The Effect of Large Firm Entry on Wage Distribution and Skill Demand*

Alaa Abdelfattah Layla O'Kane

November 14, 2023

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Abstract

This paper studies the effect of successfully bidding for a million dollar project, relative to bidding and losing, on local firms' skill demand and posted wages. Using real estate magazines and internet searches, we construct a dataset of million-dollar projects' opening year, location and runner-up sites. We then match winner and runner-up county pairs to corresponding job ads in Lightcast posting data. Utilizing a difference-in-difference research design, we find that, on average, a million-dollar project entry significantly shifts the wage distribution downward by 2.7%, but has no significant impact on the number of firms and postings in the local area. With respect to skill demand, million-dollar projects entry does not affect demand for cognitive, computer, or social skills, but significantly increases the demand for a high school degree as a minimum education requirement. These findings cast a new light on the equity impacts of large firms' entry, which seem to improve job prospects of workers without college degrees.

Keywords: Agglomeration, Million-dollar Projects, Wage Distribution, Skill Demand
JEL Codes: D22, H71, J23, J24, J31, O14, R58

*Alaa Abdelfattah: UC Davis. Email: aabdelfattah@ucdavis.edu; Layla O'Kane: Lightcast. Alaa is grateful to her advisors Giovanni Peri, Ellora Derenoncourt, and Katheryn Russ for their invaluable support and feedback, and to her family, her best friend, Ayesha Ahmed, Wing Woo and her undergraduate advisors Peter Matthews, Jeff Carpenter and Tanya Byker for their love and support. We thank Marianne Bitler, as well as participants in UC Davis Applied Micro Series for many helpful comments and Luc Chen for his research assistant-ship. This work is generously supported by a grant from Washington Center for Equitable Growth, grant IHS017100 from the Institute for Humane Studies and grant 2301-41880 from the Russell Sage Foundation and by the W.E. Upjohn Institute for Employment Research. Any opinions expressed are those of the authors alone and should not be construed as representing the opinions of any funder.

1 Introduction

Big firms matter in big ways. They are the catalysts of declining labor share (Autor et al., 2020), the producers of valuable inventions (Arora et al., 2022), and the early adopters of cutting edge technology (Acemoglu et al., 2022). They matter so much that local and state governments spend \$47 billion annually trying to attract and retain them (Bartik, 2020). Firms get this money under the banner of economic development as governments hope to foster agglomeration externalities. But are these mega projects really worth their subsidy price tag? What are the true spillover effects of large firm entry on local labor markets? Recent estimates of the effects on employment are mixed (Gupta, 2023; Chen, 2021), and on average wages negligible (Slattery and Zidar, 2020). Data limitations have prevented examining other margins of agglomeration effects, such as the demand for high skill workers at neighboring firms.

Theoretically, the effect of a large establishment entry on a local labor market is ambiguous. On the one hand, the agglomeration narrative tells a story where a large establishment entry induces the formation of an industrial cluster, which increases demand for workers– especially in entering establishment's supply chain. Higher labor demand increases wages and the demand for cognitive and computer skills as local firms adopt advanced technology used by large entrant. On the other hand, a competition framework tells a story where the entry of a large establishment raises labor cost in the short-run thus pricing some firms out of the market. This leads to a drop in employment followed by a drop in wages as the market reaches a new equilibrium. On the skill margin, faced with competition for qualified workers, local firms respond to large establishment entry by lowering their hiring standards.[1]

This paper empirically tests both stories by estimating the effect of multi-million dollar projects (MDPs) entry on local employment, wage distribution and skill demand. To this end, first we construct a dataset of million-dollar projects opening between 2010 and 2020 using announcements featured in *Southern Business and Development* magazine, *Site Selection* magazine and *Good Jobs First Subsidy Tracker 2.0*.[2] Our final sample is a group of projects for which winner county, opening year and runner-up counties are identified. Second, to overcome data scarcity on employer's skill demand, we use Lightcast online job posting data; a database collected from roughly 50,000 websites that covers the near-universe of online job postings with detailed information on employers' education, experience, and skill requirements.

[1] Competition can arise either from entering establishment or subsequent industrial cluster formed.

[2] More specifically, we look at *Site Selection* featured articles "Location Reports" and "Top Deals," and look at *Good Jobs First 2.0 Subsidy Tracker*'s featured "Megadeals."

To address firm location endogeneity, we follow Greenstone et al. (2010)'s methodology and compare counties that "won" the bid for a large establishment with "runner-up" counties that competed for it. By construction, this identification strategy focuses our analysis on multi-million dollar projects; the type and size of projects we expect to impact other employers' hiring behavior. Using standard and event-study difference-in-difference models for our analysis, the underlying assumption is that winner and runner-up counties are similar on observable factors affecting skill demand and wage distribution pre-entry. We validate this assumption by comparing winner and runner-up counties' racial composition, share of college graduates, number of higher education institutions, and industrial distribution.

Our analysis is composed of four parts. First, we examine the effect of an MDP entry on employment level, and establishment count using Lightcast online job postings (LC) and the Quarterly Census of Employment and Wages data (QCEW). Second, we estimate the effect of an MDP entry on the hourly wage and annual salary distributions to unpack potential dynamics underlying null average wage effects found by Slattery and Zidar (2020) and Chen (2021). Third, we evaluate the effect of an MDP entry on demand for different education levels, years of experience as well as cognitive, computer and social skills. Fourth, we explore local firms economic distance to entrant establishment and entering establishment's industry as potential mechanism channels. Therefore, a major contribution of this study is to provide some of the first empirical evidence on the impact of large firm entry on local labor markets' wage distribution and skill composition and evaluate findings equity implications.

On employment, we find that an MDP entry doesn't affect the number of online job postings and leads to a small, but insignificant increase in the number of unique firms posting in LC data. These findings are corroborated by our QCEW analysis which show that an MDP entry doesn't increase countywide employment level and has a positive but insignificant increase on establishment count. On wages, we find that on average an MDP entry has a negative but insignificant effect on average wages in both LC and QCEW data. We then run a series of diff-in-diff regressions on $10 hourly wage bins, and $20K annual salary bins, and find that an MDP entry significantly decreases the probability of posted hourly wages and annual salaries being in the middle bin by 2.7% and 2.1% respectively. This downward shift in posted income distributions is consistent with a competition story.

In terms of skill demand, we evaluate the effect of an MDP entry on listed education, and experience requirements as well as demand for cognitive, computer and social skills. For the former set of outcomes, we create indicator variables for education-levels and two-year experience bins.[3] For the latter, we adopt Deming and Kahn (2018)'s methodology and clas-

[3] We construct bins of the following education levels: "Not listed," "High School," "Associate and College

sify a job ad as requiring a given skill (e.g. cognitive) if it contains any of the corresponding keywords and phrases listed in Table 2. We find that an MDP entry significantly increases the probability that the minimum education requirement posted is a high school degree by about 0.8%. This increase in demand for a high-school degree corresponds to insignificant decreases in all other degrees up the academic ladder. Looking at years of experience, we find no statistically significant change in any 2-year bin. Finally, MDP entry doesn't affect local firms' demand for computer, social and management skills. Collectively, these results weight more favorably towards a competition story.

Thinking about mechanisms, we investigate how our estimates vary by local firms' economic distance to entering establishment's industry and potential heterogeneity driven by the type of establishment entering the market. Looking at firms operating within the entering establishment's industry (relative to other industries), we observe that an MDP entry prompts an insignificant decrease in demand for cognitive, computer and social skills within its industry in the first year post entry before demand returns to its previous pattern. Another competition indicator. Yet studying the heterogeneous effect of a manufacturing plant entry versus a non-manufacturing project, we find that the entry of a manufacturing plant significantly increase the demand for cognitive, computer and management skills in the first two years before the market reaches a new equilibrium in the third year. This suggests that MDPs' advertised agglomeration externalities (in the form of skill spillover) are true for manufacturing projects, but less strongly present for other project types, which now receive a substantial amount of firm-specific subsidies.

Overall, our findings suggest that on average, advertised employment and wage spillovers from subsidized million-dollar projects are not realized. Instead evidence of deskilling emerges revealing potential equity gains. We find no evidence of significant increase in employment and number of establishments. In fact, our estimates point to a downward shift of the hourly wage and annual salary distributions where the probability of observing wages/salaries in the middle of the distribution significantly decreases. Yet this downward wage shift is accompanied by higher demand for high school degrees with no increase in "high-skill" requirements like cognitive and computer skills. This is suggestive of deskilling, which improves job prospects of workers without college degrees. It also hints at a potential compression of the skill wage premium, which has often been cited as a driver of rising income inequality.

This paper speaks to three strands of literature. First, it is closely related to the agglomeration literature in general and MDPs branch in particular. This branch was spearheaded

Degrees," and "Advanced Degrees" (Masters, Ph.D...etc.). Similarly, we disaggregate years of experience into two-year bins.

by Greenstone et al. (2010) seminal paper, which introduced the use of runner-up sites as an identification solution to endogeneity of firm location.[4] Using *Site Selection* magazine's "Million-Dollar Plant" articles, which reported featured plants runner-up sites, Greenstone et al. (2010) estimate that after a new plant opening, wages increase by 2.7% and incumbent plants' in winning counties experience a 12% higher total factor of productivity five years later. Adopting the MDP identification strategy, other work in the literature evaluate the effect of MDP entry on managerial practices (Bloom et al., 2019), aggregate county employment, housing prices (Slattery and Zidar, 2020) and firm entry/exit (Patrick and Partridge, 2022; Gupta, 2023).

Our paper makes two contributions to the MDP agglomeration literature. One, diverting from Greenstone et al. (2010), our paper studies the effect of million-dollar projects opening between 2013 and 2019, i.e., post China's trade shock and the great recession. This is important because manufacturing share of total U.S employment has declined from 20% in 1980 to around 8.5% in 2010 onward (FRED). This economy-wide shift away from manufacturing might explain why unlike Greenstone et al. (2010) who estimate a 2.7% wage growth, we find no significant effect of MDPs entry on wage growth. In fact, this industrial shift is further reflected in the type of subsidized projects we use for identification, where roughly half of our sample are manufacturing plants. This sample heterogeneity allows us to expand the literature scope and test the common belief that the entry impact of a manufacturing plant differs from a non-manufacturing project–it does.

Two, to our knowledge, our paper is the first to introduce the use of Lightcast online job posting data to the MDP literature. The use of Lightcast data allows us to evaluate the effect of MDPs on new outcomes, namely employer's demand for cognitive, computer, and social skills. Exploration of these outcomes seem natural given Bloom et al. (2019)'s findings that the entry of MDPs improve management practices of other firms in winning counties, which hints at potential spillover of technology adoption. To reach their conclusion, Bloom et al. (2019) collaborate with the *Census Bureau* to design a management practice survey that was administered as a supplement with the 2010 and 2015 Annual Survey of Manufactures. While Bloom et al. (2019) focus on change in manufacturing plants' management practices, our paper measures change in demand for management, cognitive, computer and social skills across all types of establishments–not just manufacturing. And as we know from the polarization literature (Autor et al., 2003, 2006), skill demand is a proxy of technological adoption that foreshadows the evolution of labor markets and the future of work.

[4] Greenstone, Hornbeck and Moretti's 2010 paper in the *Journal of Political Economy* is widely accepted as the seminal paper in this literature. Nonetheless, Greenstone and Moretti (2004) NBER working paper was technically the first paper to introduce the alternative site identification strategy commonly used thereafter.

Second, this paper speaks to the literature on firm-specific incentives since most million-dollar projects benefit from large subsidy deals. Using different identification strategies and focusing on a different subset of subsides, Slattery and Zidar (2020) and Chen (2021) estimate that firm specific subsidies have no wage effects, but lead to employment gains in the subsidized industry. We contribute to this literature by replicating null wage effects estimated (see Table 3) and unpacking them to show that they conceal a significant downward shift across the wage distribution (see Figure 7). Furthermore, we consider skill spillover as an unexplored and potentially undervalued channel of subsidized MDPs agglomeration effect. Unexpectedly, our results show that MDPs entry don't increase demand for cognitive and computer skills. Instead, they increase the demand for a high school degree as a minimum education requirement thus improving job prospects of workers without college degrees. Put together, our paper moves this literature forward by taking into account the income distribution and equity implications of firm-specific incentives.

Third, our paper builds on the budding literature evaluating the effect of aggregate market shocks on employers' skill demand using online job posting data. Studying the effect of slack labor markets following the great recession, Hershbein and Kahn (2018) find that employers persistently increase their skill requirements, i.e., upskill. On the flip side, faced with tight labor markets during the fracking boom, Modestino et al. (2016) find that employers reduce their education and experience requirements, i.e., downskill.[5] Our paper contributes to this literature by studying the effect of a different and more recurrent event in many labor markets: the entry of a large employer. By studying firm entry, our paper expands the literature to encompass the effect of change in labor demand–not supply–on employers' hiring behavior. This expansion connects our findings to the monopsony literature in general and the literature on the labor market effects of mergers and acquisitions in particular. It also allows us to empirically test whether firms' response is more in line with an agglomeration or competition framework–our results support the latter.

The rest of the paper proceeds as follows. Section 2 describes the data. Section 3 outlines our framework, and Section 4 introduces the econometric model. Section 5 introduces the results and section 6 considers potential channels. Section 7 discusses robustness checks and Section 8 concludes.

[5] Modestino et al. (2016) use change in local unemployment as their right hand side variable to capture tightening labor markets.

2 Data

There are many factors that affect a firm's decision of where to locate its next manufacturing plant, warehouse or regional office such as workforce talent, public infrastructure (e.g. highways, airports) and proximity to suppliers. Given the size of capital and labor involved with building a new mega project especially in the automobile and aerospace industries, firms often hire site search consultants to aid with the search process. This service is in sufficient demand that all "Big Four" consulting firms have site search services to help their clients find the most suitable production sites while negotiating on their behalf the most lucrative subsidy deals from state and local governments.[6]

Therefore, a key challenge with evaluating the effect of a large-establishment entry on local labor market dynamics is that the establishment's location is not randomly selected. In fact, locations that "win" large contracts are probably significantly different from the average county across the United States. This represents an identification challenge where without a valid counterfactual, we can not isolate the effect of firm entry (and accompanying subsidy deal) from location specific trends. As a solution, this paper constructs a dataset that contains both the final firm location as well as sites that were considered by the firm and its consultants in the final stage of the site selection process. This dataset allows us to use "final stage" sites that were considered for the new establishment–but didn't get it–as a valid counterfactual. We then merge both winner and runner-up counties with online job posting data to estimate the causal effect of large establishment entries on local labor market dynamics.

2.1 Million Dollar Projects

The runner-up identification strategy was first introduced by Greenstone and Moretti (2004) who recovered firms' location preferences from *Site Selection*, a corporate real estate magazine with featured "Million Dollar Plants" articles. These articles reported where a large plant chose to locate (i.e., 'winner' site) as well as one or two finalist counties (i.e., 'runner-up' sites) that a firm was considering. They also reported the projected size of the opening facility, number of employees, and incentives/subsides offered by local economic development entities. Since *Site Selection* magazine has discontinued their million-dollar plant articles in 1999, we collect information on mega projects opening between 2010 and 2020 using announcements featured in *Southern Business and Development* magazine and other *Site Selection* featured articles like "Location Reports" and "Top Deals," in addition to *Good*

[6]The Big Four are the four largest professional services companies in the world: Deloitte, EY, KPMG, and PwC.

Jobs First Subsidy 2.0 Tracker's featured"Megadeals."[7]

Following other studies that have used these articles (Greenstone et al., 2010; Bloom et al., 2019), we refer to these announcements as "cases" and these facilities as "million dollar projects" or "MDPs." Using news coverage of these projects, for each case, we document the name of the firm, year of the site selection announcement, year of opening, type of project (new, expansion, or relocation), and counties of winner and runner-up sites. We further use descriptions of products being manufactured or facility characteristics to assign each MDP an industry designation (6-digit NAICS). We then use *Good Jobs First Subsidy Tracker 2.0* to document the size of the subsidy/incentive package awarded to each project. With a preliminary list of MDPs, we restrict our sample to facilities opening between 2013 and 2019, so we can observe outcome variables at least three years before and after establishment opening. We further exclude expansion and relocation projects from our main sample to evaluate a clean market entry.

Figure 1 captures two important features of our main MDP sample geographical distribution. First, both winner and runner-up counties are mostly concentrated in southern states. Second, while some *states* have more than one million dollar establishment, it is important to note that no winning *county* has more than one MDP. This is by construction. For counties with more than one MDP, we drop the latter MDP because it has a "contaminated" pre-period. And for a county listed as both a runner-up and winner, the county is dropped as a runner-up, with the entire case dropped from our analysis if no other runner-up county is identified for that MDP. These restrictions ensure that we have a clean counterfactual and pre-period for each establishment included in our final sample.

Table 1 summarizes characteristics of our main establishments data. First, we can see that most MDPs have only one runner-up county with opening years roughly distributed across our time span. Second, looking at average project size, we can confirm that these are mega projects with an average investment of \$333 million, average subsidy package of \$130 million and projected average employment of about 1,105 workers.[8] Third, we can see from the industrial distribution that only half of our establishments are manufacturing plants, while the other half is distributed evenly across other industries. This captures the fact that the nature of large subsidized projects has shifted over time from predominately large manufacturing plants to a mix of manufacturing plants, distribution centers, and secondary headquarters (e.g. Apple's in Austin, TX). Ultimately, what all these establishments have

[7] Megadeals are projects that received a subsidy packages with a value of \$50 million or more.

[8] Subsidy packages vary in composition across project and are often a combination of tax abatement, infrastructure development, workforce training and cash.

in common with traditional manufacturing plants, is large investments complemented by substantial government subsidies.

2.2 Lightcast Overview

The key data to analyze changes in local labor market dynamics comes from Lightcast,[9] henceforth LC, an employment analytics and labor market information company. LC collects data from roughly 50,000 websites, including job boards and company pages such that it covers the near-universe of online job postings from 2010 to 2022 for all MSAs in the United States.[10] For each job posting, we have codified education level, field of study and experience requirements as well as an average of nine skills extracted from the posting's open-text. We also have advertised wages for approximately 20% of all postings. This breadth and detail of LC's vacancy data makes it uniquely suited to help us unpack the black box of firm demand margin within and across occupations.

Using Lightcast vacancy data offers two advantages over using the Job Openings and Labor Turnover Survey (JOLTS), the primary government source on U.S. job openings. JOLTS data is the product of surveying a nationally representative sample of 21,000 U.S. business establishments across all non-agricultural industries in the public and private sectors for all 50 States and the District of Columbia. However, JOLTS data is typically available only at aggregate levels (like occupations, industries or states) and contains very little information about the characteristics of vacancies identified. In contrast, LC data is available at vacancy level with information on each opening's date, firm, firm industry (6-digit NAICS), county, occupation, wage, education, experience and skill requirement. LC's granular geographical level is essential for our identification strategy since our "treatment" happens at the county level and our control county could well be within the same state. Furthermore, LC's rich set of skills and other job posting characteristics allows us to examine change in skill demand at employer-level, our unit of interest.

