ROCKWOOL FOUNDATION
BERLIN
INSTITUTE FOR THE ECONOMY AND THE FUTURE OF WORK

CReAM Centre for Research & Analysis of Migration

DISCUSSION PAPER SERIES 24/25

Inventors' Coworker Networks and Innovation

Sabrina Di Addario, Zhexin Feng, Michel Serafinelli

JUNE 2025

ROCKWOOL Foundation Berlin
www.rfberlin.com

Centre for Research & Analysis of Migration
www.cream-migration.org

Inventors' Coworker Networks and Innovation *

Sabrina Di Addario, Zhexin Feng and Michel Serafinelli †

June 2025

Abstract

This paper presents direct evidence on how firms' innovation is affected by access to knowledgeable labor through co-worker network connections. We use a unique dataset that matches patent data to administrative employer–employee records from "Third Italy"— a region with many successful industrial clusters. Establishment closures displacing inventors generate supply shocks of knowledgeable labor to firms that employ the inventors' previous co-workers. We estimate event-study models where the treatment is the displacement of a "connected" inventor (i.e., a previous coworker of a current employee of the focal firm). We show that the displacement of a connected inventor significantly increases the hiring of connected inventors. Moreover, the improved access to knowledgeable workers raises firms' innovative activity. We provide evidence supporting the main hypothesized channel of knowledge transfer through firm-to-firm labor mobility by estimating IV specifications where we use the displacement of a connected inventor as an instrument to hire a connected inventor. Overall, estimates indicate that firms exploit displacements to recruit connected inventors, and the improved capacity to employ knowledgeable labor within the network increases innovation.

Keywords: social connections; firm-to-firm labor mobility; patents; establishment closures

JEL Classification: J20, J24, J62, O30.

*We thank Federico Barbiellini Amidei, David Card, Federico Cingano, Thomas Cornelissen, Tom Dean, Emma Duchini, Sebastian Findeisen, Albrecht Glitz, Bronwyn Hall, Lena Hensvik, Mitchell Hoffman, Pat Kline, Tingmingke Lu, Astrid Marinoni, Myra Mohnen, Enrico Moretti, Oskar Nordström Skans, Eleonora Patacchini, Santiago Pereda Fernández, Nicholas Reynolds, Andrea Weber, Alexander Whalley, Sebastien Willis, and audiences at AIEL, Bank of Italy, EALE, GEIRC, IAAE, RES, UEA, University of Essex, and University of Toronto for helpful input, comments, and suggestions, and Giovanni Angioni, Alessandro Ferrara and Fergus Herron for excellent research assistance. Michel Serafinelli gratefully acknowledges financial support from SSHRC and Connaught. We are grateful to Bartosz Korchowiec, who collaborated in the early stages of this research.

†Authors affiliations: Bank of Italy; King's College London and The Productivity Institute; King's College London, RFBerlin, ESCoE, CESifo.

1 Introduction

A prominent feature of the labor market is firms' tendency to recruit through informal networks: surveys across OECD countries indicate that 15–50 percent of jobs are found through social connections, while around 70 percent of US companies encourage referral-based hiring (Pellizzari, 2010; Saygin, Weber, & Weynandt, 2019; Friebel, Heinz, Hoffman, & Zubanov, 2019). Researchers have speculated that firms benefit from using informal networks, for example, because of a reduction in information asymmetries, turnover, and hiring costs. Studies exploring the possible advantages in terms of innovation are limited, which is a pitfall given the importance of innovation for economic growth. Inventors are strategic to innovation but are a scarce factor of production: each given firm has access to a very limited supply of inventors for recruitment with reduced frictions, and thus informal connections could be a privileged channel to recruit them (Dustmann, Glitz, Schönberg, & Brücker, 2016).

This is the first paper that presents direct evidence of the impact of increased access to knowledgeable labor (i.e., inventors) through co-worker network connections on firms' innovation.[1] In confronting the non-trivial measurement challenges involved, we take advantage of a unique dataset that matches the universe of European Patent Office (EPO) patents to administrative employer–employee records from the so-called "Third Italy"—a macro-area in the North-East of the country characterized by a high concentration of successful industrial clusters. We build on these data by constructing the firm's co-worker network of inventors.[2] To our knowledge, this is the first study to have done so. Firms' innovative activity is proxied by the number of patent applications to the EPO. Our empirical strategy exploits the establishment closures that displace inventors in the labor market, generating a shock to the supply of knowledgeable labor. Our approach is similar to that of Eliason, Hensvik, Kramarz, & Skans (2017): we argue that the inventor displacement shock may be more specific to the connected firms, which may experience increased access to knowledgeable labor and thus an improvement in their chances of patenting compared to non-connected firms.

We estimate event-study models where the treatment is the displacement of a connected inventor. This research design allows us to test for the presence of pre-trends in the outcomes and enables us to recover the dynamics of the effects of interest. We document that the displacement of a connected inventor significantly increases the hiring of connected inventors, while not affecting the recruitment of non-connected inventors.

[1] In this paper, firm j is "connected" to an inventor if the latter has previously been a coworker of at least one of firm j's employees.

[2] We include only establishments with less than 500 employees to reduce the incidence of imprecise connections, since the chances of having a real contact among the workers in very large establishments are low.

Moreover, we show that improved access to knowledgeable workers raises firms' innovative activity. Specifically, in the event study, the estimated average increase in patent applications in the five years after a connected inventor's displacement is 0.27 standard deviations. The baseline analysis uses simple patent counts, but conclusions are very similar when we use citation-weighted patent counts.

We analyze empirically the evidence in favor of our main hypothesized channel: knowledge transfer through firm-to-firm labor mobility. The underlying intuition is that knowledge, which is mostly embedded in high-skilled employees, spreads when these workers move across firms (Dasgupta, 2012). Specifically, we assess the effect of hiring a connected inventor on firms' innovative activity with an instrumental variable approach, using the displacement of a connected inventor as an instrument for the hiring of a connected inventor. Since inventors are scarce, firms compete to hire them; the firms connected to displaced inventors through their employees may have a preferential channel to recruit them. The impact of a connected inventor's displacement on the firm's capability to innovate occurs through hiring. An alternative hypothesis is that firms' hiring decisions are based on nepotism (Beaman & Magruder (2012); Wang (2013)). A positive estimated effect in the IV regression is consistent with the hypothesis that informal connections reduce hiring frictions and channel valuable information to firms, while a negative impact is consistent with the hypothesis that nepotism plays a significant role in the recruitment process.

The IV estimates indicate that hiring a connected inventor has a large positive impact on patent applications.[3] This additional output is not restricted to the patents authored or co-authored by the newly hired connected inventor, but it also refers to the patents exclusively authored by the other workers of the destination firm. Thus, the addition of a new inventor appears to "fertilize" the firm, spurring the development of new patent applications by its employees.

A potential identification concern arises in case shocks to the supply of knowledgeable labor partly capture market-level shocks (Cestone, Fumagalli, Kramarz, & Pica, 2016; Gathmann, Helm, & Schönberg, 2020)). We do not expect this to be a major issue in our context, since the closing establishments in our sample are mostly small to medium-sized (a median of around 100 employees), and thus the market effects originating from their closure are likely to be rather limited. Nevertheless, to allay concerns of market effects, we show additional estimates when controlling for the number of displaced workers in the local labor market (LLM) and industry. Furthermore, we perform a "placebo"-type analysis, showing no effect from the displacement of inventors with connections to other firms

[3] When interpreting these estimates, it is important to highlight that the hiring of a connected inventor is a major change in terms of the workforce for the average firm in our data.

in the same LLM and industry (i.e., companies different from the focal firm). Specifically, we investigate how innovation at firm j reacts to the displacement of inventors who are connected to other firms in the same LLM and industry but not to the focal firm j.[4] The results indicate that the estimated average change over the five years following the placebo event is non-significant. While we cannot completely rule out the possibility of market effects, the placebo result does not appear consistent with this possibility.

Overall, our evidence indicates that firms take advantage of displacements to recruit connected inventors. Moreover, the improved ability to employ connected inventors increases firms' patenting activity. More generally, our estimates suggest that informal connections involving knowledgeable workers reduce hiring frictions and channel valuable information to firms. We show that this process benefits firms' innovation by expanding the availability of knowledgeable labor. The documented increase in firms' patenting activity is consistent with our hypothesis of knowledge transferred through inventor mobility, while it is not with the alternative hypothesis that nepotism plays an important role in hiring decisions.

The remainder of this paper is organized as follows. Section 2 discusses the relation of our paper to previous research. Section 3 presents the data and provides some background information for "Third Italy", while Section 4 discusses our econometric strategy and presents the results and various robustness checks. Finally, Section 5 concludes the paper.

2 Relation to Previous Research

Our work is mainly related to the literature on networks, workers' mobility, and innovation.

First, our paper is linked to the research on the impact of networks on the labor market. A first set of studies within this theme uses matched employer—employee data to explore network effects on the labor market and related outcomes. The work of Eliason et al. (2017) is closest to our paper. In particular, the authors assess the causal effect of co-worker connections in the context of displacement and analyze firm-level outcomes, focusing on the impact on total hires, value-added, and job separations. Our empirical strategy builds directly on theirs, using a similar type of supply shock and conceptual framework. Using an armed-force test, Hensvik & Skans (2016) report that firms are able to hire workers with higher cognitive skills when recruiting a previous colleague of their current employees. Kramarz & Skans (2014) show that family ties are important to determine where young workers find their first job, while Eliason, Hensvik, Kramarz, & Skans (2023) focus on whether social connections can increase inequality and determine that

[4] See Eliason et al. (2017), p.5.

high-wage workers sort in high-wage firms because of their networks ("birds of a feather flock together").

A second body of work within the network literature analyzes the transmission of information through connections. Cingano & Rosolia (2012) and Glitz (2017) find that having thicker networks of employed former coworkers increases the re-employment probability of workers displaced after a firm closure. Pellizzari (2010) hypothesizes that finding a job through the network improves the quality of the match and thus raises wages, but finds heterogeneous empirical results across countries. Schmutte (2015) reports evidence of the positive sorting of high-ability workers to high-paying firms when their neighbors are employed in high-paying firms. Battisti, Peri, & Romiti (2016) determine that the people who emigrate to German districts with larger co-ethnic networks are more likely to find a job soon after arrival (see Topa (2011) for a review of additional studies in this area). Saygin et al. (2019) combines features of these first two sets of studies and analyzes work-related networks from the standpoint of both job seekers and hiring firms, using matched employer–employee data. Their evidence indicates an important contribution of networks in the transmission of job information and strongly suggests that the main channels are knowledge transfer on demand-side conditions and job referrals.

