Fine PM ($\mu g/m^3$)	
	(1)	(2)
Triple Interaction(Bins=4)	-1.009**	
	(0.396)	
4 Bins X Post	0.793**	
	(0.317)	
Proportion 2004 $\times$ Post	1.245*	0.588
	(0.640)	(0.453)
Triple Interaction(Bins=10)		-0.325**
		(0.143)
10 Bins X Post		0.255**
		(0.114)
Constant	106.4****	106.6****
	(0.289)	(0.206)
Mean of Dependent Variable	106.89	106.89
R-Squared	0.9767	0.9767
N	10,692	10,692

Notes: Standard errors clustered at the neighborhood (1km by 1km) grid cell level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, ****. Fine PM is the annual concentration of fine particular matter in $\mu g/m^3$ at the neighborhood -year level. Triple Interaction (Bins=4) is the triple interaction between three variables. The first is a variable (labeled "4 Bins" in the table) that takes the value 1 if the baseline total number of firms relocated is in the first quartile, 2 if it is the second, and so on. The second is the proportion of firms in the neighborhood that had received an industrial plot by 2004 (labeled "Proportion 2004" in the table). The third is a dummy variable that takes the value 1 if the year is 2006 or later (labeled "Post" in the table). Triple Interaction (Bins=10) is the triple interaction between three variables. The first is a variable (labeled "10 Bins" in the table) that takes the value 1 if the baseline total number of firms relocated is in the first decile, 2 if it is the second, and so on. The second is the proportion of firms in the neighborhood that had received an industrial plot by 2004 (labeled "Proportion 2004" in the table). The third is a dummy variable that takes the value 1 if the year is 2006 or later (labeled "Post" in the table).

Table A3: Impact of Random Firm Removal on Air Pollution (Fine PM, $\mu g/m^3$): Cluster at 2km X 2km Level

	Fine PM ($\mu g/m^3$)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Firms Relocated Per by 2004) $\times$ $\mathbb{1}$(Year>2005)	-0.465	-0.447	-0.577*	-0.563*	-1.145***	-1.148***
	(0.330)	(0.331)	(0.338)	(0.340)	(0.388)	(0.404)
Log(Ineligible Firms) $\times$ $\mathbb{1}$(Year>2005)		0.0817		0.0585		-0.00576
		(0.112)		(0.118)		(0.163)
Constant	106.8****	106.8****	106.9****	106.9****	106.8****	106.8****
	(0.0439)	(0.0545)	(0.0615)	(0.0708)	(0.0877)	(0.102)
Neighborhoods	All		With Relocated Firms		With Surveyor Identified Relocated Firms	
Mean of Dependent Variable	107	107	107	107	107	107
R-Squared	0.9755	0.9755	0.9767	0.9767	0.9794	0.9794
N	13032	13032	10692	10692	7146	7146

Notes: Standard errors clustered at the 2km by 2km grid cell level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, ****. Fine PM is the annual concentration of fine particular matter in $\mu g/m^3$ at the neighborhood -year level. Firms Relocated by 2004 is the total number of firms in a neighborhood who have been assigned an industrial plot in a lottery by 2004. Ineligible Firms is the total number of firms in a neighborhood who applied for relocation, but were deemed to be ineligible for relocation by the government. Randomization Inference P-Value is the randomization inference p-value from randomly assigning Log (Firms Relocated by 2004) in 1,000 simulations.

Table A4: Impact of Random Firm Removal on Air Pollution (Fine PM, $\mu g/m^3$): Without Neighborhood and Year Fixed Effects

	Fine PM ($\mu g/m^3$)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Firms Relocated Per by 2004) $\times$ $\mathbb{1}$(Year>2005)	-0.662**	-0.589*	-0.577*	-0.563*	-1.132***	-1.137***
	(0.306)	(0.314)	(0.321)	(0.325)	(0.381)	(0.407)
Log(Ineligible Firms) $\times$ $\mathbb{1}$(Year>2005)		0.157		0.0585		-0.00986
		(0.0999)		(0.115)		(0.164)
Constant	95.44****	95.34****	96.79****	96.68****	95.96****	95.68****
	(0.151)	(0.154)	(0.330)	(0.350)	(0.439)	(0.445)
Neighborhoods	All		With Relocated Firms		With Surveyor Identified Relocated Firms	
Mean of Dependent Variable	107	107	107	107	107	107
R-Squared	0.3924	0.3933	0.3860	0.3862	0.3884	0.3892
N	24930	24930	10692	10692	7326	7326

Notes: Standard errors clustered at the neighborhood (1km by 1km grid cell) level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, ****. Fine PM is the annual concentration of fine particular matter in $\mu g/m^3$ at the neighborhood -year level. Firms Relocated by 2004 is the total number of firms in a neighborhood who have been assigned an industrial plot in a lottery by 2004. Ineligible Firms is the total number of firms in a neighborhood who applied for relocation, but were deemed to be ineligible for relocation by the government.