Unfortunately, LC data advantages come at the cost of two well-documented drawbacks. First, as a by-product of relying on online job ads to capture job openings, LC over represents white collar jobs (Hershbein and Kahn, 2018; Babina et al., 2020).[11] This white-collar bias does not pose a serious threat to our results for two reasons. First, as of 2020, high-skilled jobs make up 60% of the entire U.S. workforce, so our findings will help us understand hiring demands for a significant share of the labor force.[12] Second, white-collar jobs typically

[9]Previously known as Burning Glass Technologies

[10]Job postings are at the establishment level, or the specific physical branch of a firm.

[11]See appendix B.2 for more discussion about Lightcast occupation and industrial composition.

[12]Source: the Department for Professional Employees' 2021 Fact Sheet, which relies on data derived from

have greater skill requirements, which is exactly the margin we are interested in exploring. Another downside of LC data is that vacancies represent stated but not necessarily realized firm demand. For a complete picture, one would also like to see characteristics and wages of workers eventually hired. However, this paper doesn't claim to recover general equilibrium effects. Instead, it concerns itself with understanding the dynamics of partial equilibrium as driven by firms' decisions.

Our main LC sample is the subset of postings with populated county, industry (2-digit NAICS) and employer names over the sample period 2010-2022. Focusing on winner and runner-up counties for each MDP, we exclude postings by the million dollar establishment used for identification and build a stacked dataset of postings from three years before to three years after MDP entry. Our final sample consists of approximately 12 million postings that aggregate to 422 thousand firm-county-year cells.

2.3 Skill Requirements in Lightcast

Our main analysis examines employers' demand for education, experience and four categories of skills; cognitive, computer, management and social skills. We focus on these categories given recent work documenting the role of skill premium in feeding the persistent wage gap (Autor et al., 2003; Deming and Kahn, 2018). First, education and experience are measures of human capital accumulation in which both employers and economists are interested. Second, cognitive and computer skills are useful metrics to evaluate the effect of technological change on skills and thus wages. Big firms, like MDPs, are often credited with driving innovation (Arora et al., 2022; Moretti, 2021). New technologies, in turn, are complementary to high-skill cognitive tasks. Thus, looking at MDPs' effect on demand for cognitive and computer skills in entering markets is a natural outcome of interest. Finally, with U.S. employment's industrial shift from manufacturing to service, it seems prudent to consider changes in demand for non-cognitive skills like management and social.

To create our outcome variables for education and experience, we rely on fields created by LC proprietary algorithm.[13] Using these fields, we are interested in two margins. First, whether the employer chose to list that outcome or not. Thus, we create indicator variables for whether the experience and education field are populated independently. For example,

U.S. Census Bureau and Bureau of Labor Statistics.

[13]In the raw data, there are two fields each for education and experience requirements: a minimum level (degree or years of experience) and a preferred (upper bound) level. Postings that do not list an education or experience requirement have these fields set to missing. We use the fields for the minimum levels to generate variables for the presence of an education or experience requirement as well as the number of years of education or experience required; the minimum is much more commonly specified than the preferred, and it is always available when a preferred level is listed.

consider a post advertising a coffee-shop branch manager vacancy. The ad might say something like, “looking for applicants with 3 to 4 years of customer service experience,” but doesn’t mention any education requirement. Whereas an ad for an entry-level analyst at a consulting firm might say something like, “looking for applicants with a bachelor’s in economics or statistics,” but doesn’t mention any experience requirement. Second, looking at postings that include an education (experience) requirement, we create indicator variables that capture change in the probability of an ad requiring a certain level of education and experience (in two-year bins) in response to MDP entry.

To create indicator variables that identify vacancies requiring cognitive, computer and social skills, we word-search an open text field. The challenge with this approach is to then determine what keywords correctly represent each category. To allow for comparison with earlier papers using LC data, we simply adopt their methodology. More specifically, we use Hershbein and Kahn (2018) set of keywords to create our cognitive skill variable.[14] This is a strategic choice since the authors deliberately chose a set of keywords that match the non-routine analytical job tasks used in Autor et al. (2003) and subsequently adopted by the polarization literature. For our computer outcome, we once again use Hershbein and Kahn (2018) strategy and designate an ad as requiring computer skills if it contains the key word “computer” or if it is categorized as software by LC.[15] Finally, for social and management skills, we follow a slightly modified version of Deming and Kahn (2018)’s definitions as shown in table 2.[16]

Given that each posting has an average of nine skills, a job posting is said to require a skill if at least one of the listed skills match one of the keywords/phrases listed in table 2. To ensure that our results are not driven by one firm or one posting at the year-county level, we exclude MDPs for which we have less than 120 postings for any year within the event-study time frame.[17] We then aggregate the data to firm-year-county cells, such that each cell represents the share of firm postings that had at least one of the skill’s keywords.[18]

[14]Specifically, an ad is categorized as requesting a cognitive skill if any listed skills include at least one of the following phrases or fragments: “research,” “analy,” “decision,” “solving,” “math,” “statistic,” or “thinking.” Hershbein and Kahn (2018) measure is strongly correlated and more comprehensive than Deming and Kahn (2018) “cognitive” metric, which also relies on LC’s open text.

[15]LC includes common software (e.g., Excel, PowerPoint, AutoCAD), as well as less common software and languages (e.g., Java, SQL, Python).

[16]Other skills listed in this table are explored but not presented in the main results for tractability.

[17]Failing to meet the 120 postings threshold means that we have less than 10 postings per month, which might bias our results.

[18]Note that LC doesn’t have a DUNS number or employer identification number (EIN), so we define a firm by employer name. Fortunately, LC uses a proprietary algorithm that groups variants into a standard set: for example, “Bausch and Lomb,” “Bausch Lomb,” and “Bausch & Lomb” would be grouped together. We also perform some additional cleaning on firm name, removing any remaining punctuation, and spaces.

3 Framework

When a large employer enters the market, they can affect the local labor market at both the extensive (employment and wages) and intensive (skills and occupations) margin. Governments often frame subsidy packages to million dollar establishments as an investment with industrial cluster formation as a long-term payoff. The idea is that the entry of a Tesla factory will induce tire and wire manufacturers to open shop in town thus increasing job creation. With an increase in demand for a constant supply of workers (i.e., absent increase in migration), market forces will then push wages up. These are the agglomeration externalities each county bidding for an MDP aspire to reap. However, while a wage increase improves workers' welfare, the increase in labor cost might also drive some existing firms out of business. Therefore, the net effect of MDP entry on local employment depends on which of these forces is dominant.

At the intensive margin, an MDP entry might change local firms' hiring behavior along three margins. First, faced with competition for qualified workers–from entering MDP and/or it's subsequent industrial cluster– surrounding firms might opt to lower their hiring standards, i.e.,"downskill," especially along margins like experience. For example, imagine a local IT firm competing with Apple for an experienced software engineer. Knowing that Apple probably has the winning hand, the company might widen it's search by listing a vacancy for a CS engineer with one to two years of experience instead of three to five years. Second, they might respond by "up-skilling" such that they can integrate the same cutting edge tech used by entering MDP. In this case, we expect to see an increase in the demand for computer and cognitive skills. Third, they might create new positions to implement a similar organizational structure or introduce new departments found in entering establishment. For example, a company might expand it's human resources team to foster company culture or it's marketing team to include a digital marketing officer.

Ultimately, MDP's entry can affect local labor markets' extensive and intensive margin simultaneously. However, the magnitude and significance of these changes depend on at least two observable factors. First, the effect of an MDP entry might differ by the type/purpose of the facility built. For example, we expect the construction of a manufacturing facility vis-à-vis other types of buildings (data centers, warehouses...etc.) to have a differential effect on local businesses. The opening of an IBM regional headquarters might increase foot traffic to local services, whereas a tire manufacturing plant might not. Second, an MDP entry might have heterogeneous effects across industries. Intuitively, a firm operating in the same industry might feel the brunt of the competition more than a restaurant down the block.

3.1 Million-Dollar Projects' Entry and Skill Demand

In this section, we establish million-dollar projects' entry in winning counties and provide evidence that MDPs indeed have higher skill demand relative to incumbent firms in our sample. To that end, we first plot the number of job postings by million-dollar firms in winning counties five years before and after their respective entry.[19] As we can see in Figure 2, MDP postings start to increase a year prior to MDP opening and continue increasing in the five years after. This pattern is consistent with the fact that there is an average of two years between MDP announcement and opening and firms recruiting behavior, which often start months in advance of start date. Looking at MDPs' skill requirement in contrast to incumbent firms in the three years prior to entry, Figure 3 shows that on average MDPs are 23% more likely to list an education level and 20% more likely to specify years of experience. Looking at skills, we further observe that MDPs are more likely to require cognitive, computer, social and management skills. Ex-ante, these patterns support a story where local firms face competition for high-skilled workers.

4 Empirical Strategy

The empirical strategy we employ is a series of difference-in-difference and event-study analyses that exploits variation in exposure to a million-dollar project across winner and runner-up counties for each case. The underlying assumption for all the models presented in this section is that observed factors that led megafirms to open a new establishment in a winner over a runner-up county are orthogonal to unobserved characteristics that predict skill demand, our main outcome. To verify this identifying assumption, we test whether a county's winner status can predict its demographic and labor market characteristics before MDP entry.[20]

From the left panel in figure 4, we observe that there is no statistical difference between winner and runner-up counties across all variables. This is reassuring especially for factors that we expect to be strong predictors of labor force skill composition like share of college graduates and number of higher education institutions. It is also reassuring that the distribution in employment share across industries in winner and runner-up counties is fairly similar. From the right panel of figure 4, we observe that compared to the average U.S. county,[21]

[19] For projects opening earlier than 2015, we have less than five years of pre-entry period and for the three projects opening after 2017, we do not have five year post. We further confirm MDP continued presence in winning county by searching google maps in 2023 and verifying the establishment's location and working hours.

[20] Whenever possible, we use data from 2009, the last year before the pre-period of the earliest MDP used in our data. Alternatively, we rely on the *County and City 2007 Databook*. See figure 4 notes for more details about data sources.

[21] This group include runner-up counties to accurately represent the alternative counterfactual group

winner counties are more racially diverse, have a larger number of higher education institutions and a larger share of college graduates. They also appear to have a bigger population and labor force on average, which translates to a bigger share of the national wage-bill and more establishments. Findings in figure 4 corroborates our story that runner-up counties are a more appropriate counterfactual group than a simple national average.

Employment and Wages

The strengths and weaknesses of LC vacancy data discussed in section 2.2 suggest that our data is better suited to evaluate the effect of MDP entry on skill demand. Nonetheless, for a more complete picture of MDP effects on local labor market outcomes, we start by looking at county level employment outcomes. To proxy for employment growth, we use the level and growth rate of total number of postings and unique number of firms at county-year cells. More specifically, we estimate the following diff-in-diff model:

$$Y_{ct} = \alpha + \beta MDP_c \times post_t + \alpha_c + \alpha_t + \varepsilon_{ct} \tag{1}$$

where Y_{ct} is either the number or growth rate of postings, unique firms or annual salary in county c at time t. The key coefficient of interest is β, the coefficient on the interaction between MDP indicator (MDP_c) with post entry indicator ($post_t$). Since this is a staggered diff-in-diff setting, the treatment indicator is replaced with county fixed effects (α_c) and the post-treatment indicator is replaced with year fixed effects(α_t) where a group of each is omitted (treated as reference group) for the model to be identified. The model equally weights all MDP cases and clusters standard errors at county level. We then expand equation 1 to estimate dynamic treatment effect using the following event study model:

$$Y_{ct} = \alpha + \sum_{\substack{\tau=-3 \\ \tau\neq 0}}^{3} \beta_\tau MDP_c \times 1_{t=\tau} + \alpha_c + \alpha_t + \varepsilon_{ct} \tag{2}$$

The key difference between equation 1 and 2 is that we replace our post entry indicator with a series of event study indicators from three years before to three years after MDP opening. The opening year is then denoted at $\tau = 0$ and omitted for the model to be identified.

Looking beyond simple averages at the effect of MDP entry on income, we use a series of diff-in-diff analyses to examine its effect on both hourly wages and annual salaries distributions.[22] Our outcomes then are a series of indicators for a posting's advertised wage (salary)

absent the runner-up strategy. Excluding runner-up counties from the national average doesn't affect the results.

[22]Notice that ex-ante, MDP entry can affect both hourly wages of low-skilled workers as well as annual

falling within specific wage (salary) bin. Analyzing the wage bin of a posting as an outcome allows us to observe the extent of spillovers along the wage distribution in response to the opening of a million dollar project. Using a standard diff-in-diff research design that pools pre- and post-treatment periods, we estimate the average change in wages relative to the pre-period using the following model:

$$Y_{ict} = \alpha + \beta MDP_c \times post_t + \eta_t + \gamma_s + \delta_i + \chi_o + \rho_{it} + \omega_p + \varepsilon_{itc} \tag{3}$$

where Y_{ict} is an indicator for whether the wage on posting i in county c at time t falls within a given wage bin. We also use this model to also think about MDP entry effect on education and experience requirements distribution such that wage bins are replaced by education levels (e.g. high school, bachelor's...etc.) and years of experience bins respectively. Our key coefficient of interest is β, the coefficient on the interaction between the million dollar project indicator (MDP_c) and post-entry indicator ($post_t$). The model further incorporates a group of fixed effects to account for potential confounding factors that could affect posted wages like: year (η_t), state (γ_s), industry (δ_i), occupation (χ_o) and industry-year trends (ρ_{it}). We also have case fixed effects (ω_p) so that the model estimates within a pair instead of across pairs. Once again, our model assigns all cases equal weight and clusters standard errors at the county level.

Skill Demand

Finally, to evaluate our main outcome of interest, the effect of MDPs entry on firms' education, experience and skill demand, we estimate the following diff-in-diff event study model:

$$Y_{fct} = \alpha + \sum_{\substack{\tau=-3 \\ \tau\neq 0}}^{3} \beta_\tau MDP_c \times 1_{t=\tau} + \alpha_p + \alpha_t + \alpha_c + \alpha_i + \varepsilon_{fct} \tag{4}$$

where Y_{fct} is the share of postings in company f at time t in county c that require outcome Y. The key coefficient is β_τ, the coefficient on the interaction between MDP indicator (MDP_c) with year t. For $\tau < 0$, β_τ captures anticipation effects while for $\tau > 0$, β_τ captures dynamic treatment effect. Using case fixed effects, α_p, the model forces β_τ coefficients to be identified within rather than across cases. The model further incorporates three fixed effects to account for potential confounding trends namely: year fixed effects (α_t) to account for

salaries of high-skilled workers, hence we look at both of these separately. They can be grouped if we impute annual wages of hourly workers assume 40 hour weeks or hourly wages of salaried workers by again assuming a 40 hour workweek 52 weeks a year.

shocks that affect all counties in a given year (like the pandemic in 2020), county fixed effects (α_c) to control for prior differences in outcomes across counties and industry fixed effects (α_i) to control for trend differences across industries regardless of county. The opening year is denoted as $\tau = 0$ and omitted for the model to be identified. Finally, our model weights all cases equally and clusters standard errors at county level.

5 Results

5.1 Employment and Wages

We start by looking at the effect of MDP entry on employment and wages using Lightcast data. Table 3 presents regression results from equation 1 where our dependent variables are number of postings, number of firms and annual salary and their respective growth rates. We can see from column 1 through 3, that MDP entry had a negative but statistically insignificant effect on outcome levels. For example, column 1 shows that MDP entry resulted in an insignificant drop in number of postings by an average of 6,418 postings and column 2 show a decrease of 219 unique firms postings. Similarly column 4 through 6 show that MDP entry didn't significantly affect outcomes growth rate. But whereas column 4 has a positive coefficient, columns 5 and 6 suggest that were it significant, MDPs would negatively affect firm and salary growth rates. For example, column 5 suggest that MDP entry could lead to a 4% decrease in firm growth. From columns 3 and 6, we then observe that MDP entry (insignificantly) decreased average posted salaries by \$5,217 and average salary growth by 3%.

To unpack the insignificant negative effects documented in Table 1, Figure 5 plots the event study results from equation 2 for number of postings in the left panel and number of unique firms in the right panel. The graphs plot the estimated impact of MDP entry on each outcome relative to year of opening, as well as a 95% confidence interval. Panel A shows that relative to year of opening, number of job postings didn't change after opening. Panel B suggests that there is a small but insignificant increase in number of unique firms after MDP entry. A potential concern with these findings might be that Lightcast data captures openings (i.e. employment growth) instead of actual employment level and doesn't fully cover all segments of the labor market. To address this concern, we next present the effect of MDP entry on aggregate employment and wages using Quarterly Census of Employment and Wages (QCEW) data.

Running equation 2 on countywide employment level, establishment count and total wages using QCEW data, yields reassuringly similar results to our findings using Lightcast data. For example, the left panel of Figure 6 shows a null effect of MDP entry on employment level, with estimates' magnitude suggesting that openings are a good proxy for employment. On the right panel, we see a more observable albeit insignificant increase in establishment count.[23] These results are consistent with Slattery and Zidar (2020) who use QCEW data to look at the effect of MDP entrants between 2002 and 2012 on countywide employment and income. While they observe a statistically significant increase in MDP's 3-digit industry, probably a direct effect, there is no residual increase in countywide employment.[24] In fact, Slattery and Zidar (2020) estimates for both employment and personal income are also negative and insignificant.

Taking advantage of Lightcast data posting-level structure, we next look at the effect of MDP entry on on hourly wage and annual salary distributions. Therefore, Figure 7 plots estimates from model 3 with 95% confidence interval. Beginning with the left panel, we find that MDP entry significantly dropped the probability of wages in the \$10-20 wage bin by 2.7% and increased the probability of wages in the \$10 or less and \$20 or more wage bins by 2.1% and 0.1% respectively. Similarly, the right panel captures a downward shift in the salary distribution where the probability of salaries in the \$40-60K salary bin drops significantly by 2.1% and in the \$60K or more dropped by a statistically insignificant 0.1%. On the other hand, these drops reallocate to the \$40K or less bin, which increases by 2.8%, an almost statistically significant result at the 10% level (p-value=0.104).[25]

5.2 Skill Demand

Figure 8 summarizes results from equation 3 on the effect of MDP entry on education levels and years of experience distributions. Looking at MDP effect on the educational requirement distribution (left panel), we observe that on average the probability of employers listing an education requirement increased but not significantly. However, the demand for a minimum of high school degree significantly increased but by a small amount (0.8%). This increase in the demand for a high-school degree corresponds to insignificant decreases in all other degrees up the academic ladder. In short, it seems that employers downskilled their education requirement.