A final set of studies related to networks analyzes referral programs and their impact on a variety of labor market outcomes. For example, Dustmann et al. (2016) and Glitz & Vejlin (2021) document a larger initial wage premium and longer job tenure for referred workers. Burks, Cowgill, Hoffman, & Housman (2015) find that in call centers and trucking, referred employees yield higher profits per worker than non-referred employees due to lower turnover and recruiting costs, while in high-tech sectors they produce more patents. Friebel et al. (2019) finds that having an employee referral program reduces attrition and decreases firm labor costs.

We contribute to the literature on networks by specifically analyzing inventors and innovation, and by using a research design that permits both to test for the presence of pre-trends in the outcomes and to recover the dynamics of the effects of interest. Although the mechanisms we document may also apply to other types of workers and outcomes, we focus on inventors and patenting firms since they are key drivers of economic growth and are deemed to foster sizable positive social externalities (Bloom, Schankerman, & Van Reenen, 2013; Bell, Chetty, Jaravel, Petkova, & Van Reenen, 2019).

Moreover, while the issues analyzed in this paper are of general interest, the specific case of "Third Italy" is also important. This is a macro-region rich in networks of specialized producers frequently organized in industrial districts (IDs). IDs have been effective in promoting and adapting to technological change during the period of analysis. This large economic area has been the focus of much research, both in Europe and in the United

States.[5]

Second, our paper is related to the literature on R&D spillovers, the mobility of R&D personnel, and the implications of firm-to-firm labor mobility for firm-level outcomes. Fons-Rosen (2013) finds that foreign direct investment has a greater impact on the host economy in terms of knowledge diffusion when firms relocate inventors from the already established R&D labs in their home country to newly developed labs in the host country. Maliranta, Mohnen, & Rouvinen (2009) report that the firms involved in non-R&D activities hiring workers from R&D-intensive firms tend to perform better.[6] Balsvik (2011) offers a detailed account of the productivity gains linked to worker flows from foreign multinationals to domestic firms in Norway.[7] Parrotta & Pozzoli (2012) provide evidence from Denmark regarding the positive impact of the recruitment of "knowledge carriers" –technicians and highly educated workers recruited from a donor firm—on a firm's value-added. Stoyanov & Zubanov (2012) show that Danish firms that hire workers from more productive firms increase their productivity. Fons-Rosen, Kalemli-Ozcan, Sorensen, Villegas-Sanchez, & Volosovych (2017) explore the impact of FDI on the productivity of host-country firms and show that inventor mobility across sectors is a key channel of technology transfer. Serafinelli (2019) finds evidence of labor market-based knowledge spillovers in the Veneto region of Italy.

Our findings are consistent with these empirical contributions. Unlike the above authors, who focus on the relationship between labor mobility and productivity, we also shed light on a broader question: how firms' innovation is affected by access to knowledgeable labor through co-worker network connections, particularly through inventors. Although inventors are not the only workers who may transfer relevant information from one firm to another, they undoubtedly have the largest potential to do so.

Third, our paper is related to the literature on knowledge diffusion, inventors, and innovation (Kantor & Whalley, 2014; Fons-Rosen, Scrutinio, & Szemeredi, 2016; Moretti, 2021; Ganguli, Lin, & Reynolds, 2020; Huang, Moretti, & Xia, 2023).[8] In particular,

[5] Brusco (1983); Piore & Sabel (1984); Trigilia (1990); Whitford (2001); Becattini, Bellandi, & De Propris (2014); Trigilia (2020)

[6] Bloom et al. (2013) determine the impact of technology spillovers and that of the product market rivalry of R&D (negative business-stealing effects on the product market). They analyze a 20-year panel of US firms and show that knowledge spillovers quantitatively dominate product market spillovers. Related contributions on knowledge spillovers include Breschi & Lissoni (2001), Dechezleprêtre, Martin, & Mohnen (2017), and Crescenzi & Gagliardi (2018). Kaiser, Kongsted, & Rønde (2015) show that the mobility of R&D personnel enhanced the patenting output of Danish firms during the period 1999–2004. Other papers combine register data with patent data and study features of the work history of inventors (see, for example, Kline, Petkova, Williams, & Zidar (2019), Depalo & Di Addario (2014), and Di Addario & Wu (2024)).

[7] Likewise, Poole (2013) finds a positive effect of the share of new workers previously employed by foreign-owned firms on wages paid in domestic firms in Brazil.

[8] A related body of work focuses on the effect of innovation on productivity and employment growth (Hall, Lotti, & Mairesse, 2008; Marin & Lotti, 2016).

our study is related to the research investigating network effects in science. For example, Mohnen (2022) shows that network position is crucial in determining scientific production by facilitating access to other scientists' non-redundant knowledge through coauthorship links. Another related body of the literature analyzes peer effects in the workplace induced by knowledge spillovers and finds mixed evidence. On the one hand, Waldinger (2010), for example, finds that faculty quality is a very important determinant of PhD student outcomes. On the other hand, Cornelissen, Dustmann, & Schönberg (2017) obtain only small peer effects on wages in high-skilled occupations, and Waldinger (2012) shows that even very high-quality scientists do not affect the productivity of their local peers. Other papers within this body of literature report productivity spillovers, with social pressure as a main driver (Mas & Moretti, 2009; Bandiera, Barankay, & Rasul, 2010). A final set of related studies focuses on the mobility of immigrant scientists. For example, Moser, Voena, & Waldinger (2014) analyze chemical inventions and compare the changes in US patenting by US inventors in the research fields of German Jewish émigrés to changes in US patenting by US inventors in the fields of other German chemists. They show that US patenting activity has increased in the research fields of German-Jewish refugees who emigrated after 1933.

3 Data and Descriptive Statistics

3.1 Data

Administrative Records and Patent Data

We build on the database provided by Depalo & Di Addario (2014), who linked, for the period 1987–2008, patent data from the EPO Worldwide Patent Statistical Database (PATSTAT, henceforth) and the employer–employee matched data from the Italian Social Security Institute (Istituto Nazionale di Previdenza Sociale, INPS) to study inventors' returns to patents. Specifically, we add to their work by computing the network for each firm in the sample.

The INPS dataset has information on all private sector employees . In particular, it contains register-based information for any job lasting at least one day, thus allowing for the reconstruction of the employment history of each worker in the analyzed period. The available information at the individual level includes: age; gender; municipality of residence and municipality of birth; work status (blue collar, white collar, manager, and other); type of contract (full-time versus part-time); and gross yearly earnings. The information on firms includes average gross yearly earnings, yearly number of employees, industry, location (at the municipality level), and date of firm opening and closure.

PATSTAT contains the universe of patent applications and grants presented at the EPO by any Italian "applicant" (i.e., the firm submitting a patent application and retaining the relative property rights). The database provides a detailed description of each patent submission, including its title, abstract, and technological field, the name and address of all its inventors and applicants, the dates of application filing, publication, and grant obtainment, and the citations received.

PATSTAT does not have a reliable firm identifier. Thus, INPS matched the two datasets with an exact procedure ensuring that, in the year of submission, the inventors appearing in each patent were indeed employed by an INPS firm corresponding to the PATSTAT applicant.[9] The resulting dataset includes the full work history of the inventors, namely, social security information for all firms in which inventors have worked during their career, also covering firm-year observations before their first patent application. More generally, our dataset includes the full work history of the employees working in any of the patenting firms, even if they moved from/to a non-patenting firm. Thus, the dataset includes both firms that exhibit one or more patent applications during the sample period and firms that have none.

In this paper, we assign the status of "inventor" to an employee only after her/his first patent application.[10] More precisely, we define a worker as being an inventor in year m if she/he has already submitted a patent application in year $t \leq m$. Note that we also observe all the co-workers of these inventors for all the establishment-year observations.

Co-worker Network

We construct the firm's network using co-worker links, detected from the employment history of each worker. More precisely, the employee's network comprises all her/his former co-workers in the previous five years, while the firm's network is the collection of the co-worker networks of each incumbent employee.

The co-worker network is constructed for each establishment and year. In the sample, we include only establishments with less than 500 employees to reduce the incidence of imprecise connections, since the chances of having a real contact among the workers are low in very large establishments.

Establishment Closures and Displaced Inventors

[9] See Depalo & Di Addario (2014) for an in-depth description of the matching procedure. In summary, the datasets were merged in several steps. First, the authors attributed VAT codes to PATSTAT applicants based on their name and location, after verifying them with four alternative datasets (Cebi, Infocamere, INPS, and Orbis). Then, INPS linked PATSTAT applicants to all possible INPS establishments that had the same VAT identifier and the same name and location (at the municipality level). Finally, INPS verified in its records that there was a correspondence between INPS employees/firms and PATSTAT inventors/applicants.

[10] There are $5,888$ inventors in our dataset.

Our empirical strategy uses establishment closures to identify the supply shock of knowledgeable workers within a firm's network. Considering the five-year interval necessary to form the firm's network, we are interested in the closures starting from 1992.

To identify "true" establishment closures, namely, those that are not a result of a merger, a change of tax identifier, or a spin-off, we analyze worker flows from closing establishments and denote a closure as "true" whenever the maximum cluster of outflow from the closing establishment to any other firm is below 50 percent of the workforce of the closing establishment—estimates are qualitatively similar if we use a 30 percent threshold.

Using the information on establishment closures, we can detect all the employees (independently of whether they are inventors) who are subject to displacement. We denote workers as displaced at time t if they terminate their job in the same year their establishment closes. In this paper, we are interested in the displacement of inventors, who account for approximately 0.004 percent of all the workers displaced because of an establishment closure.

Macro-region of study: "Third Italy"

This paper covers the large economic area of "Third Italy", which includes the following administrative regions located in the Center-North-East of the country: Emilia-Romagna; Friuli-Venezia Giulia; Marche; Toscana; Trentino-Alto Adige/Südtirol; and Veneto. The combined population of these regions contains around 16.9 million people (28 percent of the total population in Italy). In the 16-year analysis period, the labor market of this macro-area was overall characterized by a good performance in terms of total employment, job creation in manufacturing, migration flows, and business creation (see, for example, De Blasio & Di Addario (2005)), especially in Emilia-Romagna and Veneto.