Table A5: First Stage of Lottery Year Impacting Firm Movement to Industrial Area: Neighborhood-Level

	(1) Log(Firms Given Plot Possession By 2006)	(2) Log(Firms Given Plot Possession) By 2015)
Log(Firms Assigned Plot in Lottery by 2004)	0.997****	0.502****
	(0.0437)	(0.0467)
Constant	-0.112****	-0.00445
	(0.0169)	(0.00409)
Year	2006	2015
Mean of Dependent Variable	23.88	28.93
R-Squared	0.9818	0.9955
N	555	579

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, ****. Firms Given Plot Possession by 2006 is the total number of firms in a neighborhood who have taken possession of their industrial plot by 2006. Firms Given Plot Possession by 2015 is the total number of firms in a neighborhood who have taken possession of their industrial plot by 2015. Firms Relocated by 2004 is the total number of firms in a neighborhood who have been assigned an industrial plot in a lottery by 2004. All regressions include controls for the log of total number of firms relocated in a neighborhood.

Table A6: Correlation Between Missing or Noisy Geocoding with Timing of Firm Lottery

	(1) 𝟙[Surveyor Geocode and Google Gecode in Different Wards]	(2) 𝟙[Surveyor Geocode Missing]	(3) 𝟙[Google Geocode Missing]
Lottery Year	-0.000619	-0.00125	-0.000170
	(0.00193)	(0.00115)	(0.000930)
Constant	1.574	2.601	0.421
	(3.858)	(2.303)	(1.862)
Mean of the Dependent Variable	0.334	0.0980	0.0800
N	14061	15010	20186
R2	0.00000728	0.0000749	0.00000167

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Restricted to lottery years 2005 and earlier, since over 90% of firms received a plot by 2005.

B Matching Information on Firm Products to Annual Survey of Industries Commodity Classification (ASICC) Codes

B.1 Procedure

We performed create a custom pipeline using the GPT-4-turbo model to assign 1-, 2-, and 3-digit Annual Survey of Industries Commodity Classification (ASSIC) codes to firms based on the products they report producing. We performed extensive prompt engineering to guide the model using a set of detailed instructions that included accounting for potential typos and nuanced elements like distinguishing between manufacturing a particular product vs. manufacturing the machinery that produces that product. The output consists of a single product code assignment or a "missing" label for cases where GPT could not find a good match. The details of the prompts used are included in the next section. These requests are submitted to the GPT-4-turbo model using OpenAI's API, and the model's responses were parsed and integrated back into the output data.

GPT models are inherently non-deterministic. To minimize randomness and enhance reproducibility, we set the temperature parameter, which measures response entropy, to 0.

B.2 Human Evaluation

To evaluate the results, we randomly selected a sample of unique product descriptions and compared them to human assignments to ASICC codes done by research assistants. We compared the human assignments with the results of different versions of the GPT model concluding that GPT model assignment produced a reasonable and efficient fit for nearly all cases and was more consistent than a team of research assistants, except for some hard-to-classify products that included Hindi words, which Hindi speakers also had trouble classifying (an example being "dona pattal thali").

We also used the human evaluation to extensively test different input prompts in search of best matching. This resulted in an extensive initial prompt that covers most of the edges cases in which GPT-4 performed poorly.

B.3 Output Processing

We process the assignment requests using the Batch method of OpenAI's API. We download the resulting output as JSONL files and extract the assignment answer for each firm.

GPT provides up to 5 product codes in order from most to least preferred. We pick the most preferred code.