Looking at years of experience (right panel), we note that on average the probability of employers listing an experience requirement decreased but not significantly. And for postings

[23] In appendix C.1, we discuss QCEW data in detail and replicate our main analysis. For example, Table C1 show average effects of MDP entry on employment, establishment and total wages. Similar to table 1, estimates for all three variables are negative and not statistically significant.

[24] In appendix C.1, we decompose Figure 6 by within MDP 2-digit industry and all other industries.

[25] In Appendix C.2, we use the American Community Survey to illustrate that a simple pattern emerges for observed wages, but isn't statistically significant probably due to difference in sample size.

with a listed experience requirement, there is no statistically significant change in any bin. However, we observe a similar downskilling pattern to the one observed in education where the demand for 0-2 years of experience increases and for all other more experienced bins declines. While we have to interpret the sum of these results cautiously since the magnitude of these changes are fairly small, evidence in Figure 8 suggest that employers downskill both their education and experience requirements.

The observed but insignificant drop in demand for higher degrees is further corroborated by the null effect of MDP entries on the probability of employers specifying a college major like "finance" or "biochemistry" as shown in Figure 9 left panel. It then follows that given a degree is listed, the share of STEM majors required doesn't change much as show in Figure 9 right panel.[26] This could simply mean that less STEM related jobs are opening, but it could also indicate that when a STEM major is not a necessity, employers relax their requirement. For example, a job opening in a consulting firm could require a math major when a business degree with some math background (or rather excel expertise) would be equally appropriate.

Finally Figure 11 examines the effect of MDP entry on the probability of an ad requiring cognitive, computer, social and management skills. The left panel show that demand for cognitive and social skills didn't change much in response to MDP entry whereas demand for computer skills increased two and three years out albeit insignificantly. Demand for management skills decreased by a significant 1% the year after MDP entry and then returned to an imprecise zero two and three years after entry. Looking at the average percentage change presented in table 4, we see that the demand all four skills show negligible change. This presents a puzzle. One would have thought that employers would balance out downskilling in education with more explicit skill requirements, but that doesn't seem to be the case.

6 Mechanisms

What mechanisms might explain the observed downskilling in average education and lack of response in cognitive, computer and social skills' demand? This section aims to shed some light on the possible mechanisms by investigating how the estimated impact might vary as a function of economic distance and local county conditions.

6.1 Industry

In general, one might expect agglomeration spillovers to decline with economic distance. For example, the entrance of a Toyota factory should have a stronger impact on the hiring

[26]STEM is defined as postings listing degrees in the following fields: natural sciences, engineering, computer science, and air space. More specifically, Lightcast assigns each degree a Classification of Instructional Program (CIP) code, which we then use to identify STEM degrees.

practices of the Volvo factory located across town than on the Save Mart down the street. To test this theory, we explore whether effects are larger on firms operating within MDP industry relative to other industries. Figure 10 shows the results from equation 4 where the main coefficient is the interaction of event study indicators with MDP indicator and an indicator for whether the firm is in the same 2-digit industry as the MDP or in other industries (let's refer to this as equation 4.1). Looking at the pattern across all panels in figure 10, it seems that MDP entry prompted an insignificant decrease in demand for all outcomes within its industry in the first year post entry before demand returned to its prior pattern. Notably demand for cognitive skills increased within MDP industry by about 2% in the year before entry and dropped by 3.2% in other industries. This suggests that firms lowered their demand for cognitive skills when faced with competing demand from the MDP industry.

These patterns help explain patterns seen in the main results. Firms in the same industry as opening MDP lower their demands on all margins–education, experience and skills (cognitive, computer and social)–for the first year after MDP entry till the market reaches a new equilibrium. This downward pull by firms in MDP industry is juxtaposed by an upward pull in other industries, which sheds some light on why on average we don't see a significant positive spillover effect following MDP entry. Table F3 compares average posting by MDP vis-à-vis incumbent firms' in winner and runner-up counties in the three years prior to MDP opening.[27] A quick look indicates that MDPs' postings have higher requirements on all metrics except customer service. Therefore, it makes sense that when competing with MDPs, firms in the same industry opt to temporarily downskill.

Another reasonable expectation is that spillover effects might differ depending on the industry of the million-dollar establishment entering the labor market. Going back to our Tesla example from section 3, it is clear that a manufacturing auto-plant will increase demand for freight and other automobile parts, but it is less clear how the opening of a regional IBM office is the seed to a local industrial cluster. Therefore, we next run another variation of equation 4, let's call it 4.2, where we interact the main coefficient with an indicator for whether entering MDP classifies as a manufacturing unit.[28] Before we look at results recall from table 1 that only half of our MDP sample is manufacturing firms and thus results presented here will suffer from small sample size issues.

[27]MDP postings are postings by MDPs in the winner county across our entire sample period to increase our representative sample of MDP ads.

[28]We use assigned MDP NAICS code and categorize any MDP with 2-digit NAICS equal to "31-33" as "manufacturing."

From Figure 12, we can see that the entry of manufacturing million-dollar projects significantly increased local firms' demand for cognitive skills by 2-2.7% and computer skills by 2.2-3.9% in the first two years after entry. We also observe a similar albeit less persistently significant pattern in the demand for social and management skills. These findings suggest that despite the decline in manufacturing share of employment in the US, entry of million-dollar manufacturing projects still has a significant impact on local labor markets.

6.2 Product Cycle

We now attempt to backward induce the different labor market characteristics million-dollar establishments were looking for in their target site and examine how the initial county conditions might affect our results. From product cycle theory, we expect that a company with a product in its development phase would want to locate in an area with a concentrated share of high-skilled labor to benefit from intellectual agglomeration effects. For a concrete example, think about IBM opening their data center in North Carolina's research triangle park. Whereas a firm with a product in its production and expansion phase might wish to open its next establishment in a low-wage area to expand its operations at a lower production cost. A good example of this would be Under Armor's hundred-million dollar warehouse in Wilson county, Tennessee.

To classify our million-dollar establishments more systematically, we look at unemployment rates, education shares (high school, and bachelor's), number of higher education institutions, and poverty/wealth metrics[29] for each pair of winner and runner-up counties and compare them to the national average. We then classify MDPs whose case counties diverge from national average on six or seven of our metrics as low-skill.[30] Using this criteria, 36% of our establishments are categorized as entering low-skill labor markets, so once again we have to be wary of small sample size bias. With this metric in hand, we then run our third variation of equation 4, 4.3, where the main coefficient is the interaction of event study indicators with MDP indicator and an indicator for low/high skill cases. Figure 13 summarizes the results of running equation 4.3 and shows that low and high skilled areas both trend similarly before and after MDP entry suggesting that this is an inactive channel. Ex-ante, we would have expected figures 12 and 13 to look fairly similar since we expect manufacturing plants to locate in low-wage areas, but that does not seem to be the case.

[29] Median household income, share of households earning $75K or more, and poverty per capita.

[30] We calculate difference to capture negative diversions. If a pair of counties (winner and runner-up) had a significantly lower unemployment rate than national average, that's a positive difference. Therefore the counties are flagged only if their unemployment is significantly higher than national average. The same logic applies to the remaining metrics used for this exercise.

7 Robustness Check

Compositional Bias: One concern with using postings of all firms is that the entry of a million dollar project might affect the composition of firms in the market. This concern stems from an agglomeration story where the opening of mega projects induces the entry of new firms that are inherently different from incumbent firms. In that narrative, our coefficients are biased by the changing composition of firms and does not necessarily reflect changing employers' behavior. We assuage these concerns in two ways. First, we redirect the reader to our findings in Figure 5, which suggest that MDPs' entry didn't significantly increase the number of firms. Second, in Appendix D.1, we show that the estimated effect of MDP entry on local labor market outcomes are very close to the baseline when restricted to using postings of incumbent firms only. For this exercise, we define incumbent firms as firms that have (1) at least one job posting in the three years prior to the MDP opening, (2) at least one job posting in the three years following the MDP opening and (3) a total of at least five postings during the seven years spanning the event study.[31] Results are also robust to running our event study specification at the posting level instead of firm.

Heterogeneous and Dynamic Treatment Effects: In recent years, several papers (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021) have raised concerns about the extension of two-periods two-groups difference and difference assumptions to staggered research design where different groups are treated at different times. They show that negative weights may arise due to time and/or heterogeneous group bias. We address each of these bias channels in turn. First, time bias arises from heterogeneity in treatment time where the model compares late treated units using early treated units as control. Our empirical strategy and data construction by design eliminate this bias channel. When building our data, we restrict our sample to million dollar projects for which a specific runner-up county–that never win an MDP to the best of our knowledge–is identified. This allows us to run a case fixed effect model, where we compare winner and (never-treated) runner-up counties within each pair instead of across pairs thus eliminating any "forbidden" comparisons.

Second, heterogeneous group bias and dynamic treatment effect are concerns that treatment is not constant across groups or over time. The heterogeneous group bias is a concern that treatment path is different across groups where maybe early adopters behave differently than late adopters. The dynamic treatment effect arises from the simple observation that a policy's effect one year after introduction might not be the same as five years later (Roth

[31] This sample also excludes MDPs for which we have less than 120 postings for any year within the event time frame. Failing to meet the 120 postings threshold means that we have less than 10 postings per month, which might bias our results. This doesn't change the MDP sample from the all firms baseline specification.

et al., 2023). To address these concerns, Appendix D.2 presents results using De Chaisemartin and d'Haultfoeuille (2022) model, which is robust to dynamic and heterogeneous treatment effects for binary and staggered treatment. This model uses placebos to test the parallel trends assumption and calculates a weighted average across cohorts (different entry groups) to estimate average treatment effect for each time period after treatment in an event study model.[32]

While patterns observed in our main event study figures hold, our wage, education, and experience distribution results are more specification sensitive. For example, we can see from figure D9 that the same downward pressure on hourly wages and annual salaries is present but insignificant.[33] On one hand, the consistent appearance of a downward trend across specifications and datasets suggests that MDPs might be driving the wage distribution down. On the other hand, the sensitivity of results' significance to firms' composition and model specification suggest that while MDPs might not be shifting the wage distribution downward, as an upper bound they have no affect on the wage distribution. This conclusion is interesting in and of itself since both agglomeration and competition theories support a wage/income increase story.

8 Conclusion

We study the effect of million-dollar projects entry on local wage distribution and skill demand by comparing winner to runner-up counties in a diff-in-diff research design. This paper presents evidence that on average million-dollar projects shifts hourly wage and annual salary distributions downward, while having no effect on the total number of postings and unique firms in winner counties relative to runner-ups. These findings are corroborated by looking at employment level and establishment count using QCEW where once again MDP entry has no significant effect on either outcome. These findings raise questions about the cost-benefit value of firm-specific subsidies and whether they indeed deliver the agglomeration dream.

Looking at the effect of MDP entry on skills, we find that on average MDP entry increases the demand for high-school degree at the expense of lower demand for college and

[32]Results using De Chaisemartin and d'Haultfoeuille (2022) is similar to Callaway and Sant'Anna (2021) when we have time invariant covariates, which is the case for our event study model.

[33]Recall from equation 3 that our wages, education and experience graphs are produced at the posting level where we control for occupation (2-digit SOC), industry (2-digit NAICS) and industry-year fixed effects in addition to the standard controls included in all of our other regressions. When running our robustness check using De Chaisemartin and d'Haultfoeuille (2022) model, we don't control for industry-year fixed effects since the model is robust to heterogeneous and dynamic treatment effects and uses first-difference estimation.

advanced degrees but doesn't significantly shift the demand for years of experience. Furthermore, an MDP's entry doesn't affect local firms demand for cognitive, computer, social and management skill. Put together, these evidence suggest that faced with competition, employers attempt to encourage a wider pool of applicants to apply by lowering their formal education requirements but don't necessarily increase their skill demand. In the long run, this downskilling might lead to upward mobility as it opens job opportunities for workers down the income ladder, namely workers without college degrees.

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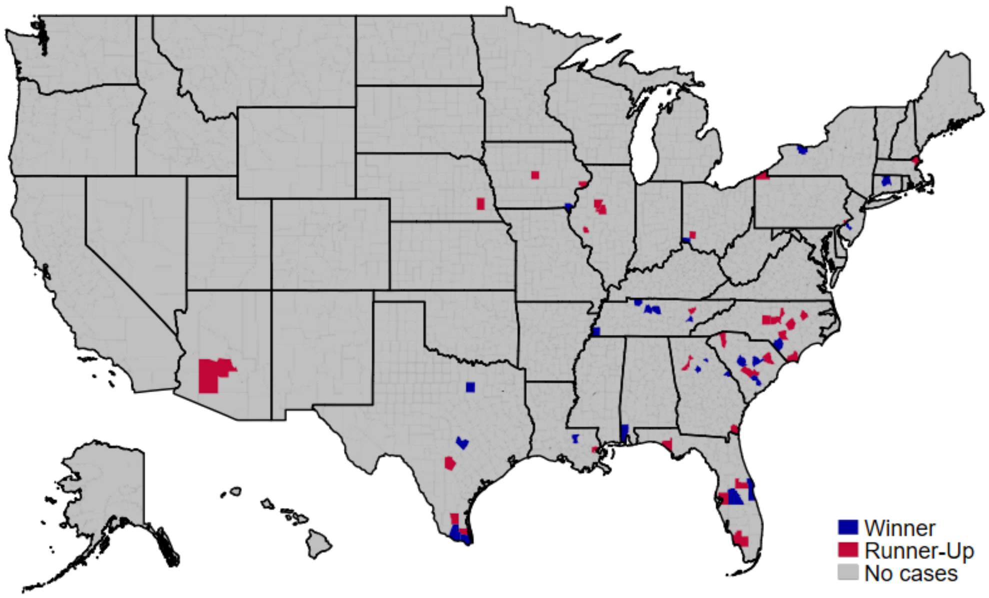
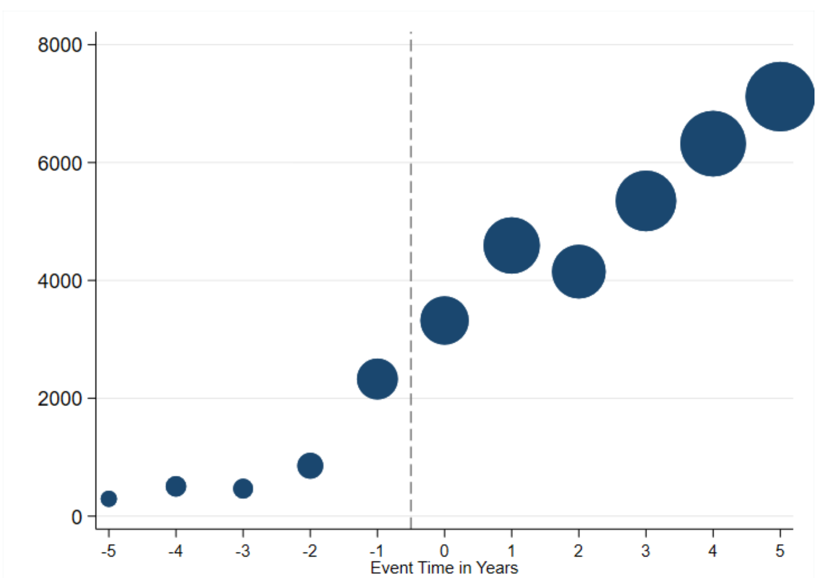
Figure 1: Geography of Million Dollar Projects Winner and Runner-up Counties



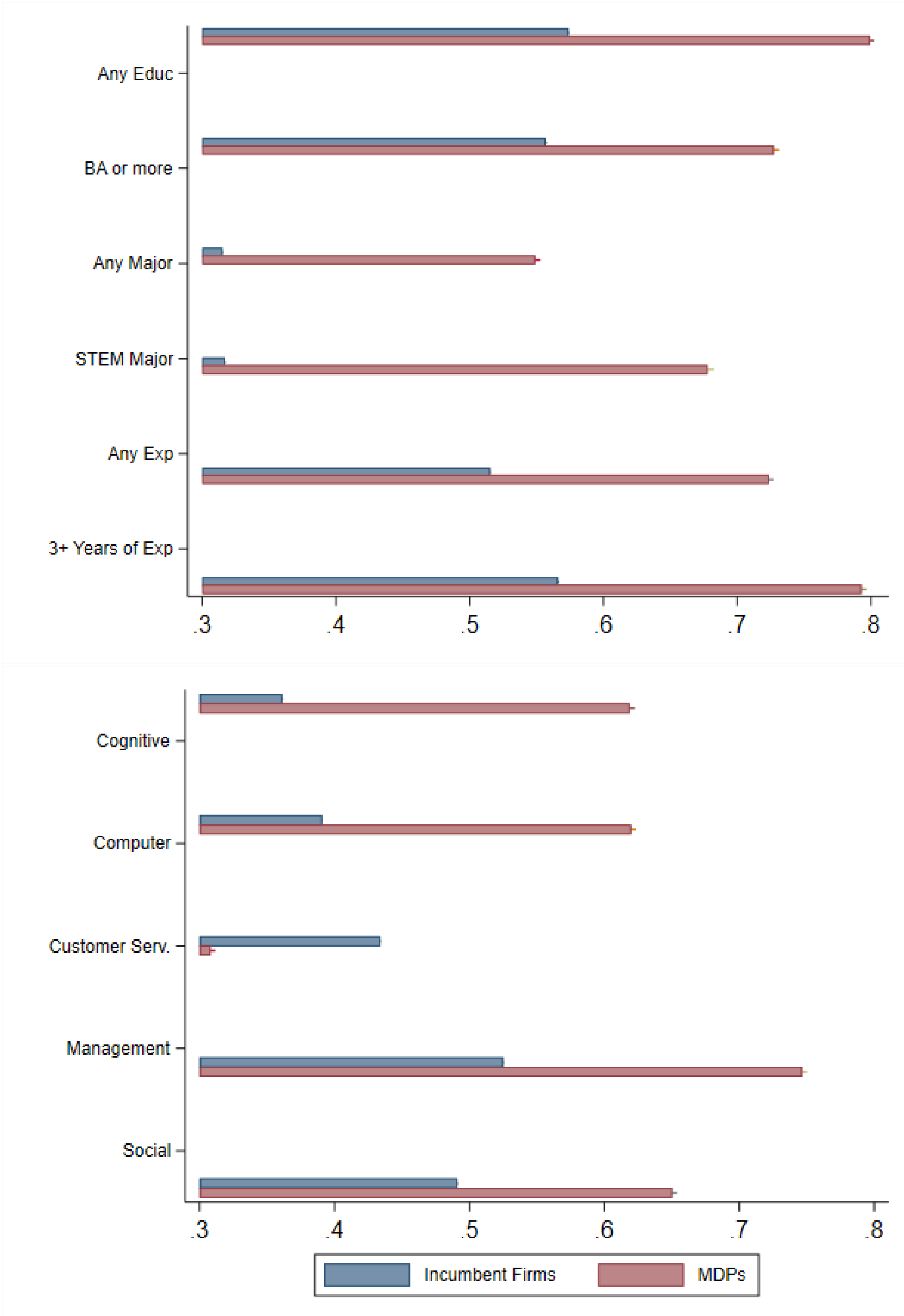
Notes: Includes only MDPs that are included in the main analysis. *Source*: *Site Selection* and *Good Jobs First Subsidy Tracker 2.0* Megadeals.