Our territorial units are the LLMs, which are territorial groupings of municipalities that partition the entire Italian territory and have been singled out by the National Institute of Statistics based on working-day resident population commuting flows.[11] LLMs can be considered self-contained labor markets since their resident population largely overlaps with the working population. In 1991, the almost $1,900$ municipalities (*Comuni*) in our six administrative regions were grouped into about 235 LLMs. A sizable fraction of these LLMs is thick with small- and medium-sized manufacturing firms within the so-called industrial districts (IDs). These firms are spatially concentrated and generally locally owned. The system is characterized by a very detailed inter-firm division of labor among a large number of firms specialized into one or a few stages of a main manufacturing

[11] Also France, with its *zones d'emploi*, and the UK, with its travel-to-work areas, partition their territories into areas with similar characteristics.

production (main industry). Firms can be vertically, horizontally, and diagonally linked, and can be specialized in a few phases of the productive process, in making contacts with the final markets, in service activities, or in manufacturing activities complementary to the main industry. The vicinity of firms creates labor market pools of specialized workers.[12]

A distinctive feature of "Third Italy" is the large presence—since the early 1970s—of networks of flexible producers frequently organized in IDs, with the level of industrial value added often greatly exceeding the national average, particularly in the areas around Bologna, Padua, and Verona (see, for example, Tattara & Valentini (2010) and Trigilia (2020)). Germany's Baden-Wuerttemberg and the British Motor Valley (centered in Oxfordshire and stretching into East Anglia and Surrey) are other examples of similar regional network-based industrial systems. Additional examples have been identified in recent decades in Japan, Scandinavia, Spain, and the United States (Saxenian, 1994; Henry & Pinch, 2000; Becattini et al., 2014).

Manufacturing firms in the dynamic districts of Third Italy specialize in industries such as metal, mechanical, electrical, and biomedical engineering, automotive, construction materials and technologies, goldsmithing, ceramics, glass, agri-food, furniture, printing and publishing, musical instruments, toys, and fashion-wear. Several of these clusters feature some leader firms, especially in Veneto.[13]

3.2 Descriptive Statistics

Our panel includes $84,173$ firm-year observations, and its main characteristics are summarized in Table 1.

Our main outcome of interest is firms' innovative activity: we take a patent application as a signal of the presence of some innovative output. The first row of Table 1 shows that the mean number of patent applications in the whole sample is 0.038; after restricting to the firms that have submitted at least one patent application during our sample period the mean number of patent applications raises to 0.318.[14]

The mean number of connected inventor hires in our sample is 0.008 (Table 1, second row). This share is low because our dataset also includes non-innovative firms, but it is nevertheless double that of non-connected inventor hires (equal to 0.004, as shown in the third row of the table).

[12] "Employers are apt to resort to any place where they are likely to find a good choice of workers with the specialized skills that they require, while men seeking employment naturally go to places where many employers need skills such as theirs and where therefore it is likely they will find a good market" (Marshall, 1890).

[13] An example is the eyewear district in the province of Belluno, where Luxottica, the world's largest manufacturer of eyeglasses, has production establishments.

[14] Notice that 90 percent of the $7,666$ firms of our sample never patent during the period of analysis.

The fourth and fifth rows of Table 1 report that the average firm employs 47 workers, with a mean co-worker network of 866 individuals. Finally, the last two rows indicate that the mean number of connected displaced inventors and non-inventors is 0.011 and 2.93, respectively.

Table 2 displays the summary statistics for the number of events, displacements, and inventor hires by year. Connected and non-connected hires are indicated separately. The table shows that almost 450 inventors have been displaced during the period of analysis. Since each inventor could have been connected to more than one company, the number of firms that may have potentially be affected by the displacement of a connected inventor is higher. Overall, 633 firms have been "exposed to the event" of interest. In the same period, more than 680 connected inventors and about 340 non-connected inventors have been hired (independently of whether they had been displaced). The table shows that there is sizable variation over time in the number of events, displacements, and inventor hires.

4 Econometric Framework and Results

The objective of our analysis is twofold. First, we aim to estimate the effect of changes in the supply of connected knowledgeable workers on the patent activity of the firm. In particular, we estimate event-study models where the event is the displacement of an inventor connected to firm j's current workers. This research design allows us to test for the presence of firm-specific pre-trends in the outcomes and to recover the dynamics of the effect of interest. Second, we aim to provide evidence supporting the main hypothesized channel of knowledge transfer through firm-to-firm labor mobility by estimating IV specifications, where we use the displacement of a connected inventor as an instrument for the hire of a connected inventor.

For identification, our econometric analysis exploits establishment closures. The underlying concept is that firm j's ability to hire through the network is affected by the displacement (from some other establishment q) of inventors connected to j's current workers. Specifically, co-worker connections generate a firm-specific shock to the supply of knowledgeable labor by directing the displaced inventors towards the connected firms. As a result, these firms experience an improvement in the chances of recruiting connected inventors.

4.1 Event-Study Approach

We use an "event-study" research design (Autor (2003) and Kline (2012)) to investigate how displacement events affect both the hiring of a connected inventor and the patenting activity of the destination firm. Specifically, the regression equation is:

$$Y_{jslt} = \beta_0 + \sum_{\tau} \beta_\tau D^{\tau}_{jt} + Trend_{st} + Trend_{lt} + \lambda_j + \alpha_t + u_{jslt}, \tag{1}$$

where the dependent variable is: (a) the number of connected inventors hired by firm j at time t (hired from any industry or LLM, without restrictions); or (b) the number of firm j's patent applications. We include year dummies (α_t) and allow for permanent differences across firms (λ_j) and industry-specific and LLM-specific (linear) trends ($Trend_{st}$ and $Trend_{lt}$). We cluster standard errors at the LLM level.

The D^{τ}_{jt} are a sequence of "event-time" dummies equal to one when the displacement of a connected inventor is τ years away. Thus, the β_τ coefficients characterize the time path of the outcome relative to the date of the event. The event time indicator "-4" is set to 1 for the fourth year preceding the event and for all the years before, and 0 otherwise. The event time indicator "+5" is set to 1 for all the periods successively following the fifth year after the event, and 0 otherwise.[15] Since the sample of treated firms is unbalanced in event time, these endpoint coefficients give different weights to firms experiencing the treatment early or late in the sample period. Therefore, in discussing the treatment effects, we concentrate on the event-time coefficients falling in the five-year interval within $\tau = 0$ and $\tau = 4$, which are identified from a nearly balanced panel of firms. We normalize β_{-1} to zero such that all post-treatment coefficients can be considered as treatment effects.
We use both the interaction weighted estimator (Sun & Abraham, 2021) and the conventional two-way-fixed effects (TWFE) estimator. Connected inventor displacements occurring later may be different from those occurring earlier, generating cohort-specific treatment effects. In the main analysis, we thus implement the interaction-weighted estimator for an event study.[16] Sun & Abraham (2021) prove that this estimator is consistent for the average dynamic effect at a given relative time even under heterogeneous treatment effects. We use the last cohort as the control cohort (and the never-treated as the control cohort in a robustness check). We use the conventional two-way-fixed effects event study design estimation in the sensitivity analysis.
An identification concern potentially arises if the shocks directed to the supply of knowledgeable labor also pick up market-level shocks. We do not expect this to be a major issue in our context, since our sample comprises mostly the closures of small to medium-sized firms, for which the market effects are likely to be quite limited (the median closing establishment has around 100 employees). Nevertheless, to allay concerns of market effects, below we show additional estimates controlling for the number of displaced workers in the

[15] In case of multiple events within a firm, we include only its first event and the time before its second event.

[16] We use the "eventstudyinteract" Stata routine available at https://economics.mit.edu/grad/lsun20/stata.

LLM and industry. In Section 4.3, we also perform a "placebo"-type analysis, exploiting the displacement of inventors connected to other firms in the same LLM and industry.

4.1.1 Evidence: Recruitment of Connected Inventors

We now turn to investigating how the hiring of connected inventors is affected by displacement events. As explained in Section 3.2, our data comprise 633 events: more than 600 firms are potentially affected by the displacement of a connected inventor.

We start by discussing the estimates of the specification in which the dependent variable of Equation (1) is the number of *connected* inventor hires at time t. The estimated coefficients (displayed in Figure 1) show that the number of connected inventor hires has a distinct peak at the time of a connected inventor displacement. The 0.045 increase in the number of connected inventor hires is equivalent to a 0.44-standard-deviation increase (the standard deviation of the number of connected hires in the sample is 0.103; see Table 1).

Next, we verify whether the development displayed in Figure 1 is also confirmed when using the number of *non-connected* inventors hired by the firm at time t as the dependent variable. However, results indicate that non-connected inventor hires are not affected by the displacement of a connected inventor (the dynamics of the coefficients of interest are reported in Figure A1).

Overall, these results are consistent with the hypothesis that firms take advantage of the displacement of a connected inventor to recruit connected knowledgeable labor.

4.1.2 Evidence: Innovation

The main goal of this paper is to measure the extent to which access to knowledgeable workers has an impact on firms' innovation. We now turn to estimate the version of Equation (1) in which the number of patent applications is the dependent variable.

Figure 2 plots the baseline β_τ coefficients. The figure has two important features. First, there is no pretreatment trend in the coefficients, lending support to the validity of our research design. This support is reinforced by the lack of pre-trends in the hiring of connected inventors (Figure 1). The second important feature of Figure 2 is that there is an upward shift in innovation after the displacement of a connected inventor.

Although the pattern in Figure 2 is clear, the individual β_τ coefficients are not estimated very precisely. It is helpful to offer more formal tests of the null hypothesis that the displacement of a connected inventor has no impact on firms' innovation. To increase statistical power we test hypotheses on the average of the β_τ coefficients over various time intervals, as in Kline (2012). The results are shown in Table 3. The estimated average increase in patent applications over the five years starting with the year of a connected inventor's displacement (i.e., the average of the coefficients on $\tau = 0$, $\tau = 1$, $\tau = 2$, $\tau = 3$, and $\tau = 4$) is significant and amounts to 0.095 patent applications. A 0.095 increase in the number of patent applications is equivalent to a 0.27-standard-deviation increase (the standard deviation of the number of patent applications in the sample is 0.35; see Table 1). In Figure A2 we control for the number of displaced workers in the LLM and industry: estimates are very similar to the baseline ones discussed above (estimates are also very similar if we split this variable into displaced inventors and displaced non-inventors).