B.4 Scripts for GPT-4 API prompting

The following is the full initial prompt provided to GPT-4:

```
You are a helpful assistant who helps match product descriptions to ASICC product codes.
We wish to match each product descriptions to one or multiple ASICC product codes I will provide,
and you should select the best match if there is one.
Please note that we distinguish products and machines to produce the products.
We consider that there might be typos in the product descriptions,
and we do the matching based on the corrected product descriptions.
Please pay attention to the noun part of the ASICC product code description,
and ensure the selected ASICC product codes match the product description well.
Please pay attention to the material of the product, when it is available.
If the product description contain multiple products,
you can choose a best one that includes all of them if possible,
or you can choose different codes for them separately.
If you are NOT SURE, you should PRINT None.

Here are some examples for guidance:

### EXAMPLES ###

If the item is general, and different versions of it will lead to codes with different first
    digit, then we should NOT assign a match.
E.g. "Steel Furniture" should be assigned to "715 manufacture of iron/alloy steel",
"Plastic Furniture" should be assigned to "421 bags/boxes/panels/containers of plastic/pvc",
while "FURNITURE" or "Furniture Chairs" SHOULD NOT HAVE AN ASSIGNMENT as the material is not
    clear.

If the item is general, but we can find a best higher level code, we should assign it to the
    hignest level code.
E.g. "Garments" or "Readymade garments" should be assigned to "6 textile and textile articles",
"Hardware Goods" should be matched to "75 non-electrical machine tools & general purpose
    machineries and components and parts thereof [no sub-group formation]",
"Steel Fabrication" should be matched to "71 iron & steel (incl stainless steel) & articles
    thereof",
"Paper products" should be matched to "55 paper and paper board".

GENERAL TERMS SUCH AS "WIRE and CABLES" or "Wire Drawing" or "MACHINERY" SHOULD BE MATCHED to "7
    base metals, products thereof & machinery equipment and parts thereof, excluding transport
    equipment" as their material is not specified,
"Steel Wires and Cables" should be matched to "71 iron & steel (incl stainless steel) & articles
    thereof",
"Copper Wire" should be matched to "72 copper, nickel & zinc articles thereof",
"Electrical Wires" should be matched to "774 lamp, filament, electrodes/anodes/connectors,
    fittings & parts",
"PVC Wires" should be matched to "424 film (non-sensitive/photographic)/foil/rolls/tape/rope of
    plastic/pvc & related materials".
```

```
Auto is mostly like to be related to motor vehicles, so "Auto Parts" should be matched to "821
    motor vehicles - passengers/goods transportation and special purpose vehicles",
"Motor Parts" should be matched to "821 motor vehicles - passengers/goods transportation and
    special purpose vehicles",
"Rear Window Mirror" should be matched to "941 glass and glassware";

A vague action such as "Stamping" should not have a match because it is not clear about the
    products,
an action that is more specifc about a product can be matched based on the product it produced,
    for example:
"Electroplating" or "Electroplating job to order" should be matched to "71 iron & steel (incl
    stainless steel) & articles thereof",
"PRINTING" SHOULD BE MATCHED to "561 printed books, newspaper, periodicals, note books, register
    etc and other printed matters",
"Dyeing of Cotton Cloth" should be matched to "63 cotton, cotton yarn and fabrics" because the
    product is cotton cloth, not dyeing material.

We also make the distinction to the following to general groups:
"Electrical Goods" or "Electric Components" etc. should be matched to "77 electrical & electronic
     machinery & equipment incl parts (excl medical & non-conventional energy equipment)",
while "Electronic Goods" should be matched to "78 electronics equipment & parts excl bio-medical
    equipment".
"Kitchen Wares" should be matched to "74 misc. manufacture of base metals, n.e.c [no sub-group
    formation]".
"Corrugated Boxes" or "Card Board Boxes" should be matched to "571 packing materials made of
    paper [paper used for packing are shown under respective heads under division 55]",
while "Corrugated Paper Rolls" should be matched to "552 paper (uncoated) used for newsprint and
    for other special purpose excl writing/printing".
"pvc Compound" should be matched to "42 plastic, pvc articles incl packaging products and
    footwear plastic or pvc [note: toys will go sub-division 933]".
"DIE", as a machine tool to cut, SHOULD be matched to "74 misc. manufacture of base metals, n.e.c
     [no sub-group formation]".
"Engineering Goods" or "Engineering Work" should be matched to "75 non-electrical machine tools &
     general purpose machineries and components and parts thereof [no sub-group formation]".

### END OF THE EXAMPLES ###

Here is the list of codes to select from:

###BEGINNING of industry codes, separated by new lines###

## One digit codes ##
1 Animal, Vegetable, Horticulture, Forestry Products, Beverages, Tobacco And Pan Masala And Non-
    Edible Water/Spirit & Alcohol Chiefly Used In Industry
2 Ores, Minerals, Mineral Fuels, Lubricants, Gas & Electricity
3 Chemical And Allied Products
4 Rubber, Plastic, Leather & Products Thereof
5 Wood, Cork, Thermocol & Paper And Articles Thereof
6 Textile And Textile Articles
7 Base Metals, Products Thereof & Machinery Equipment And Parts Thereof, Excluding Transport
    Equipment
8 Railways, Airways, Ships & Road Surface Transport And Related Equipment & Parts
9 Other Manufactured Articles And Services N.e.c
## End of one digit codes ##
```