Figure 2: Million Dollar Projects' Postings in Lightcast



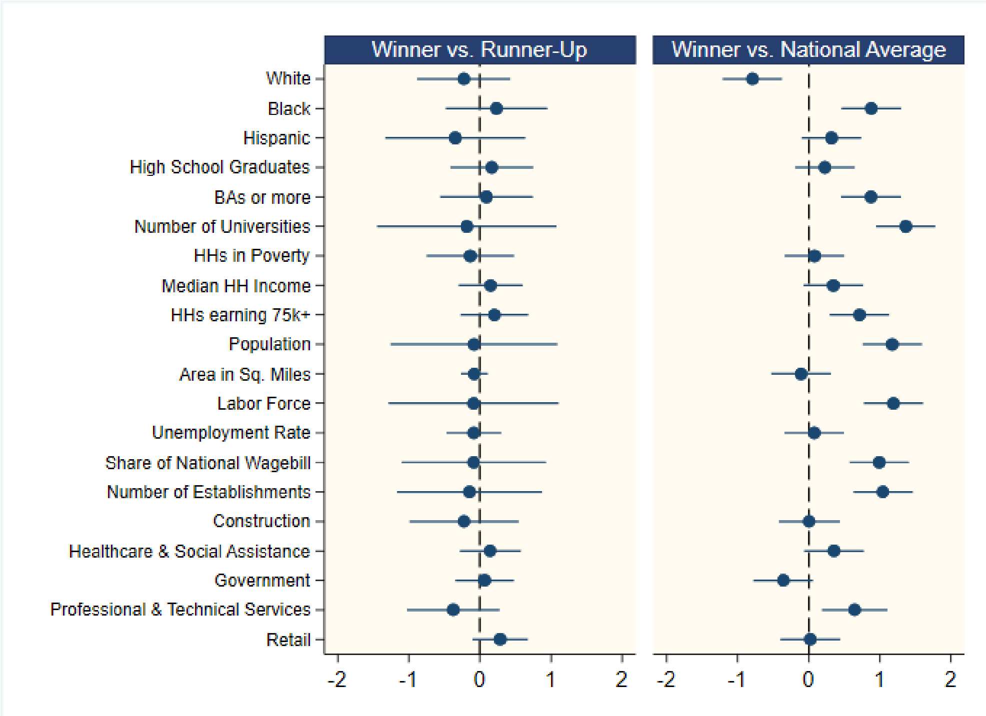
Notes: This figure includes postings from 23 of the 25 MDPs in our main analysis. For one MDP, we couldn't find postings in winner county whereas for the other (General Electric), there were many postings before entry possibly for subsidiaries in the areas. Scatter point size reflects the number of all MDPs' postings in time relative to their respective entry. *Source*: Lightcast vacancy data.

Figure 3: Million Dollar Projects Have Higher Than Average Hiring Standards



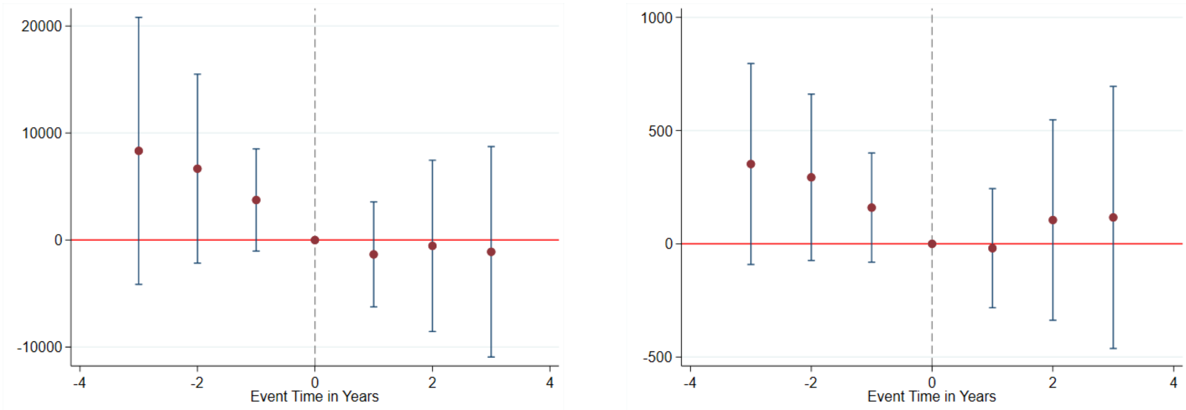
Notes: Incumbent firms' average is calculated using postings by firms in winner and runner-up counties in the three years prior to MDP entry for each pair. MDP is estimated using postings by million dollar establishments presented in table 1. BA or more is share of postings requiring a minimum of a bachelor's degree conditional on any educational level being listed. Similarly, STEM degree is conditional on a degree being listed and *3+ years* is conditional on any experience being listed. For keywords used to identify each skill see table 2. All differences are statistically significant at the 1 percent level. *Source*: Lightcast Vacancy Data.

Figure 4: Balancing Test Between Winner Counties and Potential Counterfactual Runner-Up Counties vs. National Average



Notes: Winners include only MDPs that are included in the main analysis, i.e., new MDPs with at least 120 postings per year. National average includes runner-up counties to accurately represent the alternative counterfactual group. Plotted estimates are from regressing y on winner indicator where runner-up counties take the value zero in the left panel and all other non-winner U.S. counties take the value zero in the right panel. These regressions are unweighted. *Sources*: County and City 2007 Data Book for race, education shares, population, area, share of national wagebill, number of establishments and share of industrial employment. Small Area Income and Poverty Estimates (SAIPE) 2009 data for poverty metrics. Local Area Unemployment Statistics (LAUS) 2009 data for labor market variables. And Integrated Postsecondary Education Data System (IPEDS) data for number of higher education institutions (colleges and universities).

Figure 5: The Effect of MDP Entry on Number of Postings and Firms.

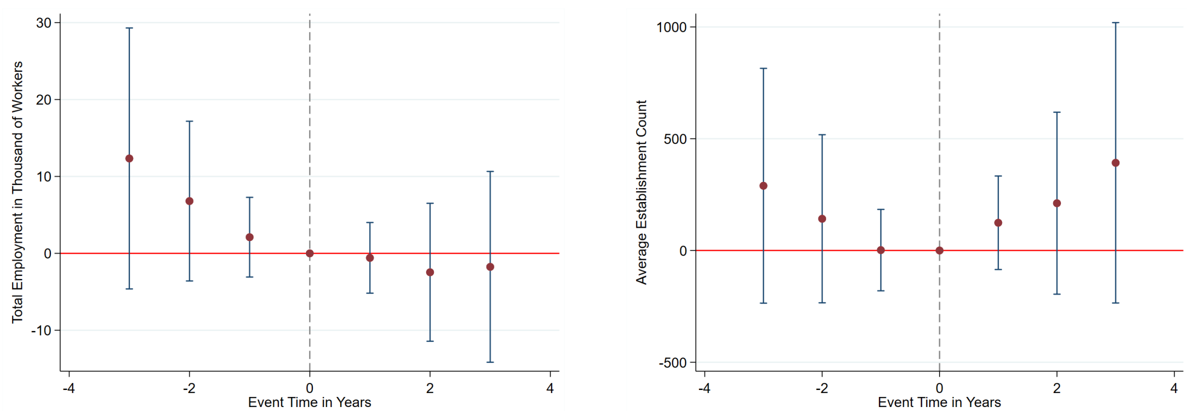


A. Number of Postings

B. Number of Firms

Notes: This figure plots the regression coefficients on the interaction between MDP and post-treatment indicators using a 3 year observation window. Observations are indexed at the year of MDP opening. County and year fixed effects are included. Sample is restricted to non-MDP employers' postings with valid county and employer name. 95% confidence intervals shown. *Sources*: Lightcast Vacancy Data.

Figure 6: The Effect of MDP Entry on Employment and Establishment Count in QCEW

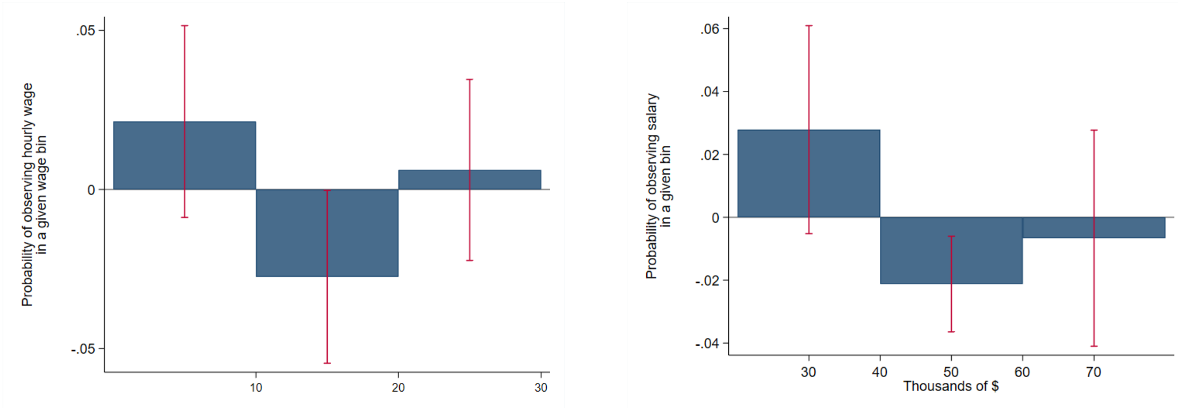


A. Employment Level

B. Establishment Count

Notes: This figure plots the coefficients on the interaction between MDP and post-treatment indicator. Observations are indexed at the year of MDP opening. Case, year, and county fixed effects are included. Sample includes government and private employment. Total employment is in thousands of workers. Estimates are clustered at county level. 95% confidence intervals shown. *Source*: Quarterly Census of Employment and Wages.

Figure 7: The Effect of Large Firm Entry on Hourly Wages and Annual Salaries

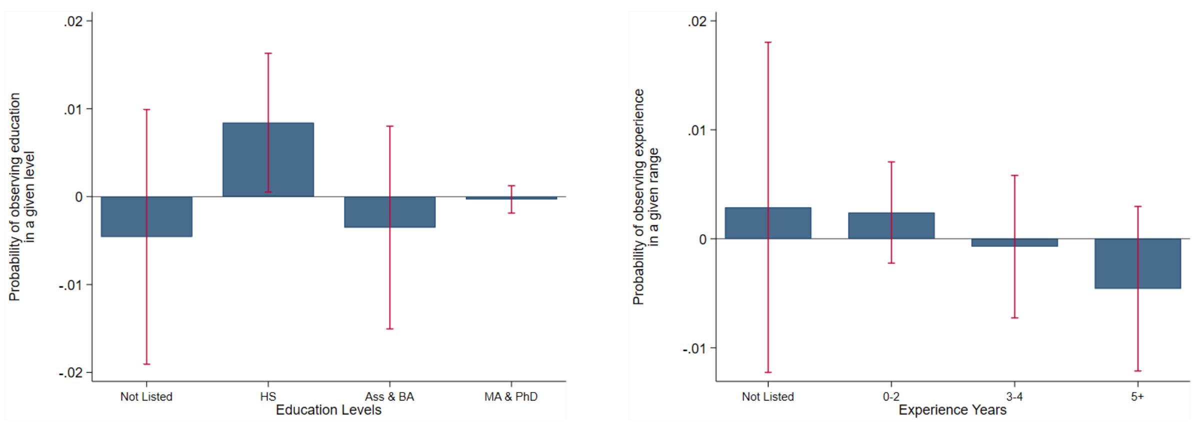


A. Hourly Wages

B. Annual Salary

Notes: This figure plots the coefficients from linear probability regressions of hourly wages (left panel) and annual salaries (right panel) being in a given bin on the interaction between job-level exposure to a million dollar establishment and an indicator for MDP opening. Case, year, state, 2-digit NAICS, 2-digit occupation and industry-year fixed effects are included. Sample is restricted to non-MDP employers' postings with valid wage data and hourly/annual rate of pay, employer name, county, industry and occupation. Note that the wage/salary variable is only populated for about 20% of all postings, so these results are for a subset of our main sample. Underlying data is also winsorized at the 1% level. Estimates are clustered at county level. For hourly wages, bin size is $10, with all wages below $10 and above $20 binned together. And for annual salary bin size is $20K with all salaries below $40K and above $60K binned together. 95% confidence intervals shown. *Source*: Lightcast vacancy data.

Figure 8: The Effect of Large Firm Entry on Education and Experience Distribution

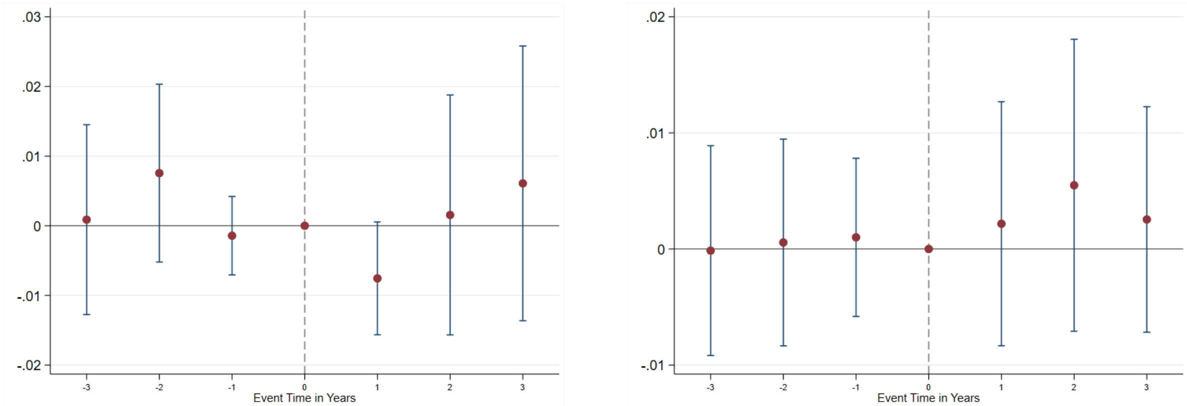


A. Education Distribution

B. Experience Distribution

Notes: This figure plots the coefficients from linear probability regressions of education (left panel) and experience (right panel) being in a given bin on the interaction between job-level exposure to a million dollar project and an indicator for MDP opening. Case, year, state, 2-digit NAICS, 2-digit occupation and industry-year fixed effects are included. Sample is restricted to non-MDP employers' postings with employer name, county, industry and occupation. Estimates are clustered at county level. For experience, bins are binned for 5 years and above, which together represent about 13% of the distribution. 95% confidence intervals shown. *Source*: Lightcast vacancy data.

Figure 9: The Effect of Large Firm Entry on Demand for Stem Degrees

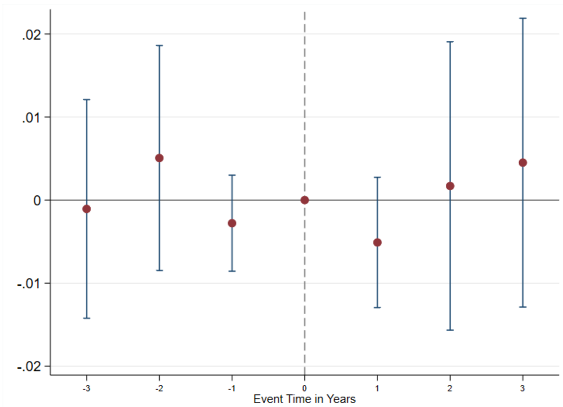


A. Any Major

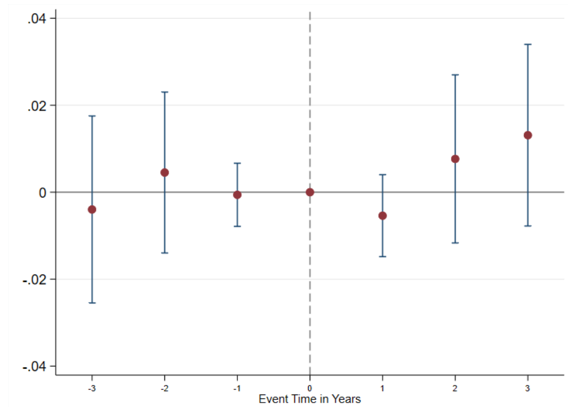
B. STEM Degrees

Notes: This figure plots the regression coefficients on the interaction between MDP and post-treatment indicators using a 3 year observation window. Observations are indexed at the year of MDP opening. Case, year, county, and 2-digit NAICS fixed effects are included. Sample is restricted to non-MDP employers' postings with valid county, employer name and 2-digit NAICS. Estimates are clustered at county level. 95% confidence intervals shown. STEM is defined as postings listing degrees in the following fields: natural sciences, engineering, computer science, and air space. More specifically, Lightcast assigns each degree a Classification of Instructional Program (CIP) code, which we then use to identify STEM degrees. *Sources*: Lightcast Vacancy Data.

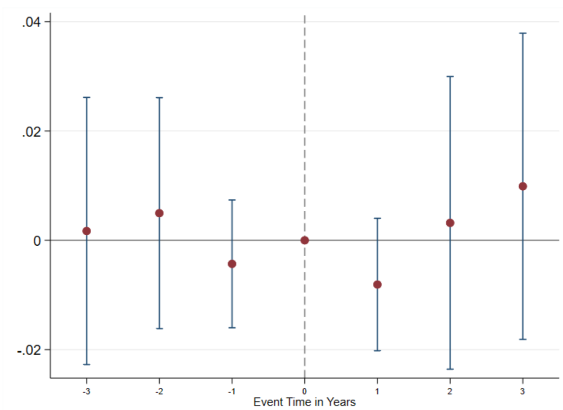
Figure 10: The Spillover Effect of MDP Entry on Demand for Cognitive, Computer, and Social Skills



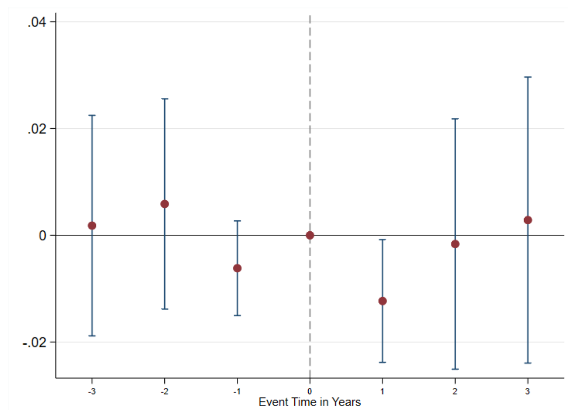
A. Cognitive



B. Computer



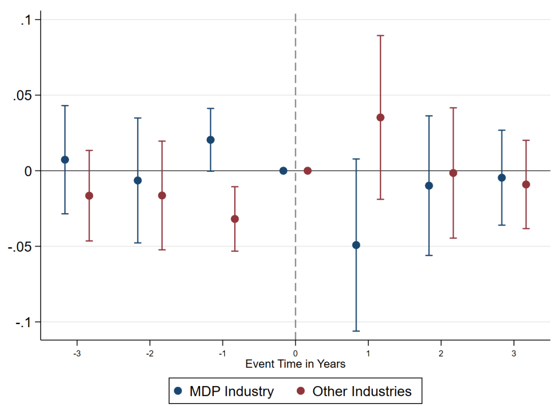
C. Social



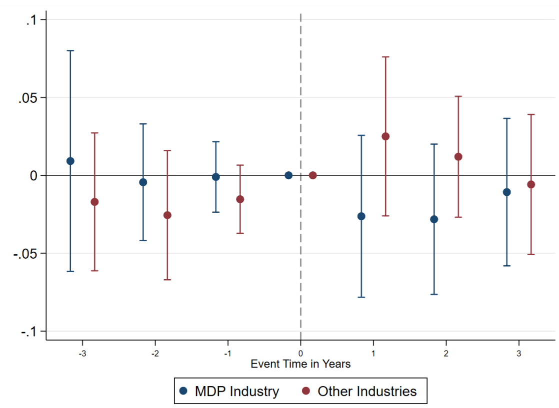
D. Management

Notes: This figure plots the regression coefficients on the interaction between MDP and post-treatment indicators using a 3 year observation window. Observations are indexed at the year of MDP opening. Case, year, county and 2-digit NAICS fixed effects are included. Sample is restricted to non-MDP employers' postings with valid county, employer name and 2-digit NAICS. Estimates are clustered at county level. 95% confidence intervals shown. *Sources*: Lightcast Vacancy Data.