4.2 IV Estimation

In this section, we provide evidence supporting the main hypothesized channel of knowledge transfer through firm-to-firm labor mobility by estimating IV specifications where we use the displacement of a connected inventor as an instrument for the hire of a connected inventor (in any LLM or industry). This approach assumes that the whole impact of a connected inventor displacement occurs through the connected inventor hire. The underlying concept is that knowledge may be partly embedded in inventors, and firms can gain access to this knowledge by hiring them. Research exploring the possibility of knowledge transfer through firm-to-firm labor mobility includes Dasgupta (2012), who studies a dynamic general equilibrium model with mobility of workers among countries, in which the long-term dynamic learning process plays a crucial role. In the model, workers learn from their managers, and knowledge diffusion takes place through labor flows.[17] In Combes & Duranton (2006)'s theoretical analysis, firms selecting their production site foresee that they can enhance their productivity by poaching workers from other companies.

The implementation of our IV strategy is as follows. Let *Inventor Hire*$^{conn.}$ denote a dummy variable equal to one in each of the five years following a connected inventor hire, and zero otherwise. The econometric equation is:

$$Y_{jslt} = \beta_h \textit{Inventor Hire}^{conn.}{}_{jt} + Trend_{st} + Trend_{lt} + \lambda_j + \alpha_t + u_{jslt}. \tag{2}$$

where the dependent variable is the number of patent applications by firm j. We instrument *Inventor Hire*$^{conn.}$ with *Displ. Inventor*$^{conn.}$, namely, a variable dummy equal to 1 in each of the five years following a connected inventor displacement, and 0 otherwise.

[17] Similar theoretical contributions include studies by Cooper (2001), Markusen (2001), Glass & Saggi (2002), and Fosfuri, Motta, & Rønde (2001).

4.2.1 Evidence

In this section, we use the displacement of a connected inventor to instrument the hiring of a connected inventor. Table 4 displays the main 2SLS estimates: the first column includes firm and time-fixed effects; the second column includes industry-specific and LLM-specific trends and the third column adds the number of displaced workers in the LLM and industry. The first-stage F-statistics range from 12 to 14. The coefficient of our variable of interest is significant at the 1 percent level. The estimated average increase in the number of patent applications submitted to the EPO over the five years starting with the year of a connected inventor's hire is 0.6. To put the magnitude of the estimated effect in perspective, we calculate the fraction of overall variation in innovation explained by the hire of a connected inventor. A change of 0.6 patent applications is equivalent to an increase of 1.71 standard deviations (recall that the standard deviation of the number of patent applications in the estimation sample is 0.35). When interpreting these estimates, it is important to keep in mind that, as discussed above, hiring a connected inventor is a major change in terms of workforce for the average firm in our data. We thus believe that the implied shift in the number of patent applications after a connected inventor hire is large but not unrealistic.

In column (4) of Table 4, we restrict the dependent variable to the yearly number of patent submissions that are not authored or co-authored by the newly hired connected inventor. The estimates indicate a 0.355 increase in the patent submissions authored by the other workers of the focal firm, excluding those with a newly hired connected inventor in the team (the result is significant at the 5 percent statistical level). This result suggests that hiring an inventor may spur firms' innovation not just through coauthorships, but also through some mechanism of "fertilization".

4.3 Validity and Robustness

Citation-Weighted Patent Counts

The baseline analysis in Section 4.1.2 uses simple patent counts. We now explore the sensitivity of our results to the use of citation-weighted patent counts (Griliches, Hall, & Pakes, 1991; Hall, Jaffe, & Trajtenberg, 2005; Dechezleprêtre et al., 2017). In constructing this dependent variable, we employ the truncation correction weights devised by Hall, Jaffe, & Trajtenberg (2001) to correct for systematic citation differences across different technology classes and for the fact that earlier patents will have more years during which they can receive citations. The estimates, shown in Figure A3 and Panel A of Table 5, are qualitatively similar to the baseline estimates. Specifically, the estimated average increase in citation-weighted patent applications in the five years after a connected inventor's displacement is 0.17 standard deviations (the standard deviation of citation-weighted patent applications in the sample is 0.8).

A Placebo Exercise

As discussed above, a potential identification concern arises if the shocks to the supply of knowledgeable labor deriving from establishment closure also pick up market-level shocks. To further explore this possibility, we perform a "placebo"-type analysis. Specifically, we investigate how innovation at firm j reacts to the displacement of inventors who are connected to other firms in the same LLM and industry but not to the focal firm j. Figure A4 and Panel B of Table 5 report the estimates. The estimated average change over the five years starting with the year of the placebo event is non-significant. While we cannot completely rule out the possibility of market effects, the placebo results suggest that the effect identified in the previous section genuinely captures the improved access to inventors through co-worker network connections.

Never Treated as the Control Cohort

For the main analysis, we use the last cohort as the control cohort. Figure A5 and Panel C of Table 5 report the estimates using the never-treated as the control cohort. The estimates are qualitatively very similar to the baseline estimates.

Conventional TWFE event study design

For the main analysis, we use the interaction-weighted estimator. Figure A6 and the first row of Panel D of Table 5 report the coefficients estimated using a conventional TWFE event study design. Specifically, this approach compares changes in patent applications of firms that experience the displacement of a connected inventor both to firms that have yet to experience such an event and to firms that will never do so during our sample period. In Figure A7 and the second row of Panel D, we drop the never-treated firms, and therefore identification originates from the differential timing of treatment onset among the treated firms. Both sets of results are qualitatively similar to the baseline results.

5 Concluding Remarks

A prominent feature of the labor market in many developed countries is the tendency of firms to hire through social connections. Nevertheless, we have very limited knowledge of the extent to which available connections have an impact on firms' innovation. The central empirical goal of this paper is to measure the extent to which access to knowledgeable workers fosters innovation. The displacement of inventors due to establishment closures generates labor supply shocks to the firms that employ their previous co-workers. Our estimates indicate that firms exploit the opportunity offered by such displacements to recruit connected inventors. Importantly, the improved capacity to employ connected inventors increases firms' patenting activity.

References

Autor, D. H. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of labor economics 21*(1), 1–42.

Balsvik, R. (2011). Is labor mobility a channel for spillovers from multinationals? evidence from norwegian manufacturing. *Review of Economics and Statistics 93*(1), 285–297.

Bandiera, O., I. Barankay, & I. Rasul (2010). Social incentives in the workplace. *The Review of Economic Studies 77*(2), 417–458.

Battisti, M., G. Peri, & A. Romiti (2016). Dynamic effects of co-ethnic networks on immigrants' economic success. Technical report, National Bureau of Economic Research.

Beaman, L. & J. Magruder (2012). Who gets the job referral? evidence from a social networks experiment. *American Economic Review 102*(7), 3574–3593.

Becattini, G., M. Bellandi, & L. De Propris (2014). *A handbook of industrial districts*. Edward Elgar Publishing.

Bell, A., R. Chetty, X. Jaravel, N. Petkova, & J. Van Reenen (2019). Who becomes an inventor in america? the importance of exposure to innovation. *The Quarterly Journal of Economics 134*(2), 647–713.

Bloom, N., M. Schankerman, & J. Van Reenen (2013). Identifying technology spillovers and product market rivalry. *Econometrica 81*(4), 1347–1393. Available from: http://dx.doi.org/10.3982/ECTA9466, doi:10.3982/ECTA9466.

Breschi, S. & F. Lissoni (2001). Knowledge spillovers and local innovation systems: a critical survey. *Industrial and corporate change 10*(4), 975–1005.

Brusco, S. (1983). The emilian model: Productive decentralisation and social integration. *Cambridge Journal of Economics 6*(2), 167–184.

Burks, S. V., B. Cowgill, M. Hoffman, & M. Housman (2015). The value of hiring through employee referrals. *The Quarterly Journal of Economics 130*(2), 805–839.

Cestone, G., C. Fumagalli, F. Kramarz, & G. Pica (2016). Insurance between firms: The role of internal labor markets. *Centre for Economic Policy Research DP* (11336).

Cingano, F. & A. Rosolia (2012). People I Know: Job Search and Social Networks. *Journal of Labor Economics 30*(2), 291–332.

Combes, P. P. & G. Duranton (2006, January). Labour pooling, labour poaching, and spatial clustering. *Regional Science and Urban Economics 36*(1), 1–28.

Cooper, D. P. (2001). Innovation and reciprocal externalities: Information transmission via job mobility. *Journal of Economic Behavior and Organization 45*(4), 403–425.

Cornelissen, T., C. Dustmann, & U. Schönberg (2017). Peer effects in the workplace. *American Economic Review 107*(2), 425–456.

Crescenzi, R. & L. Gagliardi (2018). The innovative performance of firms in heterogeneous environments: The interplay between external knowledge and internal absorptive capacities. *Research Policy 47*(4), 782–795.

Dasgupta, K. (2012). Learning and knowledge diffusion in a global economy. *Journal of International Economics 87*(2), 323–336.

De Blasio, G. & S. Di Addario (2005). Do workers benefit from industrial agglomeration? evidence from displaced workers. *Journal of Regional Science 45*(4), 797—-827.

Dechezleprêtre, A., R. Martin, & M. Mohnen (2017). Knowledge spillovers from clean and dirty technologies. *Grantham Research Institute on Climate Change and the Environment Working Paper No. 135*.

Depalo, D. & S. L. Di Addario (2014). Shedding light on inventors' returns to patents. *Development Studies Working Papers , Centro Studi Luca d'Agliano* (375).

Di Addario, S. L. & A. Wu (2024). Who becomes an inventor? the role of firms in talent discovery. *mimeo*.

Dustmann, C., A. Glitz, U. Schönberg, & H. Brücker (2016). Referral-based job search networks. *The Review of Economic Studies 83*(2), 514–546.

Eliason, M., L. Hensvik, F. Kramarz, & O. N. Skans (2017). The causal impact of social connections on firms' outcomes. *CEPR Discussion Paper No. DP12135*.