Two digits codes
11 Animal & Food Products Of Animal Origin
12 Fruits, Vegetables, Cereals & Pulses And Other Vegetable Produces Like Lac, Gum Etc. And Preparation Thereof
13 Other Food And Edible Products & Preparations
14 Products Of Horticulture Incl Tissue Culture; Hydroponics And Forestry
15 Beverages, Tobacco And Pan Masala
16 Miscellaneous Non-Edible Substances For Industrial Use
21 Salts, Sulpher, Plastering Materials, Lime & Cement
22 Ores (Base Metal), Slag, Ash
23 Mineral Fuels: Oils, Products & By-Products
24 Gas (Fuel) Natural And Manufactured
25 Electrical Energy
29 Non-Metallic Mineral, Mineral Products Refractories
31 Inorganic Chemical, Compound Of Precious Materials Etc
32 Organic Chemicals
33 Pharmaceutical And Medical Products Excl Dental Materials
34 Fertilizer/Pesticides/Plant Protection Materials
35 Dyeing, Tanning, Colouring, Ink & Paint Etc
36 Essential Oil, Cosmetics & Perfumes, Dental Materials, Wax Polishing/Cleaning Materials
37 Explosives, Pyrotechnic Products, Matches And Certain Combustible Products, Pyrophoric Alloys
38 Photographic, Cinematographic Goods & Other Photo-Sensitive Materials [This Excl Apparatus Equipment And Parts Thereof]
39 Misc Chemical Goods Incl Albuminoidal Substances Modified Starches (Excl Sub-Division 124) And Glues, Enzymes
41 Rubber And Manufacture Of Rubber [This Incl Synthetic Rubber] [No Sub-Division Formation]
42 Plastic, Pvc Articles Incl Packaging Products And Footwear Plastic Or Pvc [Note: Toys Will Go Sub-Division 933]
43 Hides, Skins And Leather
44 Article Of Leather, Sadlary And Harness, Travel Goods, Hand Bags And Similar Products Of Animal Gut
45 Fur Skins And Artificial Fur & Articles Thereof
49 Misc Products/Articles Of Rubber/Pvc/Leather Etc [This Will Incl Mixed Products Of Rubber/ Leather Etc.]
51 Wood And Pulp Of Wood And Products Thereof Excl Forestry
52 Cork, Thermocols And Articles Thereof
53 Manufacture Of Straw, Basketware And Wickerware
54 Pulp Of Wood & Other Fibrous Materials
55 Paper And Paper Board
56 Printed Books, Newspaper, Periodicals, Registers Etc
57 Packing Materials And Containers Of Paper
61 Silk And Silk Products [This Includes Art Silk]
62 Wool/Animal Hair, Yarn & Fabrics
63 Cotton, Cotton Yarn And Fabrics
64 Synthetic (Man-Made) And Mixed Textiles
65 Jute, Coir & Other Natural Fibre Yarn & Textile
66 Special Woven Fabric And Articles Thereof [No Sub-Group Formation]
67 Floor Coverings Etc [No Sub-Group Formation]
68 Impregnated, Coated, Covered, Laminated Textile Fabrics [No Sub-Group Formation]
69 Misc Textile Yarn, Fabrics, Articles & Waste N.e.c [No Sub-Group Formation]
71 Iron & Steel (Incl Stainless Steel) & Articles Thereof
72 Copper, Nickel & Zinc Articles Thereof
73 Aluminium, Tin, Lead & Other Base Metals & Articles Thereof
74 Misc. Manufacture Of Base Metals, N.e.c [No Sub-Group Formation]