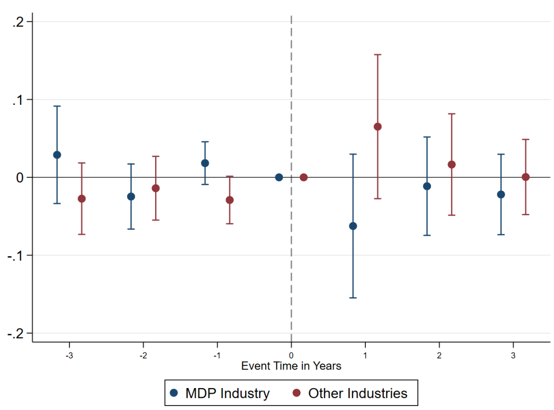
Figure 11: The Effect of Large Firm Entry on Demand Within MDP Industry



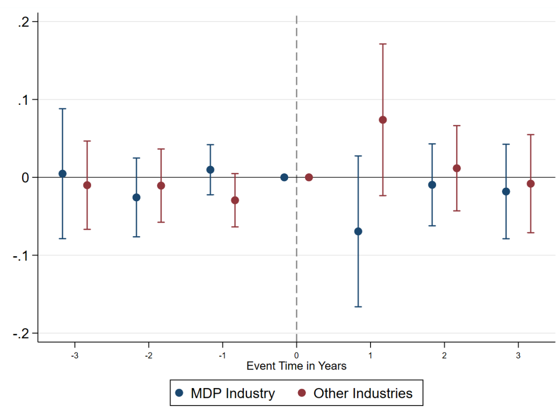
C. Cognitive



D. Computer



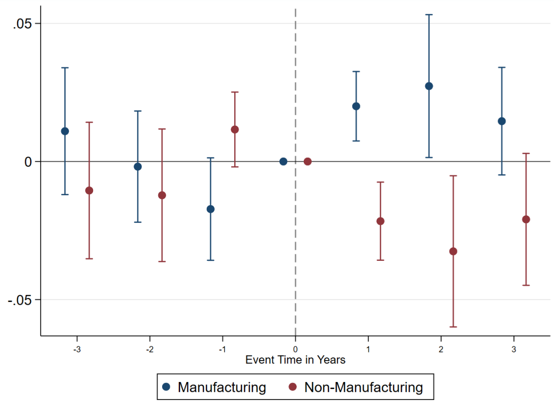
E. Social

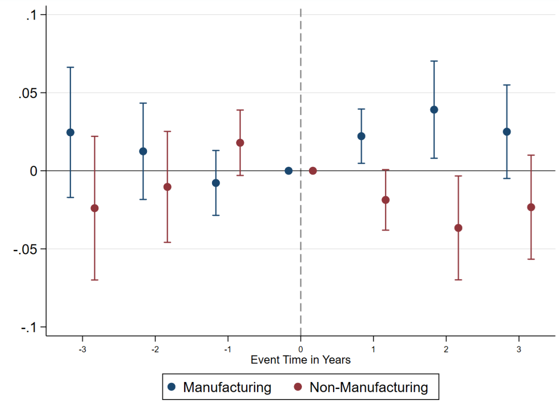


F. Management

Notes: This figure plots the regression coefficients on the interaction between MDP, pre/post-treatment indicators and indicator for whether the firm is in the same 2-digit industry as the MDP. Observations are indexed at the year of MDP opening. Case, year, state, and 2-digit NAICS fixed effects are included included as well as interaction terms between MDP $\times$ post-treatment, MDP $\times$ industry indicator and post treatment $\times$ industry indicator. Sample is restricted to non-MDP employers' postings with valid county, employer name and 2-digit NAICS. Estimates are clustered at county level. 95% confidence intervals shown. *Sources*: Lightcast Vacancy Data.

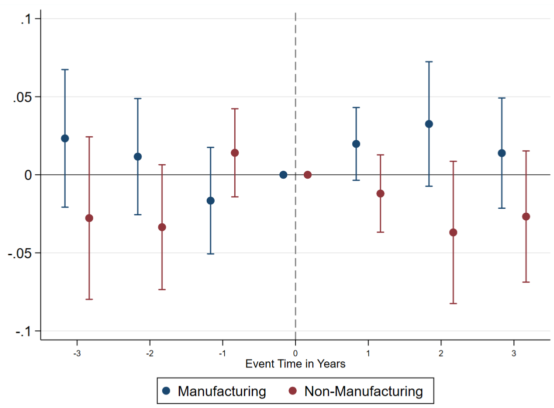
Figure 12: The Effect of Large Firm Entry of Manufacturing MDP on Demand

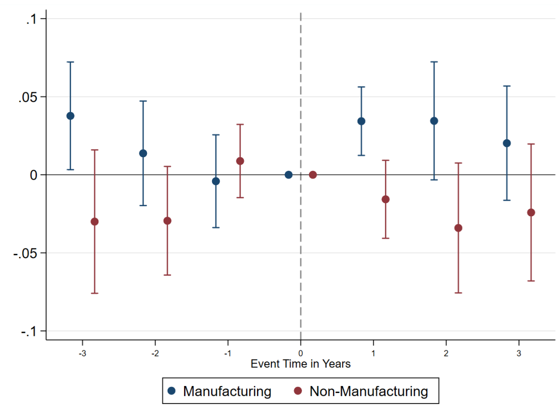




C. Cognitive

D. Computer



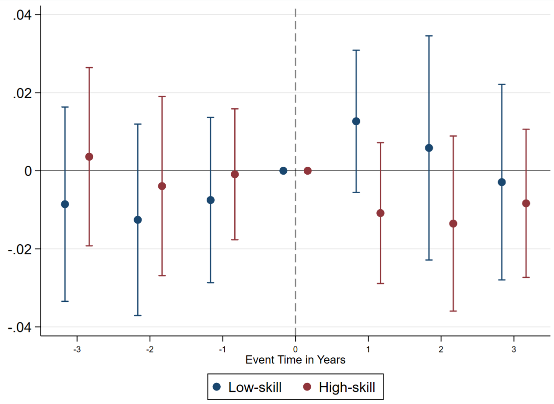


E. Social

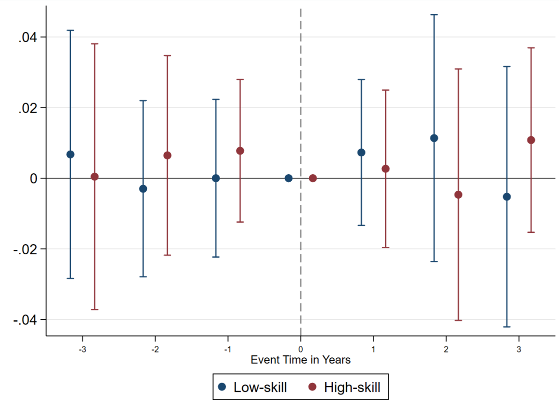
F. Management

Notes: This figure plots the regression coefficients on the interaction between MDP, pre/post-treatment indicators and indicator for whether the MDP has a 2-digit manufacturing NAICS code so 31-33. Observations are indexed at the year of MDP opening. Case, year, state, and 2-digit NAICS fixed effects are included as well as the following interaction terms: MDP $\times$ post-treatment, MDP $\times$ manufacturing indicator and post treatment $\times$ manufacturing indicator. Sample is restricted to non-MDP employers' postings with valid county, employer name and 2-digit NAICS. Estimates are clustered at county level. 95% confidence intervals shown. *Sources*: Lightcast Vacancy Data.

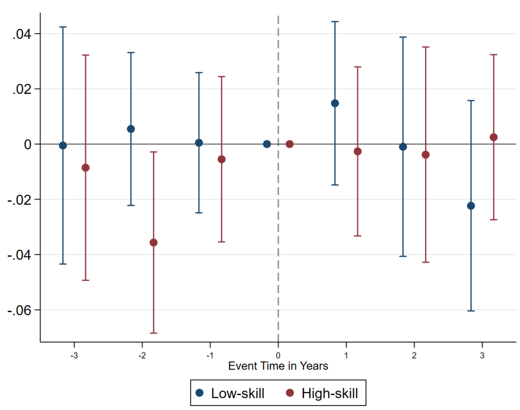
Figure 13: The Effect of Large Firm Entry on Demand in Low-Skill Counties



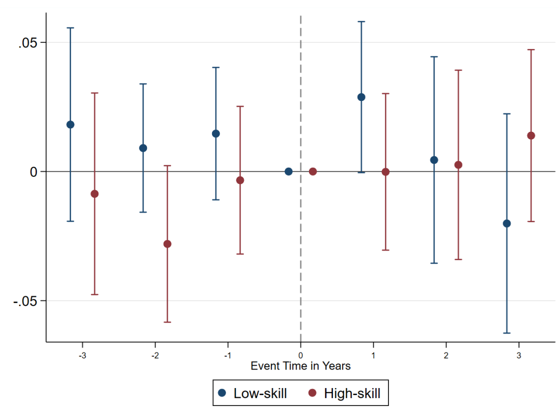
C. Cognitive



D. Computer



E. Social



F. Management

Notes: This figure plots the regression coefficients on the interaction between MDP, pre/post-treatment indicators and indicator for whether the winner county has lower skill level than average U.S. county. Observations are indexed at the year of MDP opening. Case, year, state, 2-digit NAICS and industry-year fixed effects are included. Regression also includes the following interaction terms: MDP $\times$ post-treatment, MDP $\times$ skill-level indicator and post treatment $\times$ skill-level indicator. Sample is restricted to non-MDP employers' postings with valid county, employer name and 2-digit NAICS. Estimates are clustered at county level. 95% confidence intervals shown. *Sources*: Lightcast Vacancy Data.

Table 1: Million Dollar Projects Characteristics

	(1)
Number of MDPs	25
Number of loser counties per winner county:	
1	19
2+	6
Year of opening:	
2013-2015	15
2016-2019	10
Average Project Size:	
Investment (millions)	\$333
Subsidy package (millions)	\$130
Projected employment	1,105
Industries:	
Manufacturing	15
Professional, Scientific, and Technical Services	3
Management of Companies and Enterprises	2
Transportation and Warehousing	2
Other	3

Notes: This sample only includes million dollar establishments with verified opening date in media outlets and for which there are incumbent firms in both winning and losing counties that are observed at least once before and once after the plant opening date. This sample was restricted to exclude MDPs with contaminated runner-up county and/or pre-period. The projected investment and employment averages are only available for 18 plants. Incentive deals are also not disclosed for three of the 25 firms. *Source*: *Site Selection* and *Good Jobs First Subsidy Tracker 2.0* Megadeals.

Table 2: Description of Job Skills

Job Skills	Keywords and Phrases
Character	Organized, detail oriented, multitasking, time management, meeting deadlines, energetic
Cognitive	Problem solving, research, analytical, critical thinking, math, statistics
Computer	Computer, spreadsheets, common software (e.g., Microsoft Excel, PowerPoint), specialized software (e.g., Java, SQL, Python)
Customer service	Customer, sales, client, patient
Financial	Budgeting, accounting, finance, cost, expense
Management	Management, supervisory, leadership, mentoring, staff
Social	Communication, teamwork, collaboration, negotiation, presentation, persuasion
Writing	Writing

Notes: These eight skill groups are a slightly modified version of the ten skill groups defined in Deming and Kahn (2018) table 1. Each skill is identified by text searching for its corresponding keywords and phrases in a posting's open text skill field. For a more comprehensive categorization, we often use a more generic format of a keyword to capture the variations with which it appears in Ads. For example, for the keyword "analytical" under cognitive, we search for "analy" to cover both "analysis" and "analytical." To identify specialized software under computer, we rely on Lightcast's specialized software variable. *Source:* Lightcast vacancy data.

Table 3: The Effect of Large Firm Entry Effect on Firms and Salaries

	Number of			Growth Rate		
	Postings	Firms	Salary ($)	Postings	Firms	Salary
	(1)	(2)	(3)	(4)	(5)	(6)
$MDP_c \times Post_t$	-6,418	-219	-5,217	0.01	-0.04	-0.03
	(5,209)	(203)	(4,460)	(0.041)	(0.045)	(0.031)
R^2	0.927	0.902	0.938	0.990	0.981	0.661
N	399	399	399	399	399	399

Notes: All the above regressions are estimated at county level and include county and year fixed effects. Growth rates are calculated using natural logarithms. Data balanced three years before and after MDP entry for each case. Sample is restricted to non-MDP employers' postings with valid county, and employer name. Regression are clustered at county level. 95% confidence intervals shown. Dashed *Sources*: Lightcast Vacancy Data.

Table 4: The Effect of MDP Entry on Education, Experience and Skills Demand

	Panel A: **Experience and Education**				
	Any Experience	3+ Experience	Any Education	Masters or PhD	Any Degree
$MDP_c \times Post_t$	0.011	-0.004	0.017	-0.002	-0.002
	(0.014)	(0.007)	(0.015)	(0.003)	(0.014)
Mean	0.488	0.521	0.531	0.051	0.273
Percent Change	0.023	-0.007	0.032	-0.039	-0.007
N	982,918	598,236	982,918	602,906	982,918
	Panel B: **STEM and Skills**				
	STEM Degree	Computer	Cognitive	Social	Management
$MDP_c \times Post_t$	-0.003	-0.002	0.010	0.005	0.003
	(0.004)	(0.007)	(0.006)	(0.010)	(0.005)
Mean	0.289	0.373	0.254	0.487	0.516
Percent Change	-0.01	-0.005	0.039	0.01	0.004
N	410,082	982,918	982,918	982,918	982,918

Notes: All the above regressions are estimated at firm level and include the following fixed effects: case, year, county, 2-digit NAICS and industry-year. Sample is restricted to non-MDP employers' postings with valid county, employer name and 2-digit NAICS. All estimates are clustered at county level. Data balanced three years before and after MDP entry for each case. 95% confidence intervals shown. *Sources*: Lightcast Vacancy Data.

A Literature Review

Table A1: The Effect of Large Firm Entry on Employment and Wages in the Literature

Authors	**Data**	**Projects Opening Years**	**Project Type**	**Identification Strategy**	**Employment and Wage Estimates**
Gupta (2023)	Longitudinal Business Database 1990-2015 Longitudinal Employer Household Dynamics	1995-2008	About half the projects are manufacturing	MDP Diff-in-Diff	* MDP entry doesn't increase aggregate employment but affects distribution across firm age within industry.
Chen (2021)	County Business Pattern (CBP) and Quarterly Census of Employment and Wages (QCEW)	2000-2013	Half the projects are manuf.	Synthetic Control	* 4-Digit Industry employment (proxy for direct employment) increases by 865 jobs. * County level employment significantly increases by 1430 jobs on average. * Average establishment count and weekly earnings do not significantly change.
Qian and Tan (2021)	ZIP Code Business Patterns	1990-2010	High-technology industries	Propensity score (spatial) matching using a Lasso-Logistic regression	* Average income of workers increase by 1.5% in the inner ring relative to the outer ring 6 to 10 years post entry.
Slattery and Zidar (2020)	QCEW	2002-2017	Manuf. & non-manuf. projects	MDP Diff-in-Diff	* County level employment increases by 1500 in 3-D industry in winning relative to runner-up counties. * No evidence of effects on other 2-D, 1-D, or countywide employment outcomes outside the directly affected three-digit sector. * Negative but insignificant coefficient on personal income.
Bloom et al. (2019)	Annual Survey of Manufactures (ASM) 2005-2015	2005-2013	Manuf. & non-manuf. projects	MDP Diff-in-Diff	* Employment increases by 1.4% * Employment effects are not statistically different across manuf. and non-manuf. MDPs
Greenstone, Hornbeck and Moretti (2010)	Census of Population 1970-2000	1982-1993	Manufacturing	MDP Diff-in-Diff	* Wages increase by 2.7%
Greenstone and Moretti (2004)	CBP	1982-1993	Manufacturing	MDP Diff-in-Diff	* 1.2% increase in average wage bill of the 1-digit industry as the new plant

Notes: (1) "MDP Diff-in-Diff" means the project uses the winner and runner-up identification strategy introduced by Greenstone and Moretti (2004). (2) Data sources cited are for employment and wage outcomes reported in the table and are not necessarily the datasets used for each respective paper's main outcome. For example, Greenstone et al. (2010) use ASM and Census of Manufactures for their main analysis, but when looking at wages they use the decennial census. (3) Chen (2021) averages effects over the first 3 years after establishment opening and uses industry and county employment from CBP data imputed by Eckert et al. (2020). (4) Slattery and Zidar (2020)'s sample is constructed of projects that received large subsidies not necessarily large investments. It also includes expansion and relocation projects. (5) Patrick and Partridge (2022) do a replication and extension exercise of Greenstone et al. (2010) and find that the latter's results are sensitive to sample selection and specification.

B Data

B.1 Million Dollar Projects Data

To construct our MDP dataset, we start with Bloom et al. (2019) MDPs data and extend it in two ways. First, we assign opening dates for MDPs announced in 2010 or later by relying on news outlets coverage of opening ceremonies or first product launch.[34] This leads us to limit Bloom et al. (2019) initial lists to MDPs for which an open date is found and a runner-up county is identified (not only runner-up states). Second, we extend the dataset by web searching MDPs announced from 2018 to 2020, for an opening date plus a winner and a runner-up county. More systematically, we looked at all "Top Deals of the Year" in *Site Selection* mid-year edition from 2010 to 2020 and *Good Jobs First Subsidy 2.0 Tracker*'s "Megadeals." The latter is defined as projects that received a subsidy packages with a value of $50 million or more.