Eliason, M., L. Hensvik, F. Kramarz, & O. N. Skans (2023). Social connections and the sorting of workers to firms. *Journal of Econometrics 233*(2), 468–506.

Fons-Rosen, C. (2013). Knowledge flows through fdi: the case of privatisations in central and eastern europe. *Mimeograph Universitat Pompeu Fabra*.

Fons-Rosen, C., S. Kalemli-Ozcan, B. E. Sorensen, C. Villegas-Sanchez, & V. Volosovych (2017). Foreign investment and domestic productivity: Identifying knowledge spillovers and competition effects. Technical report, National Bureau of Economic Research.

Fons-Rosen, C., V. Scrutinio, & K. Szemeredi (2016). Colocation and knowledge diffusion: evidence from million dollar plants.

Fosfuri, A., M. Motta, & T. Rønde (2001). Foreign direct investment and spillovers through workers' mobility. *Journal of International Economics 53*(1), 205–222.

Friebel, G., M. Heinz, M. Hoffman, & N. Zubanov (2019). What do employee referral programs do? Technical report, National Bureau of Economic Research.

Ganguli, I., J. Lin, & N. Reynolds (2020). The paper trail of knowledge spillovers: evidence from patent interferences. *American Economic Journal: Applied Economics 12*(2), 278–302.

Gathmann, C., I. Helm, & U. Schönberg (2020). Spillover effects of mass layoffs. *Journal of the European Economic Association 18*(1), 427–468.

Glass, A. & K. Saggi (2002). Multinational firms and technology transfer. *The Scandinavian Journal of Economics 104*(4), 495–513.

Glitz, A. (2017). Coworker networks in the labour market. *Labour Economics 44*(C), 218–230.

Glitz, A. & R. Vejlin (2021). Learning through coworker referrals. *Review of Economic Dynamics 42*, 37–71.

Griliches, Z., B. H. Hall, & A. Pakes (1991). R&d, patents, and market value revisited: is there a second (technological opportunity) factor? *Economics of Innovation and new technology 1*(3), 183–201.

Hall, B. H., A. Jaffe, & M. Trajtenberg (2005). Market value and patent citations. *The RAND Journal of Economics 36*(1), 16–38.

Hall, B. H., A. B. Jaffe, & M. Trajtenberg (2001). The nber patent citation data file: Lessons, insights and methodological tools. Technical report, National Bureau of Economic Research.

Hall, B. H., F. Lotti, & J. Mairesse (2008). Employment, innovation, and productivity: evidence from italian microdata. *Industrial and corporate change 17*(4), 813–839.

Henry, N. & S. Pinch (2000). Spatialising knowledge: placing the knowledge community of motor sport valley. *Geoforum 31*(2), 191–208.

Hensvik, L. & O. N. Skans (2016). Social Networks, Employee Selection, and Labor Market Outcomes. *Journal of Labor Economics 34*(4), 825–867.

Huang, K., E. Moretti, & X. Xia (2023). Local innovation through investment in education: Evidence from chinese cities. *Mimeograph*.

Kaiser, U., H. C. Kongsted, & T. Rønde (2015). Does the mobility of r&d labor increase innovation? *Journal of Economic Behavior & Organization 110*, 91–105.

Kantor, S. & A. Whalley (2014). Knowledge spillovers from research universities: evidence from endowment value shocks. *Review of Economics and Statistics 96*(1), 171–188.

Kline, P. (2012). The impact of juvenile curfew laws on arrests of youth and adults. *American Law and Economics Review 14*(1), 44–67.

Kline, P., N. Petkova, H. Williams, & O. Zidar (2019). Who profits from patents? rent-sharing at innovative firms. *The Quarterly Journal of Economics 134*(3), 1343–1404.

Kramarz, F. & O. N. Skans (2014). When strong ties are strong: Networks and youth labour market entry. *Review of Economic Studies 81*(3), 1164–1200.

Maliranta, M., P. Mohnen, & P. Rouvinen (2009). Is inter-firm labor mobility a channel of knowledge spillovers? evidence from a linked employer-employee panel. *Industrial and Corporate Change 18*(6), 1161–1191.

Marin, G. & F. Lotti (2016). Productivity effects of eco-innovations using data on eco-patents. *Industrial and corporate change*, dtw014.

Markusen, J. (2001). Contracts, intellectual property rights, and multinational investment in developing countries. *Journal of International Economics 53*(1), 189–204.

Marshall, A. (1890). *Principle of Economics*. McMillan and co., London,8th ed.

Mas, A. & E. Moretti (2009). Peers at work. *American Economic Review 99*, 112–145.

Mohnen, M. (2022). Stars and brokers: Knowledge spillovers among medical scientists. *Management Science 68*(4), 2513–2532.

Moretti, E. (2021). The effect of high-tech clusters on the productivity of top inventors. *American Economic Review 111*(10), 3328–3375.

Moser, P., A. Voena, & F. Waldinger (2014). German jewish émigrés and us invention. *American Economic Review 104*(10), 3222–55.

Parrotta, P. & D. Pozzoli (2012). The effect of learning by hiring on productivity. *The RAND Journal of Economics 43*(1), 167–185.

Pellizzari, M. (2010). Do friends and relatives really help in getting a good job? *ILR Review 63*(3), 494–510.

Piore, M. & C. Sabel (1984). Italian small business development: Lessons for u.s. industrial policy. *American Industry in International Competition. Cornell University Press John Zysman and Laura Tyson (eds.).*

Poole, J. P. (2013). Knowledge transfers from multinational to domestic firms: evidence from worker mobility. *Review of Economics and Statistics 95*(2), 393–406.

Saxenian, A. (1994). *Regional Advantage: Culture and Competition in Silicon Valley and Route 128.* Harvard University Press.

Saygin, P. O., A. Weber, & M. A. Weynandt (2019). Coworkers, networks, and job-search outcomes among displaced workers. *ILR Review*, 0019793919881988.

Schmutte, I. M. (2015). Job referral networks and the determination of earnings in local labor markets. *Journal of Labor Economics 33*(1), 1–32.

Serafinelli, M. (2019). "good" firms, worker flows, and local productivity. *Journal of Labor Economics 37*(3), 747–792.

Stoyanov, A. & N. Zubanov (2012). Productivity spillovers across firms through worker mobility. *American Economic Journal: Applied Economics 4*(2), 168–198.

Sun, L. & S. Abraham (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics 225*(2), 175–199.

Tattara, G. & M. Valentini (2010). Turnover and excess worker reallocation. the veneto labour market between 1982 and 1996. *Labour 24*(4), 474–500.

Topa, G. (2011). Labor markets and referrals. In *Handbook of social economics*, Volume 1, pp. 1193–1221. Elsevier.

Trigilia, C. (1990). Work and politics in the third italy's industrial districts. *Industrial Districts and Inter-Firm Co-operation in Italy, Geneva: International Institute for Labor Studies F. Pyke, G. Becattini and W. Sengenberger (eds.)*, 160–184.

Trigilia, C. (2020). Innovazione e territorio. *Podcast DIST - Lezioni Italiane, Puntata 5.*

Waldinger, F. (2010). Quality matters: The expulsion of professors and the consequences for phd student outcomes in nazi germany. *Journal of Political Economy 118*(4), 787–831.

Waldinger, F. (2012). Peer effects in science: Evidence from the dismissal of scientists in nazi germany. *The Review of Economic Studies 79*(2), 838–861.

Wang, S.-Y. (2013). Marriage networks, nepotism, and labor market outcomes in china. *American Economic Journal: Applied Economics 5*(3), 91–112.

Whitford, J. (2001). The decline of a model? challenge and response in the italian industrial districts. *Economy and Society 30*(1), 38–65.

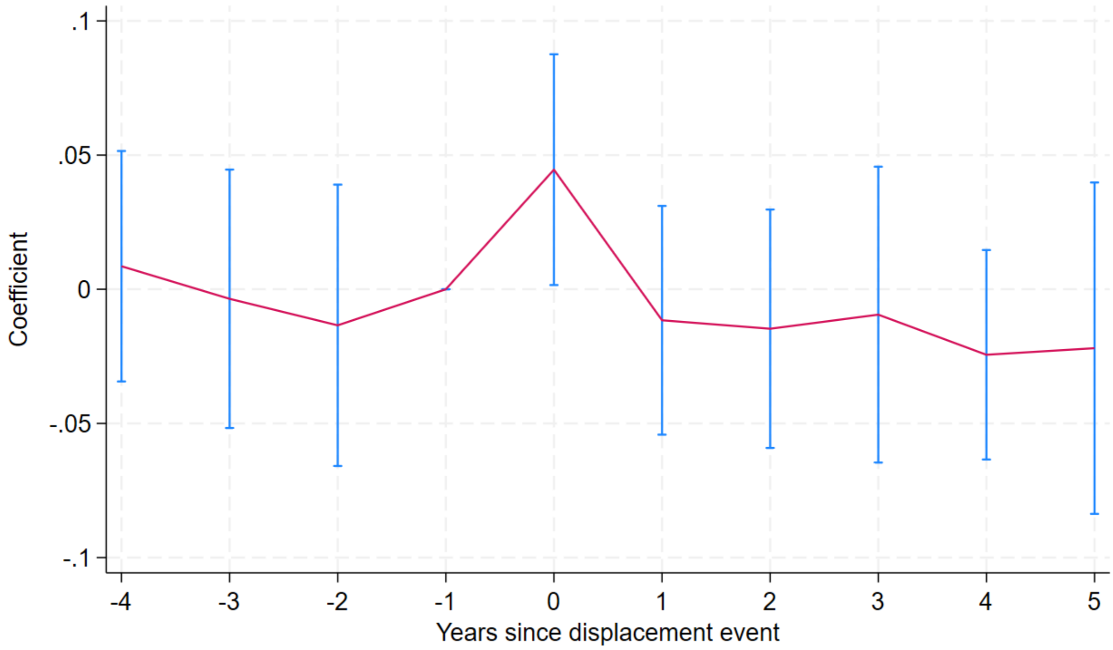

FIGURE 1. Connected inventor hires, relative to the year of a connected inventor displacement. The figure plots point estimates of leading and lagging indicators for the displacement of a connected inventor using the interaction-weighted estimator (Sun and Abraham, 2021). The dependent variable is the number of connected inventor hires (from any industry or LLM) for firm j of industry s and local labor market (LLM) l at time t. Event time indicator "-4" is set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" is set to 1 for all periods successively following the fifth year after the event, and 0 otherwise. In case of multiple events within a firm, we include only its first event and the time before its second event. The control cohort is taken as the last cohort. The period prior to the event is omitted. The bands around the point estimates are 95 percent cluster-robust confidence intervals, with LLM used as the clustering level.