75 Non-Electrical Machine Tools & General Purpose Machineries And Components And Parts Thereof [No Sub-Group Formation]
76 Non-Electrical Industry Specific Equipment/Machineries Incl Parts Thereof
77 Electrical & Electronic Machinery & Equipment Incl Parts (Excl Medical & Non-Conventional Energy Equipment)
78 Electronics Equipment & Parts Excl Bio-Medical Equipment
79 Special Purpose Machineries And Equipment And Parts [This Encl Medical/Bio-Medical/Surgical Laboratory/Body Fitness Machinery & Parts Thereof]
81 Railway/Metro-Railway/Trams & Rolling Stock
82 Road Surface Vehicle Excl Railways & Parts N.e.c
84 Human Being/Animal Driven Cart Etc
85 Aircraft And Spacecraft, Ship & Associated Transports
91 Optical, Photographic, Watch And Other Precision Equipment, Musical Instruments And Parts Thereof
92 Precious & Semi-Precious Stone/Jewellary; Works Of Art And Other Decorative Items N.e.c
93 Sports, Athletic Goods, Toys & Amusements Equipment And Human Safety Articles
94 Glass And Fibre Glass, Ceramic, Porcelain, Asbestos And Cement And Articles Thereof Incl Articles Of Stone
95 Miscellaneous Classified Manufacturing Articles And Parts Thereof
96 Misc Non Classified Manufactured Articles & Parts
97 Service Related Items
99 Miscellaneous Items Of Asi N.e.c
End of two digits codes

Three digits codes
111 Live Animals Chiefly For Food
112 Meat & Meat Products Edible
113 Fish & Fish Products Incl. Crustaceans & Other Aquatic Invertebrates Chiefly Used For Human Consumption. [This Sub-Division Does Not Incl. Marine Mammals, Caviar Or Caviar Substitutes Prepared From Fish Eggs]
114 Dairy Products, Poultry, Birds, Egg, Honey, Other Edible Products Of Animal Origin
115 Animal Fats & Oils And Cleavages Products Incl. Edible Fats, Animal Waxes [This Chapter Does Not Incl. Cocoa, Butter Fat, Fatty Acid]
116 Preparation Used For Animal Feeding
119 Other Produce Of Animal Origin
121 Edible Fruits & Nuts; Edible Vegetables And Certain Roots And Tubes And Their Products. [This Sub-Division Incl Both Fresh & Preserved Fruits & Nuts & Vegetables Incl. Cashewnut/Coconut Kernel]
122 Tea, Mate, Coffee And Spices
123 Cereals (Including Rice) And Pulsed Unmilled
124 Products And Milling Industries; Malt & Malted Milk, Starches, Inulin, Wheat Gluten Etc.; Flour & Flakes Of Potato And Dried Leguminous Vegetables. [This Sub-Division Excludes Rice]
125 Vegetable Oils & Fats & Their Cleavage Products And Vegetable Waxes
126 Oil Seed, Oilgenous Fruits, Misc Grains, Seeds And Misc Fruits; Edible Flour And Meals Of Oil Seed. [This Heading Incl Palm Nuts And Kernals Mango Kernels But Not Cashewnut Or Cocnut Kernels Which Will Fall Under 121]
127 Lac Gum, Resins And Other Vegetable Saps & Extracts
128 Residues & Waste Prepared Animal Fodder Excl Oilseed
129 Vegetable Products N.e.c Incl Waste, Fodder, Vegetable Plaiting Like Baboos, Bamboo Canes Split Used For Plaiting
131 Sugar, Molasses, Khandsari, Gur [This Sub-Division Does Not Incl Chemically Pure Sugars But Will Include Sacrose, Lactose, Maltose & Glucose Excl Medicaments Under Division 33]
132 Chocolate, Cocoa & Cocoa Preparations & Sugar Confectionery
133 Macaroni, Noodles, Couscous & Similar Products
134 Bakery Products