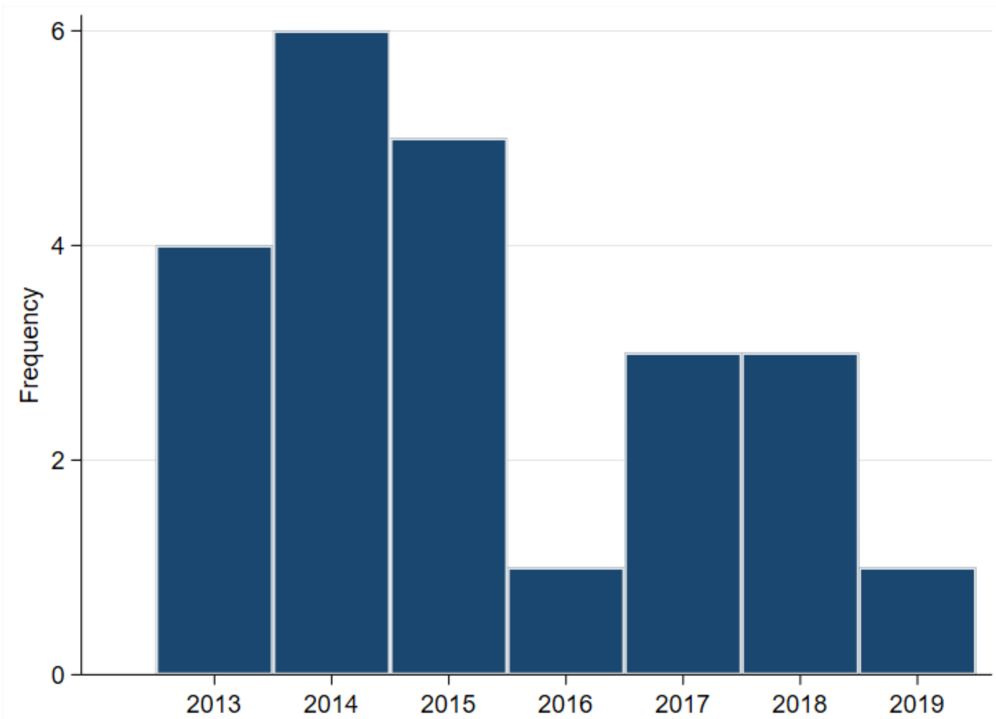
With a preliminary list of MDPs, we then apply the following restrictions: 1. restrict to firms openings between 2013 and 2019, so we can observe outcome variables at least three years before and after MDP opening –this is an outcome data constraint. 2. restrict to establishments for which we have 120 postings at the year-county level for the seven years of the event study (drops one establishment). 3. restrict to "new" projects, i.e., drop expansion and relocation projects. 4. resolve any MDP winner or runner-up counties overlaps as mentioned in section 2.1. This leaves us with 25 *new* MDP openings between 2013 and 2019 with their distribution shown in figure B1 below. For reference, Greenstone et al. (2010) identified a total of 82 MDPs between 1973 and 1998, of which 47 met their qualifying criteria.

B.2 Industry and Occupation Composition in Lightcast

It is estimated that by 2014 between 60 and 70 percent of all job postings could be found online (**?**). Taking advantage of this shift, several private-sector companies began to track online job postings using web-crawling and data-scraping methods. In our study, we employ data from one such firm, namely Lightcast, previously known as Burning Glass Technologies. This appendix discusses the representativeness of LC data relative to other official and publicly used data. Absent propriety data from companies like Lightcast and careerbuilder,

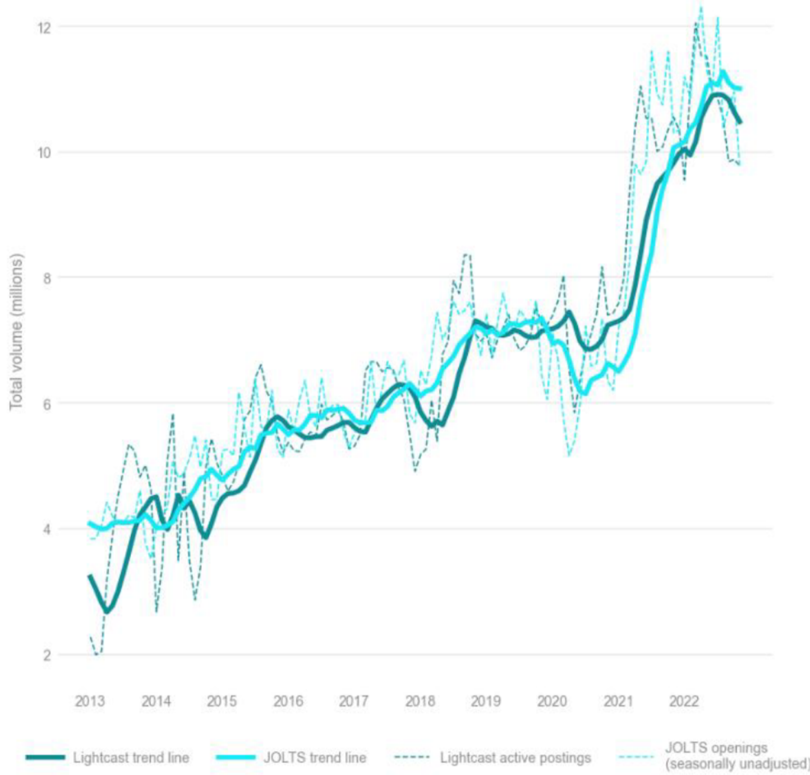
[34]The time range considered is determined by the fact that 2010 is the earliest we can observe our outcome variable due to data constraints.

Figure B1: Million Dollar Projects Opening Years



Notes: Includes only MDPs that are included in the main analysis. *Source*: *Site Selection* and *Good Jobs First Subsidy Tracker 2.0* Megadeals.

Figure B2: Labor Market Demand Captured by Lightcast Data



Notes: Correlation between Lightcast and JOLTS have 0.92 series correlation since 2013. *Source*: *Lightcast online job postings data* and *Job Openings and Labor Turnover Survey (JOLTS)*

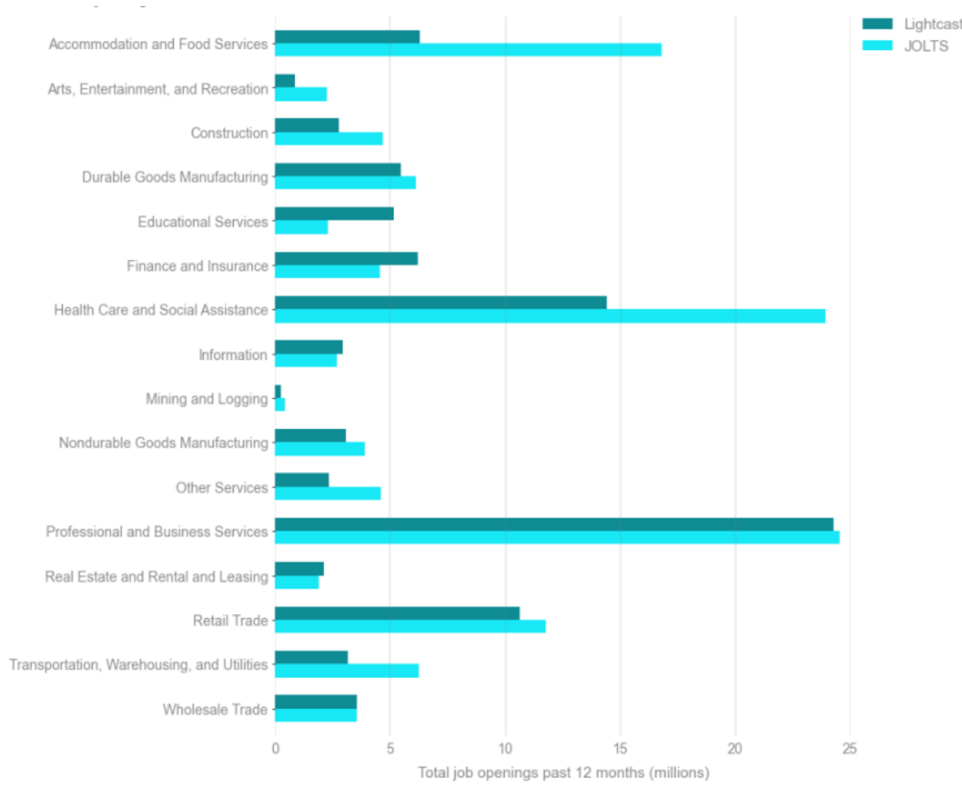
previous research used Job Openings and Labor Turnover Survey (JOLTS) data.[35] Figure B2 plots the volume of job openings recorded by Lightcast and JOLTS respectively. We can see from the Figure that Lightcast tracks JOLTS documented vacancies quite well since 2014, which is reassuring.

To investigate LC industrial composition, we compare LC industry composition to JOLTS. Ex-ante, we expect that vacancies from certain industries and occupations are less likely to be posted electronically and thus industry distribution across the two datasets won't line-up exactly. For example, we can imagine that restaurants looking for extra kitchen staff or a hotel looking to hire an extra life guard won't post those vacancies online. In B3, we plot the distribution of LC ads across major industry groups (teal), as well as the distribution of job vacancies in JOLTS (aqua).[36] Figure B3 shows that all industries are represented and most

[35] JOLTS data is the product of surveying a nationally representative sample of 21,000 U.S. business establishments across all non-agricultural industries in the public and private sectors for all 50 States and the District of Columbia. However, JOLTS data is typically available only at aggregate levels (like occupations, industries or states) and contains very little information about the characteristics of vacancies identified.

[36] Groups are limited to two-digit NAICS as classified in JOLTS data.

Figure B3: Industry Distribution in Lightcast and JOLTS

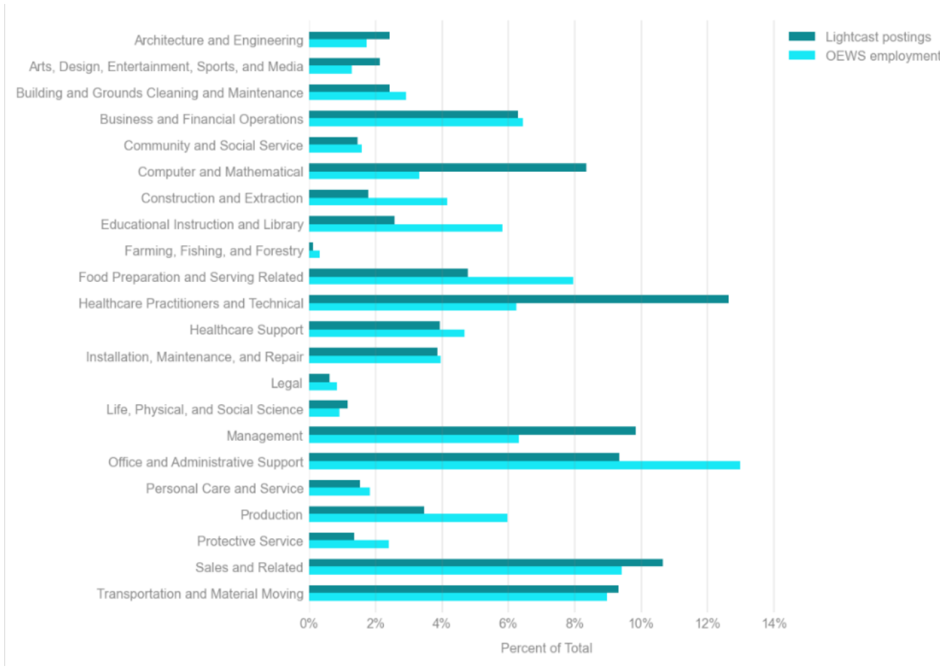


Period: 2022. *Source*: *Lightcast online job postings data* and *Job Openings and Labor Turnover Survey (JOLTS).*

industries are a close match. Nonetheless, LC is comparatively less representative in "Accommodation and Food Services", "Health Care" and "Transportation" sectors where word of mouth, offline postings, or perpetually open positions play a large role in recruitment.

To investigate LC's occupation distribution, we compare the occupational distribution of LC job ads to actual employment occupational distribution as documented by the Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS) data. Ex-ante, we do not expect online job ads to precisely match official employment statistics since occupations differ in turnover rates that would necessitate new hires (flows), and since they also differ in the extent to which they use vacancy postings (rather than informal hiring channels) to fill a slot. In Figure B4, we plot the distribution of LC ads and OEWS employment across major occupation groups (Standard Occupational Classification - SOC). Perhaps not unexpectedly, LC has a much larger representation of "Computer and Mathematical" (more than two times the OES shares), "Management," and "Healthcare Practitioners" occupations. On the other hand, LC data under-represents "Food Preparation and Serving," "Production," and "Construction" occupations. These types of occupations are less frequently posted on-

Figure B4: Occupation Distribution in Lightcast and OEWS

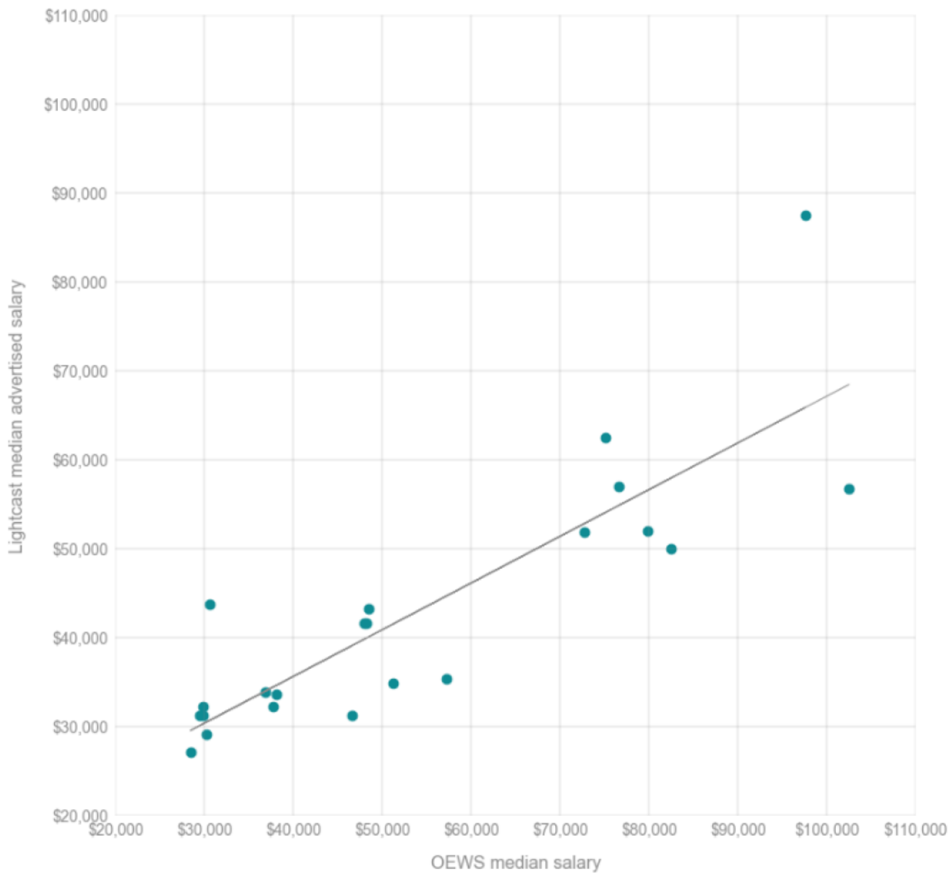


Period: May 2020 to May 2021. *Source*: *Lightcast online job postings data* and *Bureau of Labor Statistics Occupational Employment and Wage Statistics (OEWS).*

line and are often recruited through offline channels such as physical "help wanted" ads or through word-of-mouth.

Finally, Lightcast advertised salary data is gathered from wages that are explicitly stated within job postings nationally. Figure B5 below compares the median annual wages of all employment across the US to the median advertised salaries of postings in the Lightcast data. Reassuringly, we see a correlation of 0.86 between Lightcast median advertised salary and OEWS median salary. Future iterations of this paper will expand on this section to investigate the representative of LC data over time and establish LC skill measures with average skill requirement in the American Community Survey. For now, we direct the readers to Hershbein and Kahn (2018) data appendix, where these exercises have been carried out for LC data from 2010 to 2015.

Figure B5: Correlation Between Lightcast and OEWS Median Salary



Period: May 2020 to May 2021. *Source*: *Lightcast online job postings data* and *Bureau of Labor Statistics Occupational Employment and Wage Statistics (OEWS).*

C Aggregate Employment and Wage Effect

To comprehensively evaluate extensive margin effects of MDPs' entry, this appendix presents the effect of million-dollar projects entry on total county wages, employment and establishment counts using the Quarterly Census of Employment and Wages (QCEW) and on wage distribution using the American Community Survey (ACS).

C.1 Quarterly Census of Employment and Wages

We use the Quarterly Census of Employment and Wages (QCEW) annual industry files from 2010 to 2022 to evaluate the effect of MDP entry on total wages, aggregate employment level and establishment count. Using the QCEW data comes with three advantages. First, it is geographically comprehensive, thus rendering results presented here more comparable to our main analysis (than the ACS). Second, it is fundamentally a byproduct of the unemployment insurance (UI) data and thus is the closest publicly available estimate to confidential administrative data. Third, in the absence of job posting data, it was the data of choice by previous papers in the agglomeration and place-based policy literature. Thus, by estimating MDP effects using QCEW, we can compare our results to previous estimates in the literature and shed light on what QCEW estimates fail to capture using Lighcast data.

While QCEW data comes with three advantages, it's aggregated structure, at the industry-county level, means that we can't evaluate wage/salary distribution nor exclude MDP entry used for identification.[37] This has two practical implications. First, since we only have county level outcomes, in lieu of wage distribution, we run our county level event study model, which was introduced in section 4 and copied here for ease of reference.[38] Second, similar to our ACS analysis below, analysis in this appendix captures aggregate MDP effect (direct and spillover) on employment and wages.

$$Y_{ct} = \alpha + \sum_{\substack{\tau=-3 \\ \tau\neq 0}}^{3} \beta_\tau MDP_c \times 1_{t=\tau} + \alpha_c + \alpha_t + \varepsilon_{ct}$$

From the left panel of Figure 6, we see that MDP entry held off a downward trend in employment level, which could be explained by the increase in establishment county observed

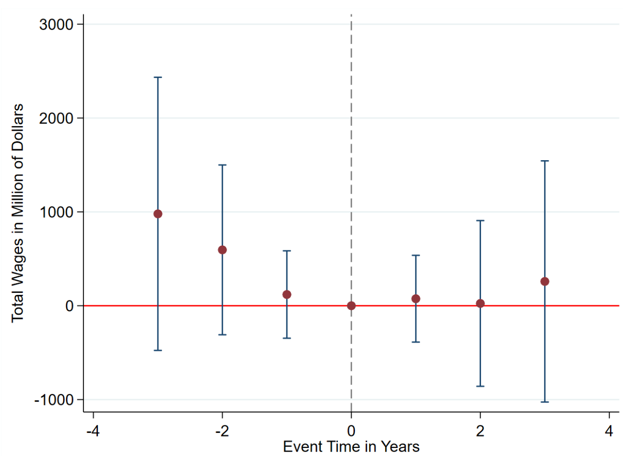
[37] QCEW is also disaggregated by ownership namely private,local, state and federal government establishments. Results shown here are aggregated across both private and public ownership, but results are robust to only looking at MDP effect on private ownership outcomes (employment, establishment count and total wages.