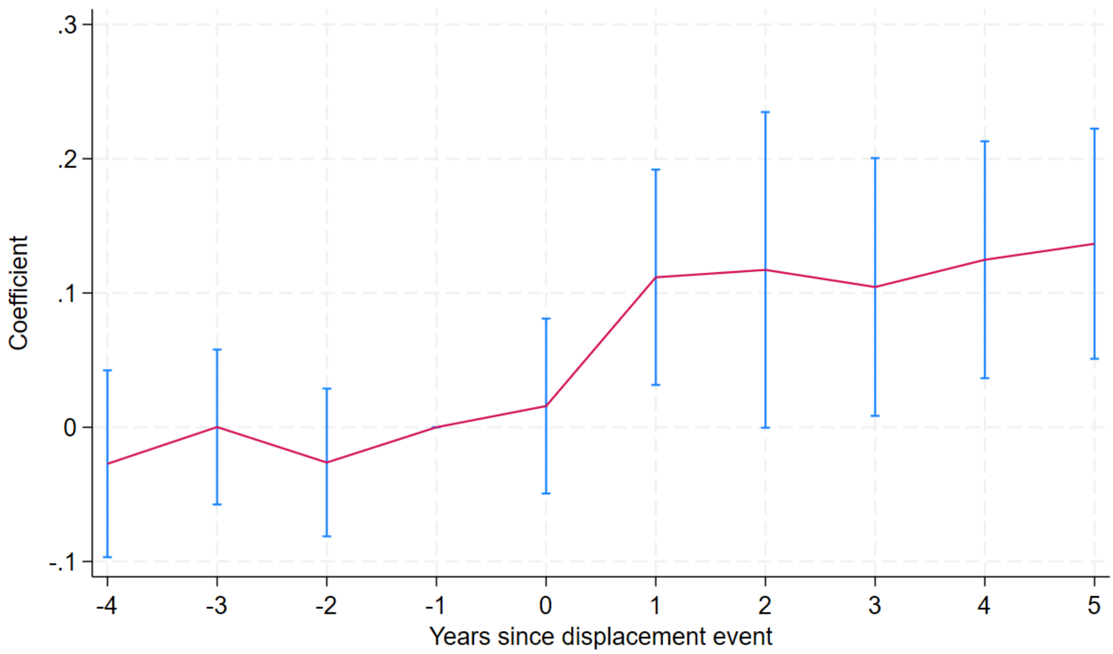

FIGURE 2. Patent applications, relative to the year of a connected inventor displacement. The figure plots point estimates of leading and lagging indicators for the displacement of a connected inventor using the interaction-weighted estimator (Sun and Abraham, 2021). The dependent variable is the number of patent applications. Event time indicator "-4" is set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" is set to 1 for all periods successively following the fifth year after the event, and 0 otherwise. In case of multiple events within a firm, we include only its first event and the time before its second event. The control cohort is taken as the last cohort. The bands around the point estimates are 95 percent cluster-robust confidence intervals, with LLM used as the clustering level.

TABLE 1. Summary statistics for the estimation sample.

	Mean	SD	Min	Max
No. of Patent Applications	0.038	0.354	0	20
Inventor Hires $^{conn.}$	0.008	0.103	0	7
Inventor Hires $^{nonconn.}$	0.004	0.137	0	31
Employees	47.413	70.404	6	499
Displaced Inventors$^{conn.}$	0.011	0.203	0	35
Displaced Non-Inventors$^{conn.}$	2.934	14.119	0	510
Firm Network	865.692	$1,226.655$	1	$23,233$

Note: The sample contains $84,173$ observations for $7,666$ firms. The table reports unweighted means. *No. of Patent Applications* is the average number of patent applications submitted by the firms in the sample. *Inventor Hires*$^{conn.}$ is the number of connected inventor hires. *Inventor Hires* $^{nonconn.}$ is the number of non-connected inventor hires. *Employees* is the average number of employees employed by the firms in the sample. *Displaced Inventors*$^{conn.}$ is the number of connected inventors who are displaced in a given year. *Displaced Non-Inventors*$^{conn.}$ is the number of connected non-inventors who are displaced in a given year. *Firm Network* is the number of former co-workers of current employees.

TABLE 2. Numbers of Events, displacements, and hires by year

Year	Events	Displaced inventors	Displaced non-inventors	Connected inventor hires	Non-connected inventor hires
1992	30	5	3,239	16	1
1993	28	17	4,236	16	5
1994	5	7	2,793	16	5
1995	1	9	3,471	31	11
1996	21	51	5,489	39	18
1997	23	24	22,063	27	12
1998	64	29	5,074	34	86
1999	19	10	8,767	26	31
2000	16	12	3,500	55	28
2001	77	43	6,272	54	11
2002	37	21	4,687	50	17
2003	62	17	5,381	53	25
2004	96	62	4,490	67	23
2005	90	35	6,037	49	25
2006	23	36	8,173	51	10
2007	23	36	6,221	47	18
2008	18	33	5,426	51	17
Total	633	447	105,319	682	343

Note: The table reports the summary statistics for the number of events, displacements, and inventor hires by year, with connected and non-connected hires indicated separately.

TABLE 3. Connected inventor displacements and patent applications—event study.

Dependant variable: *No. Patent applications*	$\tau = 0$	$\tau \in [1, 2]$	$\tau \in [3, 4]$	$\tau \in [0, 4]$
	0.016	0.114**	0.115***	0.095**
	(0.033)	(0.047)	(0.045)	(0.040)

Note: Estimates refer to Equation (1) whereby the dependent variable is the number of patent applications. The table corresponds to Figure 2. The sample size is $7,232$ (624 firms). The reduced sample size compared with Table 1 stems from the fact that the analysis sample excludes the never-treated and is before the treated periods for the last-treated cohort. Samples include only firms with more than five observations in the period of interest. The period prior to the event is omitted. In case of multiple events within a firm, we include only its first event and the time before its second event. The model includes year and firm fixed effects, industry and LLM trends. Numbers in parentheses are standard errors clustered at the LLM level. $\tau \in [a, b]$ refers to the average of the coefficients between period $\tau = a$ and period $\tau = b$. $*p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

TABLE 4. Connected inventor hires and patent applications—2SLS estimates

Dependent variable	All patent applications			W/o conn. hires
	(1)	(2)	(3)	(4)
	Panel A: 2SLS estimates			
Inventor Hire$^{conn.}$	0.643***	0.697***	0.697***	0.355**
	(0.220)	(0.245)	(0.244)	(0.160)
F-stat, 1st *stage*	14.07	12.33	12.35	12.35
$No.\ obs.$	$80,121$	$80,121$	$80,121$	$80,121$
Industry and LLM Trends	-	+	+	+
Displaced$_{slt}$	-	-	+	+
	Panel B: First stage estimates			
Displ. Inventor$^{conn.}$	0.054***	0.051***	0.051***	0.051***
	(0.014)	(0.015)	(0.015)	(0.015)
	Panel C: Reduced form estimates			
Displ. Inventor$^{conn.}$	0.035***	0.036***	0.036***	0.018**
	(0.010)	(0.010)	(0.010)	(0.009)

Note: Estimates refer to Equation (2). In columns (1)–(3), the dependent variable is the number of patent applications, while in column (4) it is the number of patent submissions excluding those authored or co-authored by the newly hired connected inventor(s). The estimation sample includes only firms with more than five observations in the period of interest. Numbers in parentheses are standard errors clustered at the LLM level. Firm, and time-fixed effects are always included. $Displaced_{slt}$ denotes the number of displaced workers in the same LLM $\times$ industry $\times$ year. *$p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

TABLE 5. Citation-weighted patent counts, placebo, never treated as control cohort, and conventional TWFE event study design

Panel A: **Citation-weighted patent counts**				
Dependant variable: *No. Citation-Weighted Patent Applications*	$\tau = 0$	$\tau \in [1, 2]$	$\tau \in [3, 4]$	$\tau \in [0, 4]$
	-0.112	0.241***	0.148**	0.133**
	(0.083)	(0.080)	(0.058)	(0.054)
Panel B: **Placebo**				
Dependant variable: *No. Patent Applications*	$\tau = 0$	$\tau \in [1, 2]$	$\tau \in [3, 4]$	$\tau \in [0, 4]$
	0.009	-0.008	-0.024	-0.011
	(0.011)	(0.012)	(0.017)	(0.010)
Panel C: **Never treated as control cohort**				
Dependant variable: *No. Patent Applications*	$\tau = 0$	$\tau \in [1, 2]$	$\tau \in [3, 4]$	$\tau \in [0, 4]$
	-0.015	0.067***	0.036*	0.038***
	(0.022)	(0.015)	(0.019)	(0.014)
Panel D: **Conventional TWFE event study design**				
Dependant variable: *No. Patent Applications*	$\tau = 0$	$\tau \in [1, 2]$	$\tau \in [3, 4]$	$\tau \in [0, 4]$
Baseline Sample	-0.011	0.067***	0.045**	0.042***
	(0.025)	(0.020)	(0.019)	(0.014)
Treated Only	-0.004	0.074***	0.066**	0.055***
	(0.023)	(0.024)	(0.026)	(0.019)

Note: Estimates refer to Equation (1). In Panel A, the dependent variable is the number of citation-weighted patent applications. In Panels B, C, and D, the dependent variable is the number of patent applications. The sample size is $7,232$ (624 firms) in Panel A, $27,175$ ($4,139$ firms) in Panel B, $81,055$ ($7,381$ firms) in Panel C, $81,059$ ($7,385$ firms) in *Baseline Sample* in Panel D, and lowered to $7,609$ (628 firms) for the *Treated only* sub-sample. Estimation samples include only firms with more than five observations. The model includes year and firm fixed effects, industry and LLM trends. Numbers in parentheses are standard errors clustered at the LLM level. $\tau \in [a, b]$ refers to the average of the coefficients between period $\tau = a$ and period $\tau = b$. *$p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Appendix