135 Fruit Juices & Vegetable Juices & Syrup, Pickles Chutneys Fruit Pulp Etc
139 Miscellaneous Edible Preparations And Food Products N.e.c [This Incl Food Colouring & Flavouring Material, Food Preservatives But Excl Yeasts Used For Laboratory Use]
141 Live Trees, Plants, Bulbs, Roots, Cut Flower & Ornamental Foliage
142 Produce Of Hydroponics
143 Produce Of Tissue Culture
144 Forestry & Logging Products
145 Produce Of Seri Culture
151 Beverages, Spirits And Vinegar
152 Soft Drinks, Mineral Water And Other Edible Preparations Of Water
153 Tobacco And Manufactured Tobacco Substitutes
154 Ice Including Edible Ice Products
156 Pan And Pan Masala And Related Ingredients
161 Natural Water & Ice For Industrial Use [This Excl Water For Clinical Use]
163 Misc Non-Edible Substances Of Animal/Vegetable Origin N.e.c
211 Salts, Sulpher, Lime, Stone, Granites & Marble
213 Gypsum, Plaster
214 Clay, Kaolin, Earth, Graphite, Sand, Quartz
215 Abrasive (Excluding Quartz) [Quartz Classified Under Sub-Division 214]
219 Crude Minerals
221 Iron Ores & Concentrates
222 Copper Ores & Concentrate
223 Aluminium Ores & Concentrates
224 Nickel Ores & Concentrates
225 Ash And All Residues Of Base Metals
226 Slags - All Types
227 Ores Of Precious And Semi-Precious Metals
229 Misc Ores & Concentrates N.e.c
231 Coal, Lignite: Products & By-Products
232 Petroleum Products & By-Products
233 Diesel Products & By-Products
234 Nuclear Fuel Incl Radio-Actives & Isotopes Compound; Alloys; Dispersions And Mixtures
239 Mineral Fuels, Solvent, Lubricants & Oils N.e.c
241 Gas (Fuel) Natural And Manufactured
251 Electrical Energy
291 Refractory Bricks, Blocks, Tiles & Similar Refractory Products [Ceramic Products Classified Under 943]
311 Inorganic Elements, Excluding Base Metals, Rare Gas,Halides And Sulphur Compunds
312 Inorganic Acids, Oxygen Compounds, Carbonates & Carbide
313 Sodium And Potassium Compounds
314 Inorganic Alkali And Compounds Thereof
315 Inorganic Halogen And Sulphur Compounds Of Metals/Non-Metals
316 Inorganic Nitrogen And Phosphorus Compounds
317 Inorganic Gases Including Rare Gases In Different States
319 Misc. Inorganic Compounds N.e.c
331 Vitamins
332 Hormones, Glands And Products Thereof
333 Antisera, Blood Fractions, Immulogical Products And Vaccines
334 Anti-Biotics & Preparations Thereof
335 Alkaloids & Preparations Thereof
336 Anti-Psychotic/Sedative/Hypnotic Medicines
337 Pharmaceutical Products Incl Family Planning Goods
338 Homeopath, Ayurvedic & Unani Medicines
339 Other Medicaments And Preparations Thereof
341 Organic Manures/Fertilizer

342 Inorganic Fertilizer [Crude Minerals Used As Fertilizer Is Classified Under Sub-Division 219]
343 Misc Fertilizer/Manures
344 Insecticides/Pesticides/Weedicites
349 Misc Chemical And Related Materials Used In Agriculture
351 Dyeing, Tanning Materials And Their Derivatives
352 Colouring Materials, Ink, Artist Ink, Paint Etc [This Excl Food Colours Vide Sub-Division 139]
353 Polishing (Non-Wax), Emulsifying, Distemper And Related Materials
361 Essential Oil And Essence
362 Cosmetics, Perfumes
363 Soap, Detergent, Whitening & Cleaning Materials [This Excl Medicated Products]
364 Wax & Polishing Materials
365 Dental & Dentistry Materials Excl Wax
371 Propellant/Explosive Powder
372 Detonator/Percussions Fuse Etc
373 Fire Works, Signaling Flare & Other Polytechnic Articles
374 Ferro-Cerium & Related Products
381 Photographic Film, Paper And Plates
382 Cinematography/Video Film, Cassette
383 X-Ray Film & Plates N.e.c
384 Misc Photosensitive Non-Photographic Film, Plates, Cloth, Drums Etc
389 Misc Photography, Cinematography Supplies
421 Bags/Boxes/Panels/Containers Of Plastic/Pvc
422 Tubes/Pipes/Basin & Sanitary Fittings Of Plastic/Pvc
423 Footwear Plastic/Pvc
424 Film (Non-Sensitive/Photographic)/Foil/Rolls/Tape/Rope Of Plastic/Pvc & Related Materials
425 Sheet/Linear/Cloth/Laminated Sheet Of Plastic/Pvc
426 Misc Articles Of Plastic/Pvc
427 Bakellite, Acrylic & Similar Items & Articles Thereof
429 Articles, Parts Of Plastic/Pvc N.e.c
431 Hides
432 Skins
433 Leather
441 Leather Bags, Cases, Purse & Other Novelty Items
442 Leather Apparels
443 Leather Footwear & Parts Thereof
449 Misc Leather Manufactured Items
451 Fur Skins And Articles Thereof
452 Artificial Fur And Articles Thereof
511 Wood & Wood By-Products [This Excl Forestry & Logging Products Classified Under Sub-Division 144]
512 Wooden (Incl Plywood) Furniture, Boxes (Incl Packing Box) And Other Wooden Articles
513 Charcoal
519 Miscellaneous Wooden Products
521 Cork And Articles Thereof
522 Thermocol And Products Thereof
531 Manufacture Of Straw, Basketware, Wickerware, Caneware
541 Pulp Of Wood & Other Fibrous Materials
551 Paper Used For Writing/Printing/Graphic Design/Computer Stationary
552 Paper (Uncoated) Used For Newsprint And For Other Special Purpose Excl Writing/Printing
553 Paper Coated, Cellulose Wading, Impregnated
554 Craft Paper And Paper For Special Use
555 Boards, Paper Boards All Kind
561 Printed Books, Newspaper, Periodicals, Note Books, Register Etc And Other Printed Matters