[38] Note that our results don't differ much if we extend our time frame to a year earlier and make our reference/base year the year before entry (-1), which is more standard in the event study literature.

in the right panel. However, neither of these patterns are statistically distinguishable from zero. Findings here confirm our main findings that MDP entry does not have a statistically significantly positive effect on neither employment nor establishment count. It is worth highlighting that both panels of figure 6 mirror very closely pattern and magnitude observed in figure 2 despite the different nature of the underlying source for each data. This supports our belief that Lightcast posting data is tracking actual employment level and establishment count.

From Figure C1, we observe no significant effect of MDP entry on total wages paid to workers in winner counties relative to runner-up counties. This result doesn't either support nor contradict our findings that million-dollar projects are applying a downward pressure on the wage distribution. In fact, the widening error bars two and three years post entry suggest that maybe MDPs are affecting wage dispersion.

Figure C1: The Effect of MDP Entry on Total Wages in QCEW



Notes: This figure plots the coefficients on the interaction between MDP and post-treatment indicator. Observations are indexed at the year of MDP opening. Case, year, and county fixed effects are included. Total wages are in millions of dollars. Estimates are clustered at county level. 95% confidence intervals shown. *Source*: Quarterly Census of Employment and Wages.

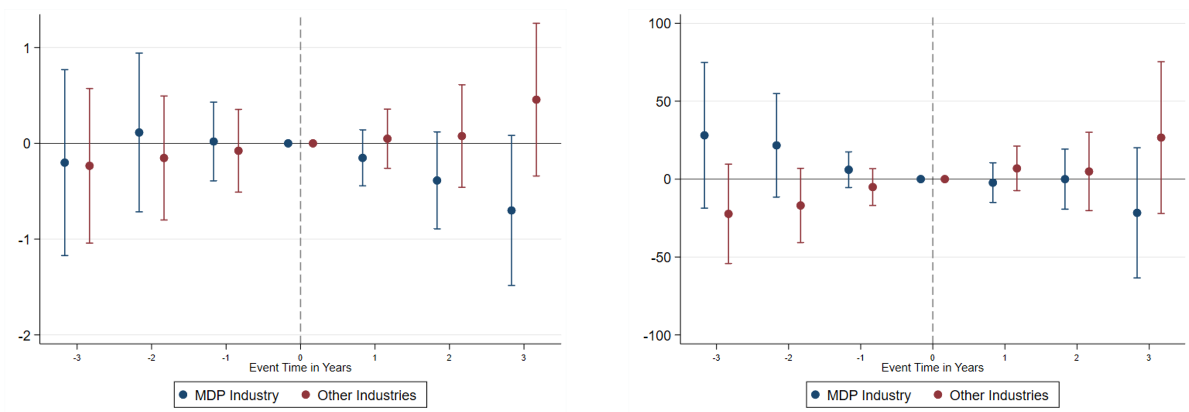
Table C1: The Spillover Effect of MDP Entry on Employment, Establishment and Wages in QCEW

	Number of			Growth Rate		
	Establishment	Employment*	Total Wages**	Establishment	Employment	Total Wages
	(1)	(2)	(3)	(4)	(5)	(6)
$MDP_c \times Post_t$	-11.24	-8.71	-529.25	0.01	0.01	0.01
	(298.840)	(7.964)	(724.201)	(0.013)	(0.013)	(0.016)
N	463	463	463	463	463	463
R^2	0.998	0.996	0.989	0.999	0.999	0.999

Notes: *Employment is in 1000s of workers and ** Total wages are in millions of dollars. All the above regressions are estimated at county level and include county and year fixed effects. Growth rates are calculated using natural logarithms. Data balanced three years before and after MDP entry for each case. Regression are clustered at county level. 95% confidence intervals shown. Dashed *Source*: QCEW Data.

As discussed in our main mechanism section, it is reasonable to expect that MDP effects might differ in MDP industry relative to other industries in the county. In fact, in this context, MDP industry captures direct effect while other industries captures indirect or spillover effect. Similar to our results in section 6.1, the difference between these two groups is visually observable, but not statistically significant as shown in Figures C2 and C3 below.

Figure C2: MDP Effect on Employment and Firms Count in QCEW by Industry

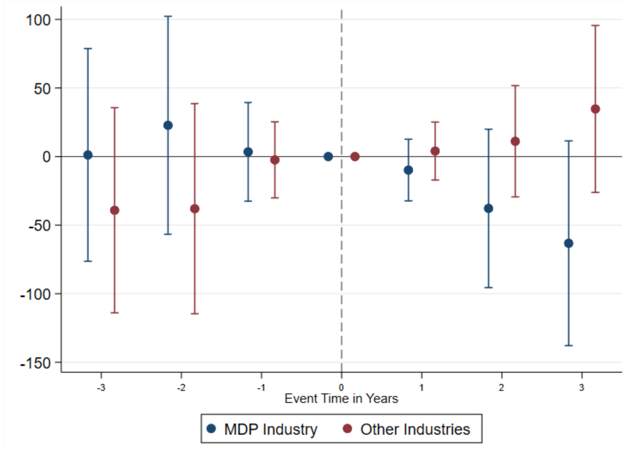


A. Employment Level

B. Establishment Count

Notes: This figure plots the coefficients on the interaction between MDP, post-treatment and MDP-industry indicators. Observations are indexed at the year of MDP opening. Case, year, and county fixed effects are included. Sample includes government and private employment. Total employment is in thousands of workers. Estimates are clustered at county level. 95% confidence intervals shown. *Source*: Quarterly Census of Employment and Wages.

Figure C3: MDP Effect on Total Wages in QCEW by Industry



Notes: This figure plots the coefficients on the interaction between MDP, post-treatment and MDP-industry indicators. Observations are indexed at the year of MDP opening. Case, year, and county fixed effects are included. Total wages are in millions of dollars. Estimates are clustered at county level. 95% confidence intervals shown. *Source*: Quarterly Census of Employment and Wages.

C.2 American Community Survey

We use the American Community Survey (ACS) public use 1% annual microdata files from 2010 to 2021 (last year of ACS available at time of writing).[39], and limit the data to employed workers and zoom-in on MDPs' winner and runner-up counties. While the ACS allows us to recover changes to **actual** earned wages instead of posted wages, it comes with many caveats, which we now list. First, for confidentiality reasons, the Census Bureau only reports county fips for counties with at least 100,000 people.[40] Therefore, by relying on ACS county identifier, we only match to 60% of MDPs' winner and runner-up counties. Second, unlike Lightcast data where we could identify and remove postings by million-dollar projects used for identification, in ACS we don't observe employers' names and thus can't distinguish between direct and spillover effects. In other words, results presented here are the aggregate effect of MDPs entries. Finally, keep in mind the ACS by construction is a cross-sectional and thus we are not tracking wage changes for surveyed individuals but rather changes in wages over time for individuals in winner relative to runner-up counties.

To evaluate the effect of MDP entries on actual wages using ACS data, we utilize the same model used in our main analysis (equation 3, pasted below for ease of reference), and

[39]Source: Data accessed through IPMUS USA.

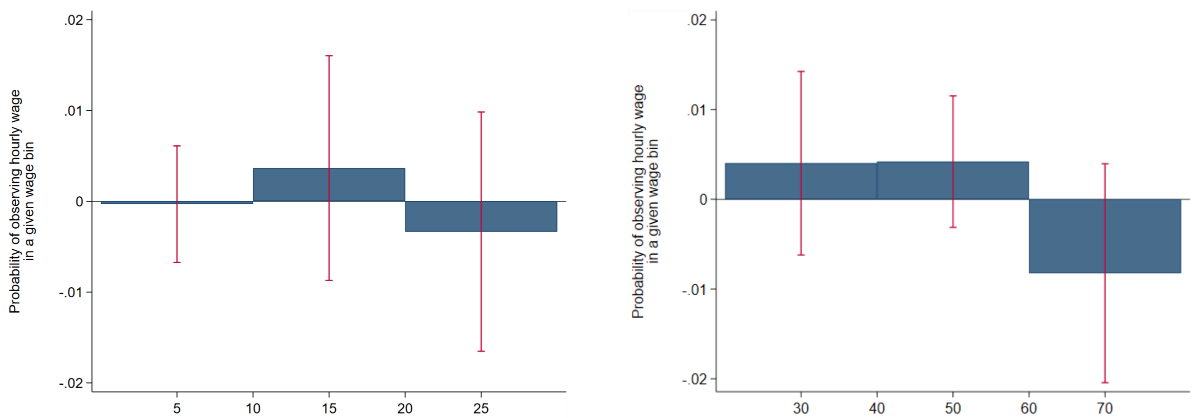
[40]For counties with populations below 100,000, Census only provides Public Use Microdata Areas (PUMAs) information (instead of county identifiers), which in rural areas can include several counties. This introduces significant measurement error, which is why we choose to focus our analysis on observations for which we can see county.

add further controls, namely gender, race and educational attainment indicators as well as age and age squared interacted with year dummies.

$$Y_{ict} = \alpha + \beta MDP_c \times post_t + \eta_t + \gamma_s + \delta_i + \chi_o + \rho_{it} + \omega_p + \varepsilon_{itc}$$

As observed in both panels of Figure C4 below, MDP entries do not have a significant effect on neither observed hourly wages nor annual salary distributions. However, it is worth noting that despite the insignificance, we see a drop in the highest bin, which seem to transfer to the lower wage/salary bins. This is consistent with findings in our main results.

Figure C4: MDP Effect on Hourly Wages and Annual Salaries in ACS



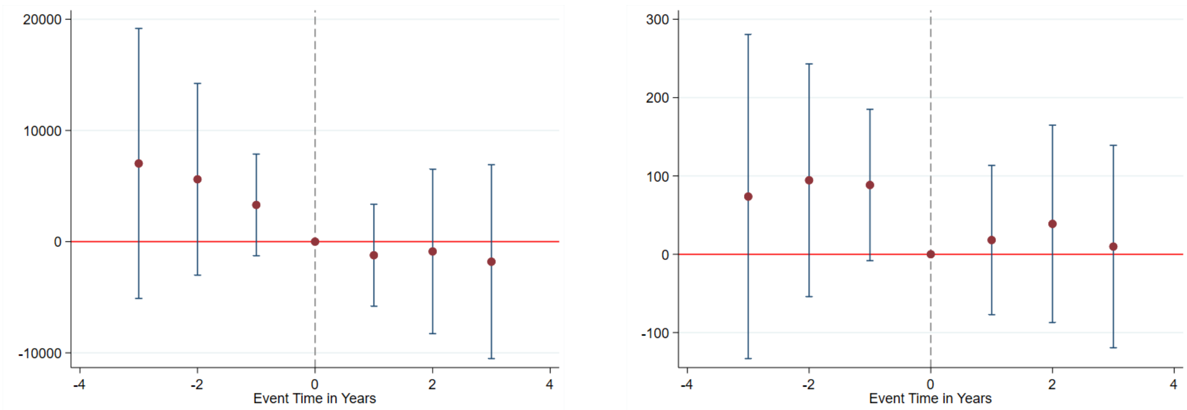
A. Hourly Wages B. Annual Salary

Notes: This figure plots the coefficients from linear probability regressions of hourly wages (left panel) and annual salaries (right panel) being in a given bin on the interaction between job-level exposure to a million dollar establishment and an indicator for MDP opening. Case, year, state, 2-digit NAICS, 2-digit occupation, industry-year, gender, race and educational attainment fixed effects are included as well as age and age squared interacted with year dummies. Sample is restricted to employed workers. Underlying data is also winsorized at the 1% level. Estimates are clustered at county level. For hourly wages, bin size is $10, with all wages below $10 and above $20 binned together. And for annual salary bin size is $20K with all salaries below $40K and above $60K binned together. 95% confidence intervals shown. *Source*: American Community Survey data.

D Robustness Check

D.1 Compositional Bias

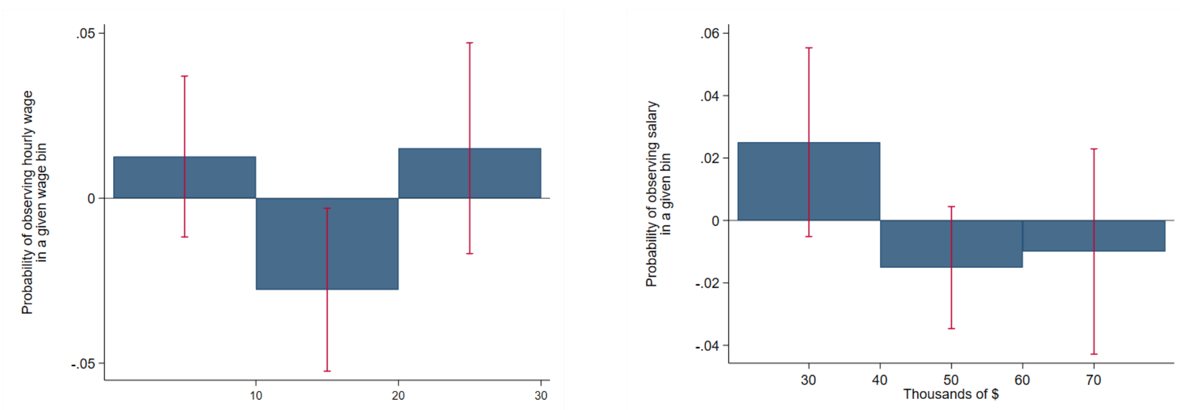
Figure D1: The Effect of Large Firm Entry on Postings and Firms Number
Incumbent Firms



A. Number of Postings B. Number of Firms

Notes: This figure plots the regression coefficients on the interaction between MDP and post-treatment indicators using a 3 year observation window. Observations are indexed at the year of MDP opening. County and year fixed effects are included. Sample is restricted to non-MDP employers' postings with valid county and employer name. 95% confidence intervals shown. *Sources*: Lightcast Vacancy Data.

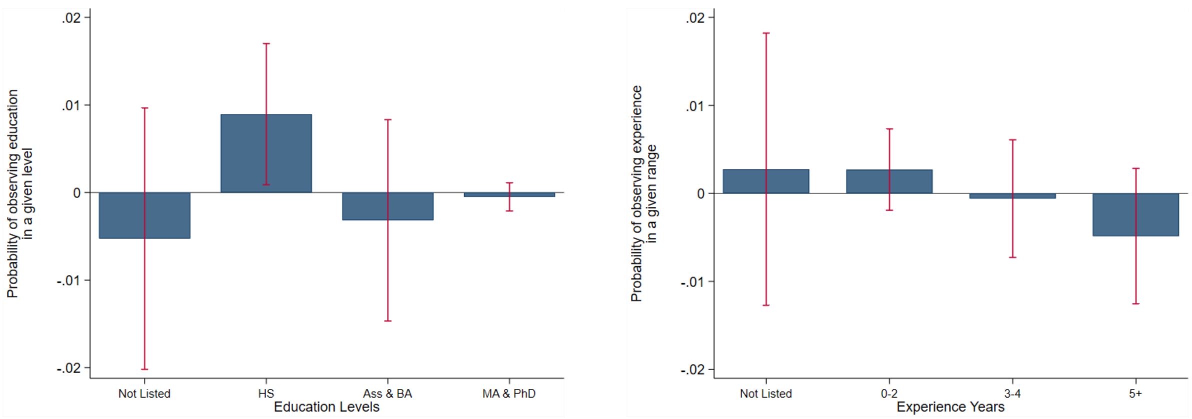
Figure D2: The Effect of Large Firm Entry on Hourly Wages and Annual Salaries
Incumbent Firms



A. Hourly Wages B. Annual Salary

Notes: For specification details, see notes below main figure 7. For hourly wages, bin size is \$10, with all wages below \$10 and above \$20 binned together. And for annual salary bin size is \$20K with all salaries below \$40K and above \$60K binned together. 95% confidence intervals shown. *Source*: Lightcast vacancy data.

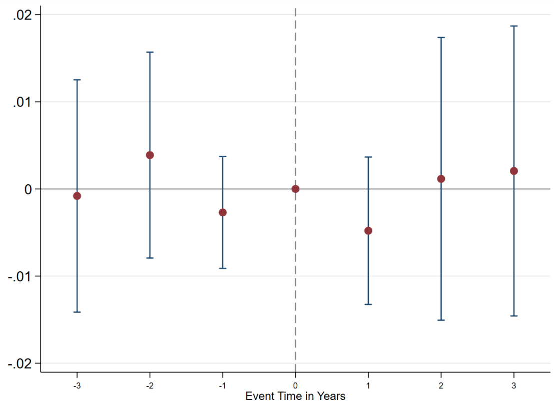
Figure D3: The Effect of Large Firm Entry on Education and Experience Distribution
Incumbent Firms



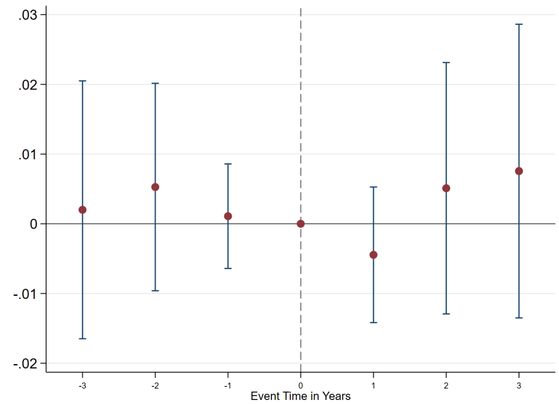
A. Education Distribution B. Experience Distribution

Notes: This figure plots the coefficients from linear probability regressions of education (left panel) and experience (right panel) being in a given bin on the interaction between job-level exposure to a million dollar project and an indicator for MDP opening. Case, year, state, 2-digit NAICS, 2-digit occupation and industry-year fixed effects are included. Sample is restricted to non-MDP employers' postings with employer name, county, industry and occupation. Estimates are clustered at county level. For experience, bins are binned for 5 years and above, which together represent about 13% of the distribution. 95% confidence intervals shown. *Source*: Lightcast vacancy data.