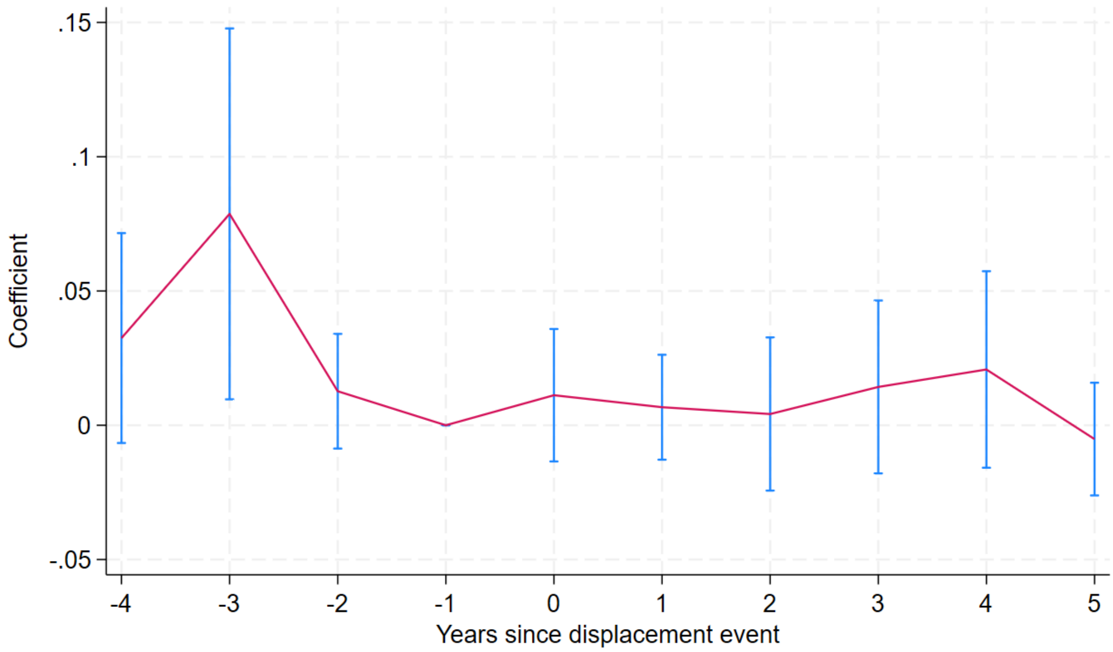

FIGURE A1. Non-connected inventor hires, relative to the year of a connected inventor displacement. The figure plots point estimates of the leading and lagging indicators for the displacement of a connected inventor using the interaction-weighted estimator (Sun and Abraham, 2021). The dependent variable is the number of non-connected inventor hires (from any industry or LLM) for firm j of industry s and local labor market (LLM) l at time t. Event time indicator "-4" is set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" is set to 1 for all periods successively following the fifth year after the event, and 0 otherwise. The period prior to the event is omitted. The control cohort is taken as the last cohort. The bands around the point estimates are 95 percent cluster-robust confidence intervals, with LLM used as the clustering level.

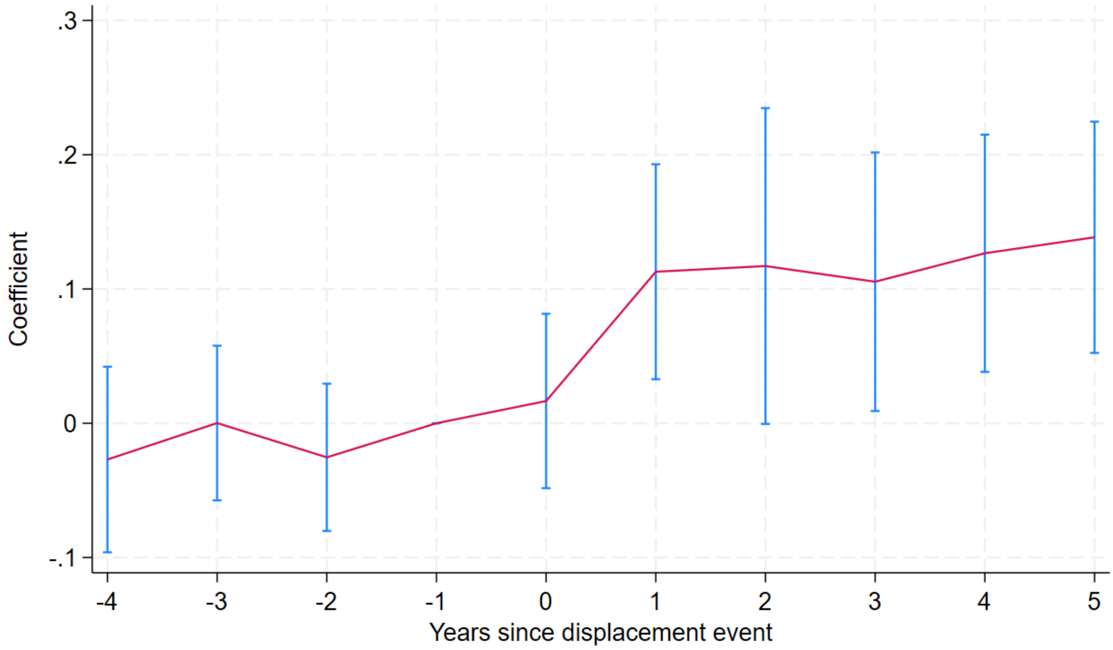

FIGURE A2. Patent applications, relative to the year of a connected inventor displacement—controlling for the number of displaced workers in the LLM and industry. The figure plots point estimates of leading and lagging indicators for the displacement of a connected inventor using the interaction-weighted estimator (Sun and Abraham, 2021), controlling for the number of displaced workers in the LLM and industry. The dependent variable is the number of patent applications. Event time indicator "-4" is set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" is set to 1 for all periods successively following the fifth year after the event, and 0 otherwise. In case of multiple events within a firm, we include only its first event and the time before its second event. The control cohort is taken as the last cohort. The bands around the point estimates are 95 percent cluster-robust confidence intervals, with LLM used as the clustering level.

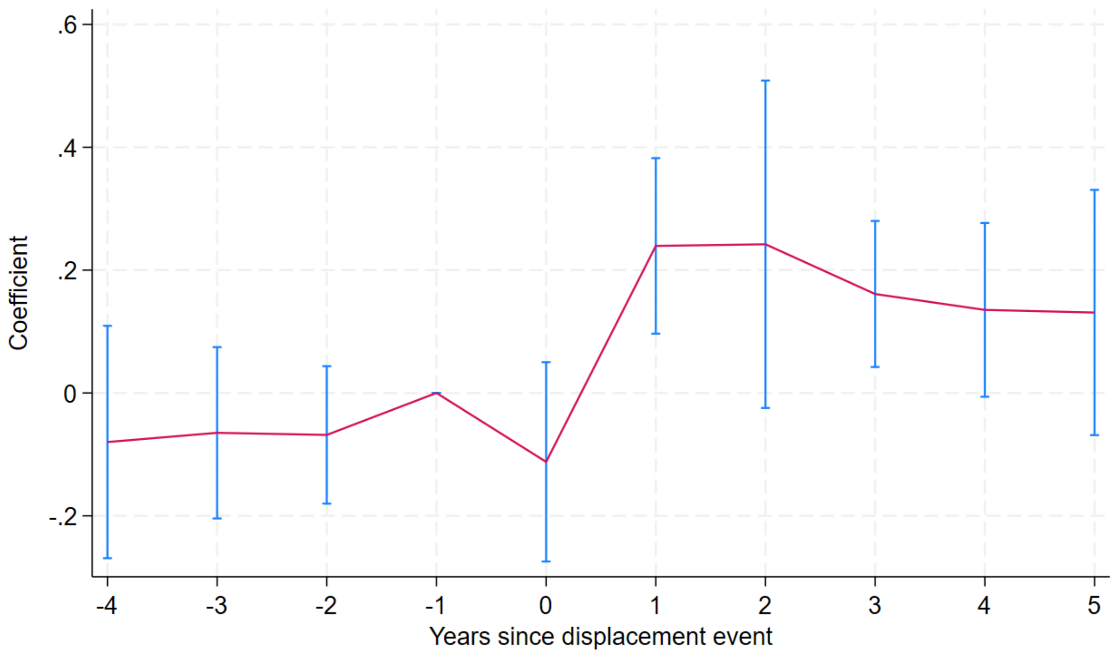

FIGURE A3. Citation-weighted patent applications, relative to the year of a connected inventor displacement. The figure plots point estimates of the leading and lagging indicators for the displacement of a connected inventor using the interaction-weighted estimator (Sun and Abraham, 2021). The dependent variable is the number of citation-weighted patent applications. Event time indicator "-4" is set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" is set to 1 for all periods successively following the fifth year after the event, and 0 otherwise. The period prior to the event is omitted. The control cohort is taken as the last cohort. The bands around the point estimates are 95 percent cluster-robust confidence intervals, with LLM used as the clustering level.