571 Packing Materials Made Of Paper [Paper Used For Packing Are Shown Under Respective Heads Under Division 55]
573 Misc Articles Of Paper Used As Container Etc
611 Silk Worms Incl Cocoons, Raw Silk, Raw Silk Waste
612 Silk & Art Silk Yarn Incl Silk Thread & Waste Thereof
613 Silk Fabrics Incl Silk Waste Fabrics
614 Silk Made Up Articles Incl Apparel
619 Other Silk Textile Goods
621 Wool Incl Fine, Raw, Coarse; Waste Of Animal Hair Incl Fur [Fur & Articles Thereof Classified Under Division 45]
622 Yarn Of Wool/Animal Hair Excl Fur [Fur & Articles Thereof Classified Under Division 45]
623 Fabrics Made Of Wool/Animal Hair & Waste Thereof [This Sub-Division Excludes Fur And Articles Thereof]
624 Made Up Articles Of Wool, Animal Hair Incl Apparel [This Sub-Division Excludes Fur And Articles Thereof]
629 Other Textile Products, Made Of Wool & Animal Hair.
631 Ginned Cotton, Cotton, Cotton Waste (Raw)
632 Cotton Yarn, Fibre Incl Cotton Thread
633 Cotton Fabrics Incl Cotton Hosiery Fabrics
634 Made Up Articles Of Cotton Incl Apparel
639 Other Cotton Textile Goods N.e.c
641 Man-Made Fibre Raw, Tow Of Viscose, Polyester, Filaments, Chips, Powder And Waste
642 Man-Made Yarn/Fibre And Waste Thereof
643 Fabrics Of Man-Made Fibre
644 Made-Up Articles Of Man-Made Fabrics
649 Man-Made Fibre Articles N.e.c
651 Raw Fibre Of Jute, Coir, Sisal, Hemp, Mista & Other Natural Fibre And Waste Thereof
652 Processed Fibre/Yarn Of Jute, Coir, Sisal, Hemp, Mista And Other Natural Fibre
653 Fabrics, Cloth Of Jute, Coir, Sisal, Hemp, Mista Etc
654 Man-Made Articles Natural Fibre
659 Other Jute And Natural Fibre Goods N.e.c
711 Pig Iron/Ferro Alloy Etc In Primary Form
712 Semi-Finished Products Of Iron/Steel
713 Finished Products Of Iron/Steel
714 Stainless Steel In Primary & Finished Forms
715 Manufacture Of Iron/Alloy Steel
721 Copper & Copper Alloy, Refined Or Not, Unwrought
722 Copper And Copper Alloy, Worked
723 Nickel And Nickel Alloys, Refined Or Not, Unwrought
724 Nickel And Nickel Alloys, Worked
725 Zinc And Zinc Alloys, Refined Or Not, Unwrought
726 Zinc And Zinc Alloys, Worked
731 Aluminium And Aluminium Alloys, Unwrought
732 Aluminium And Aluminium Alloys, Worked
733 Tin And Tin Alloys Unwrought
734 Tin And Tin Alloys Worked & Tin Plates Iron/Steel Products
735 Lead And Lead Alloys, Unwrought
736 Lead And Lead Alloys, Worked
737 Other Base Metals & Alloys Thereof, Unwrought
738 Other Base Metals & Alloys Thereof, Worked
761 Agricultural & Forestry Machineries/Parts Thereof
762 Food, Beverages & Tobacco Processing Machineries & Parts
763 Minings, Quarrying & Metallurgical Machineries/Parts
764 Construction/Cement Machineries & Parts
765 Textile, Leather & Rubber Processing, Paper Printing Machineries & Parts Thereof

766 Non-Electrical Domestic/Office Appliances & Parts
767 Chemical/Plastic/Glass/Weapon/Ammunition Machineries And Parts Thereof
768 Lift And Lifting Equipment, Fixed Or Mobile & Parts Thereof
769 Misc Non-Electrical Machineries And Parts Thereof, N.e.c
771 Electrical Machinery/Equipment
772 Electrical Motors, Generators, Transformer, Power Pack [This Incl Pump Set Fitted With Electric Motor]
773 Switch, Switch-Gear, Control Panel, Circuit Breakers Etc And Parts Thereof
774 Lamp, Filament, Electrodes/Anodes/Connectors, Fittings & Parts
775 Measuring/Controlling/Regulating Instruments
776 Battery, Accumulators, Cells And Parts Thereof
777 Domestic And Office Electrical Equipment
778 Electro Magnet, Fans, Armature, Coils & Electro-Magnetic Equipment
779 Electrical Equipment, Parts And Accessories, N.e.c
781 Telephone/Telecommunication/Transmission Equipment
782 Audio/Video/Sound Apparatus & Parts
783 Computer & Computing Equipment & Peripherals & Parts
784 Electronic Valves/Tubes & Components
785 Electronic Cards & Its Components
789 Other Electronic Components & Parts
791 Non-Conventional Energy Generation Equipment
792 Machineries For Re-Cycling Materials
793 Special Application Equipment, Nuclear Reactor Etc & Parts
794 Fabricated & Structural Construction & Machinery
795 Medical/Bio-Medical, Surgical, Laboratory And Health Fitness Equipment & Parts
811 Railways, Metro-Railways, Trams & Rolling Stock
812 Railways Rolling Stock N.e.c
813 Metro Railways And Tramways & Rolling Stock
821 Motor Vehicles - Passengers/Goods Transportation And Special Purpose Vehicles
822 Chassis/Body - Motor Vehicles, Parts N.e.c
823 Motor Cycle, Scooter, Moped & Parts N.e.c
824 Non-Motorized Cycles/Wheel Chairs & Parts N.e.c
845 Cart, Animal Driven/Hand-Driven
851 Aircraft/Helicopter & Other Flying Machines
852 Ships, Boats And Other Waterways Transports
911 Optical & Photographic Equipment & Parts
912 Precision Equipment For Measuring Solar Other Non-Conventional Energy
913 Survey, Design & Laboratory Equipment & Parts
914 Clock Scientific/Quartz And Parts Thereof
915 Musical/Fine Arts Instruments & Parts Thereof
921 Precious & Semi-Precious Stone/Jewellary Etc
922 Works Of Art Including Imitation, Fancy And Decorative Items
923 Hair, Fine Fibre, Natural/Artificial & Articles Thereof
931 Sports And Athletic Accessories
932 Human Safety Articles & Parts Thereof
933 Toys And Amusement Articles
934 Arms & Ammunitions & Parts Thereof
935 Domestic/Industrial Safety Aricles & Parts Thereof
941 Glass And Glassware
942 Fibre Glass & Articles Thereof
943 Ceramic, Porcelain And Articles Thereof
944 Asbestos, Cement And Articles Thereof
951 Currency Coins
952 Common Purpose Stationary Items
954 Advertising Materials/Boards (Completed) N.e.c

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961 Manufactured Items & Parts N.e.c
971 Sales, Maintenance, Repair & Trade Services
972 Hotel And Restaurant Services
973 Communication, Transport & Storage Services
974 Real Estate, Leasing & Rental Services, Financial Intermediation Services
975 Legal, Accounting, Auditing & Book Keeping Services
976 Film/Video/Advertising/Decorative Industry Services
977 Architectural, Engineering & Other Technical/Consultancy Services
978 Services Provided By Extra Territorial Organisation
979 Community, Social, Personal Services & Misc
992 Unspecified Inputs/Outputs
999 Total Consumption/Control Totals
## End of Three digits codes ##

### END of codes to select from###

"The codes provided are hierarchical in terms of digits. Codes with 3 digits
are more specific than codes with 2 digits. You should prefer to choose the
finest code possible.
```

We follow this with a message asking for the assignment given the particular firm description

```
The company we are looking at produces: FIRM DESCRIPTION.
Which are the best matches from the codes PROVIDED earlier?
Please provide up to five (5) matches, separated by ';' and list them in order from best to worse
    .
You do not need to provide a code if the product is too vague.
If not possible to select any option, you should PRINT 'None'.
```