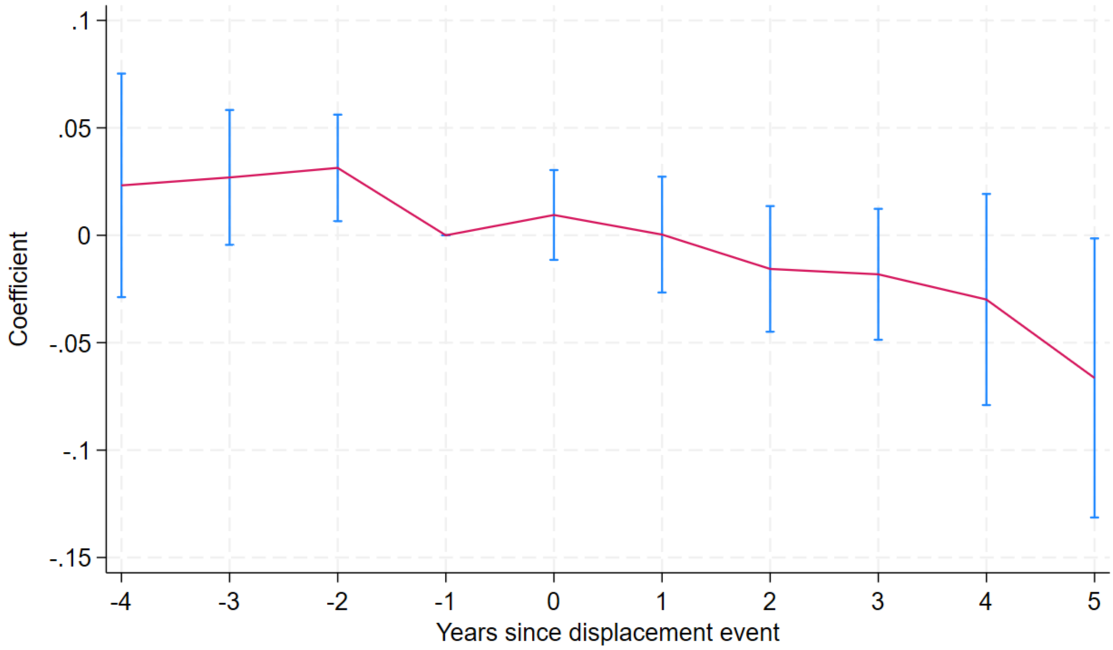

FIGURE A4. Patent applications, relative to the year of a connected inventor displacement—Placebo. The figure plots point estimates of the leading and lagging indicators for the displacement of inventors who are connected to other firms in the same LLM and industry but not to the focal firm j using the interaction-weighted estimator (Sun and Abraham, 2021). The dependent variable is the number of patent applications. Event time indicator "-4" is set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" is set to 1 for all periods successively following the fifth year after the event, and 0 otherwise. The period prior to the event is omitted. The control cohort is taken as the last cohort. The bands around the point estimates are 95 percent cluster-robust confidence intervals, with LLM used as the clustering level.

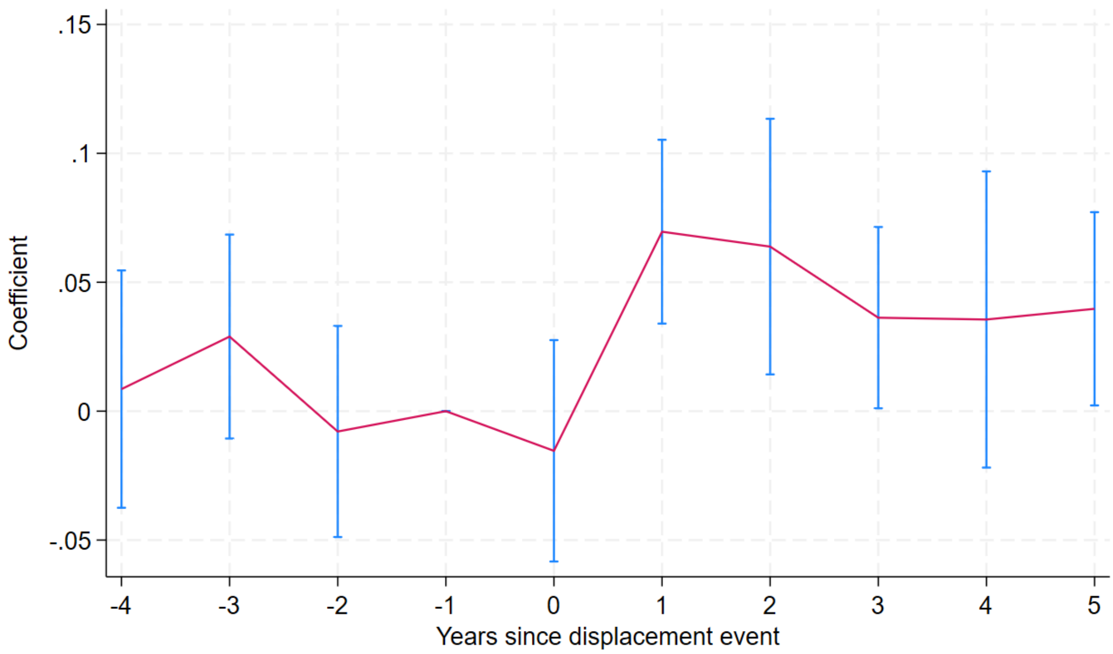

FIGURE A5. Patent applications, relative to the year of a connected inventor displacement—never treated used as the control cohort. The figure plots point estimates of the leading and lagging indicators for the displacement of a connected inventor using the interaction-weighted estimator (Sun and Abraham, 2021). The dependent variable is the number of patent applications. Event time indicator "-4" is set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" is set to 1 for all periods successively following the fifth year after the event, and 0 otherwise. The period prior to the event is omitted. The control cohort is taken as the never treated. The bands around the point estimates are 95 percent cluster-robust confidence intervals, with LLM used as the clustering level

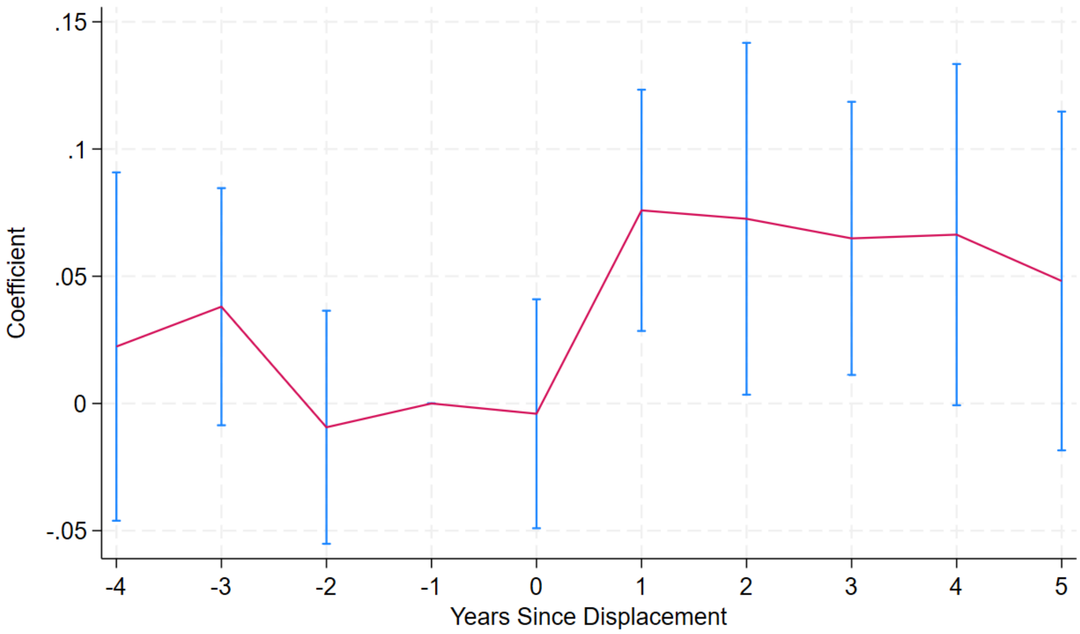

FIGURE A6. Patent applications, relative to the year of a connected inventor displacement—conventional TWFE. The figure plots point estimates of the leading and lagging indicators for the displacement of a connected inventor using a conventional TWFE event study design. The dependent variable is the number of patent applications. Event time indicator "-4" is set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" is set to 1 for all periods successively following the fifth year after the event, and 0 otherwise. The period prior to the event is omitted. The bands around the point estimates are 95 percent cluster-robust confidence intervals, with LLM used as the clustering level is LLM

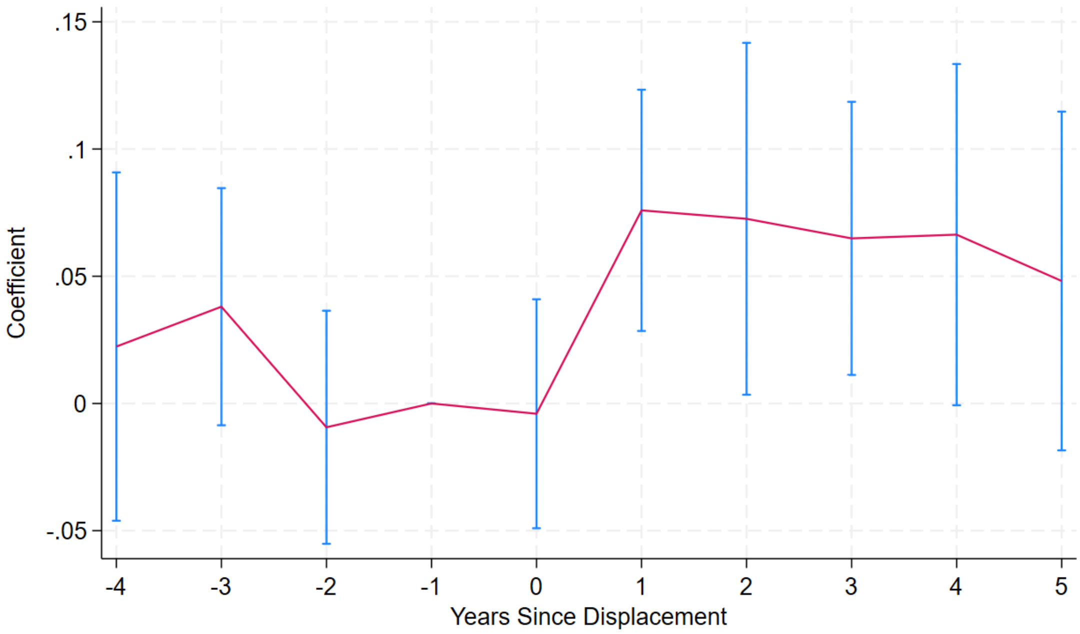

FIGURE A7. Patent applications, relative to the year of a connected inventor displacement—conventional TWFE and treated firms Only. The figure plots point estimates of the leading and lagging indicators for the displacement of a connected inventor using a conventional TWFE event study design. The dependent variable is the number of patent applications. Event time indicator "-4" is set to 1 for periods up to and including 4 periods prior to the event and 0 otherwise. Event time indicator "+5" is set to 1 for all periods successively following the fifth year after the event, and 0 otherwise. The period prior to the event is omitted. The bands around the point estimates are 95 percent cluster-robust confidence intervals, with LLM used as the clustering level.