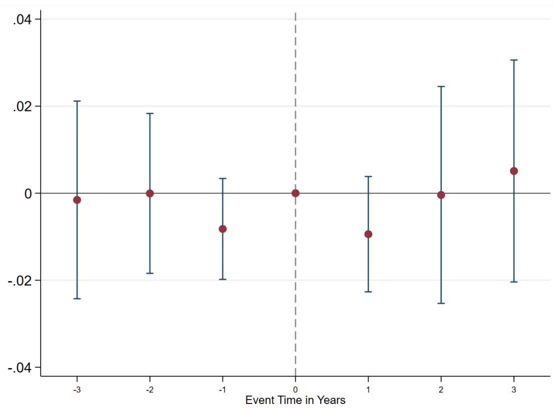
Figure D4: The Effect of Large Firm Entry on Demand for Cognitive, Computer, and Social Skills - Incumbent Firms



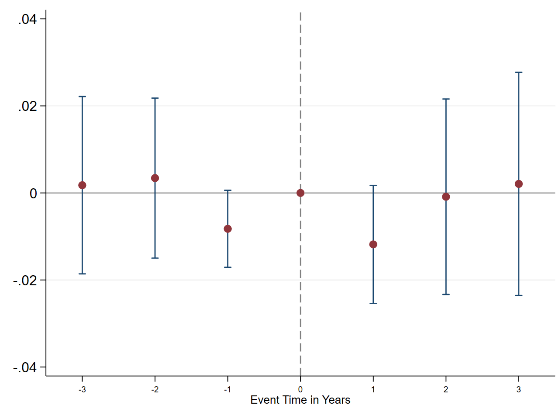
A. Cognitive



B. Computer



C. Social

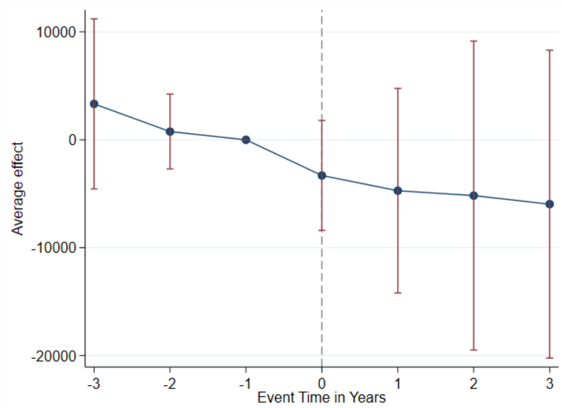


D. Management

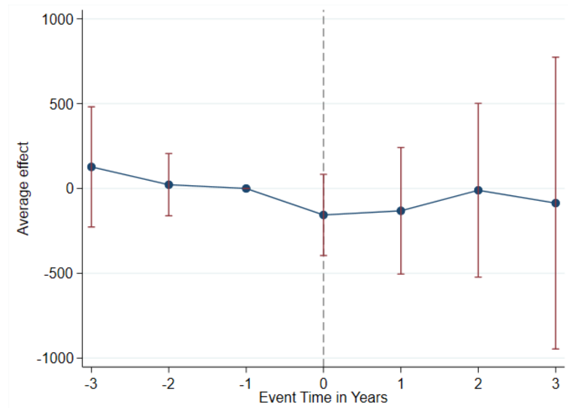
Notes: This figure plots the regression coefficients on the interaction between MDP and post-treatment indicators using a 3 year observation window. Observations are indexed at the year of MDP opening. Case, year, county and 2-digit NAICS fixed effects are included. Sample is restricted to non-MDP incumbent employers' postings with valid county, employer name and 2-digit NAICS. Estimates are clustered at county level. 95% confidence intervals shown. *Sources*: Lightcast Vacancy Data.

D.2 Robust Diff-in-Diff Model

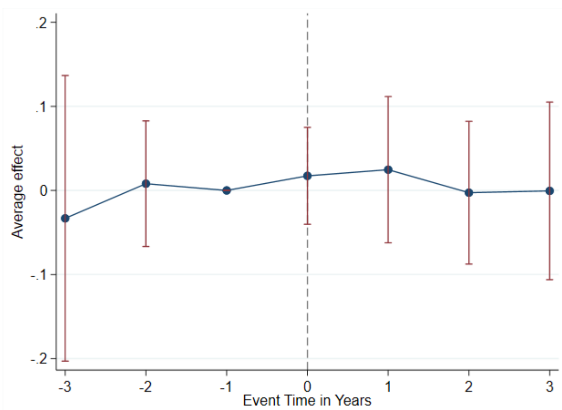
Figure D5: The Effect of MDP Entry on Number of Postings and Firms
Heterogeneous and Dynamic Robust



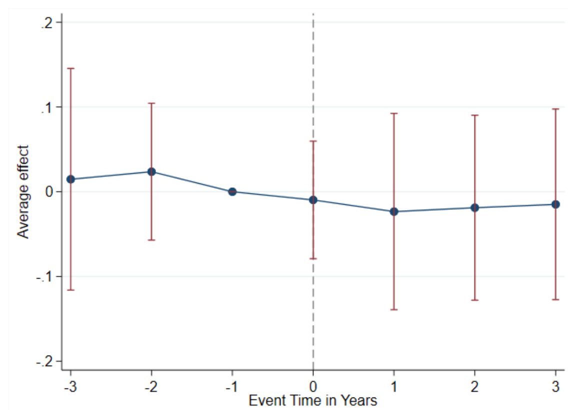
A. Number of Postings



B. Number of Firms



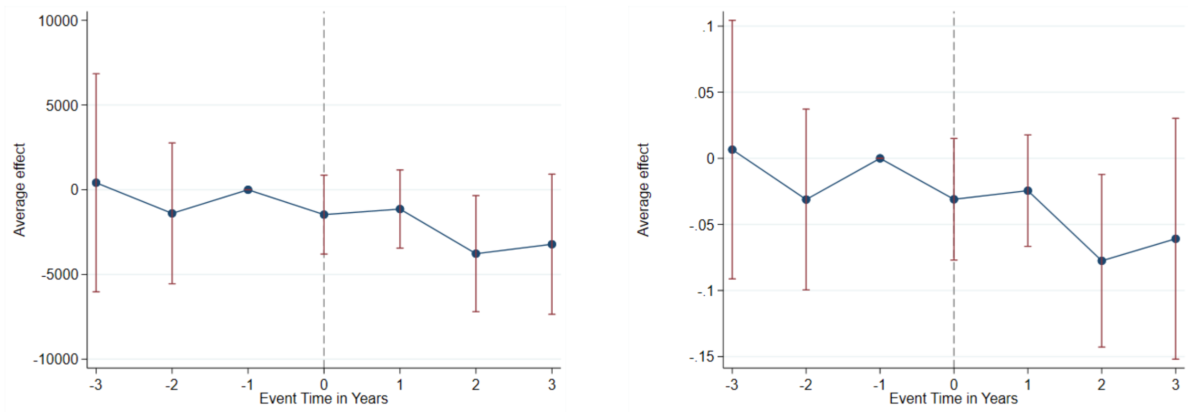
C. Postings Growth



D. Firms Growth

Notes: This figure plots the regression coefficients on the interaction between MDP and post-treatment indicators using a 3 year observation window. This specification uses placebos to estimate pre-trends (De Chaisemartin and d'Haultfoeuille, 2020). County and year fixed effects are included. Sample is restricted to non-MDP employers' postings with valid county and employer name. 95% confidence intervals shown. Growth means taking natural logarithm of level variable. *Sources*: Lightcast Vacancy Data.

Figure D6: The Effect of MDP Entry on Salaries - Heterogeneous and Dynamic Robust

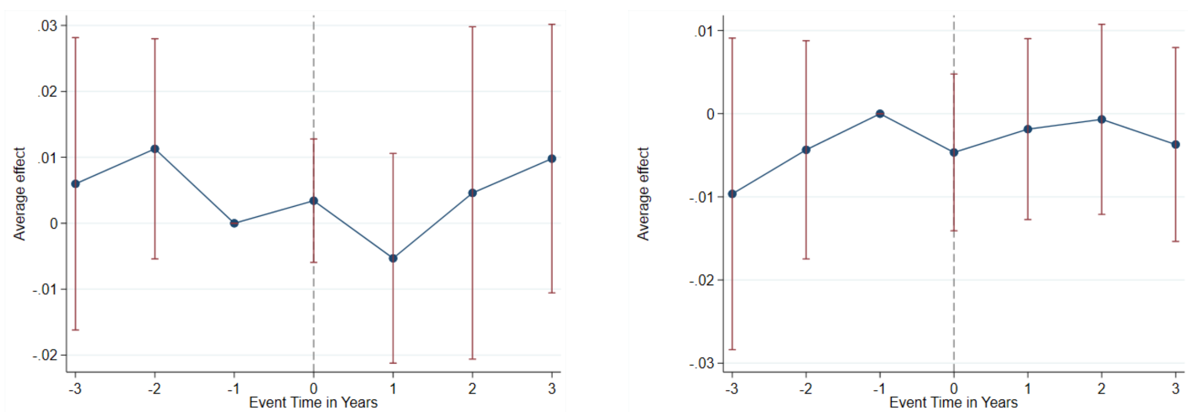


A. Wages

B. Wages Growth

Notes: This figure plots the regression coefficients on the interaction between MDP and post-treatment indicators using a 3 year observation window. This specification uses placebos to estimate pre-trends (De Chaisemartin and d'Haultfoeuille, 2020). County and year fixed effects are included. Sample is restricted to non-MDP employers' postings with valid county and employer name. 95% confidence intervals shown. Growth means taking natural logarithm of level variable. *Sources*: Lightcast Vacancy Data.

Figure D7: The Effect of Large Firm Entry on Demand for Stem Degrees
Heterogeneous and Dynamic Robust

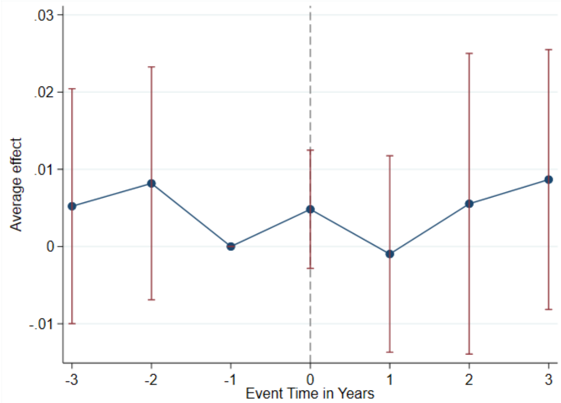


A. Any Major

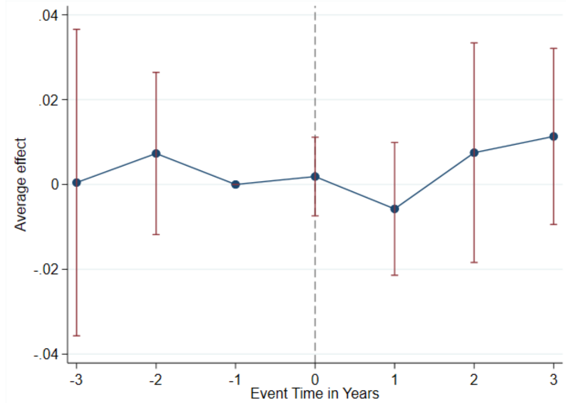
B. STEM Degrees

Notes: This figure plots the regression coefficients on the interaction between MDP and post-treatment indicators using a 3 year observation window. This specification uses placebos to estimate pre-trends (De Chaisemartin and d'Haultfoeuille, 2020). Case, year, county and 2-digit NAICS fixed effects are included. Sample is restricted to non-MDP employers' postings with valid county, employer name and 2-digit NAICS. Estimates are clustered at county level. 95% confidence intervals shown. *Sources*: Lightcast Vacancy Data.

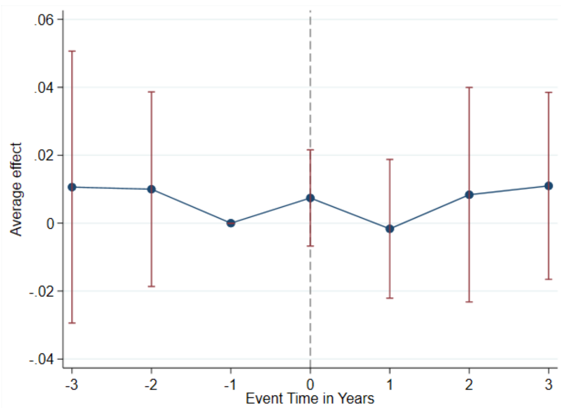
Figure D8: The Spillover Effect of MDP Entry on Demand for Cognitive, Computer, and Social Skills - Heterogeneous and Dynamic Robust



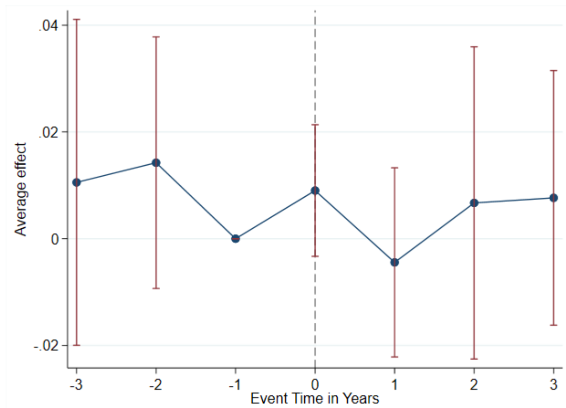
A. Cognitive



B. Computer



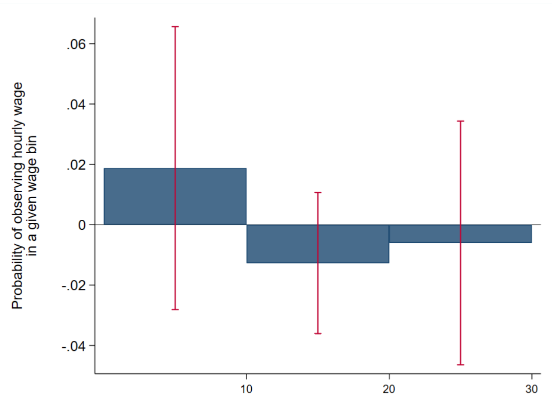
C. Social



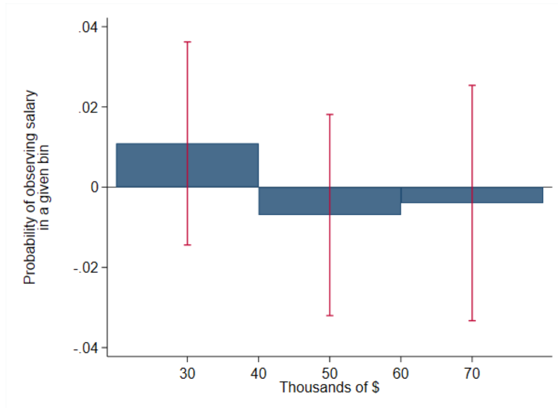
D. Management

Notes: This figure plots the regression coefficients on the interaction between MDP and post-treatment indicators using a 3 year observation window. This specification uses placebos to estimate pre-trends (De Chaisemartin and d'Haultfoeuille, 2020). Case, year, county and 2-digit NAICS fixed effects are included. Sample is restricted to non-MDP employers' postings with valid county, employer name and 2-digit NAICS. Estimates are clustered at county level. 95% confidence intervals shown. *Sources*: Lightcast Vacancy Data.

Figure D9: The Effect of Large Firm Entry on Hourly Wages and Annual Salaries - Robust



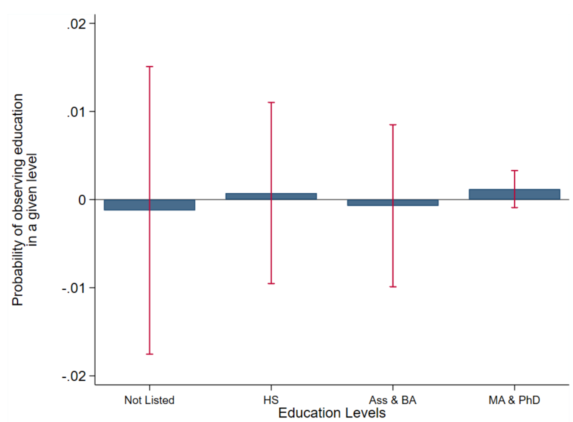
A. Hourly Wages



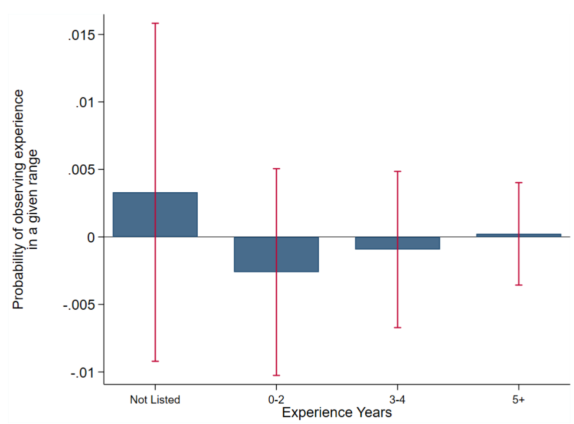
B. Annual Salary

Notes: For specification details, see notes below main figure 7. For hourly wages, bin size is \$10, with all wages below \$10 and above \$20 binned together. And for annual salary bin size is \$20K with all salaries below \$40K and above \$60K binned together. 95% confidence intervals shown. *Source*: Lightcast vacancy data.

Figure D10: The Effect of Large Firm Entry on Education and Experience Distribution Robust Model



A. Education Distribution



B. Experience Distribution

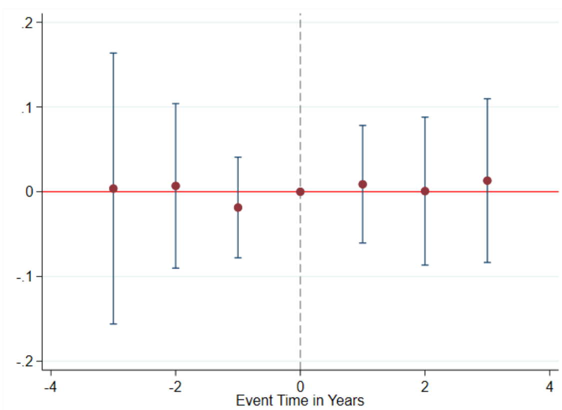
Notes: This figure plots the coefficients from linear probability regressions of education (left panel) and experience (right panel) being in a given bin on the interaction between job-level exposure to a million dollar project and an indicator for MDP opening. Case, year, state, and 2-digit NAICS fixed effects are included. Sample is restricted to non-MDP employers' postings with employer name, county, industry and occupation. Estimates are clustered at county level. For experience, bins are binned for 5 years and above, which together represent about 13% of the distribution. 95% confidence intervals shown. *Source*: Lightcast vacancy data.

E Additional Results

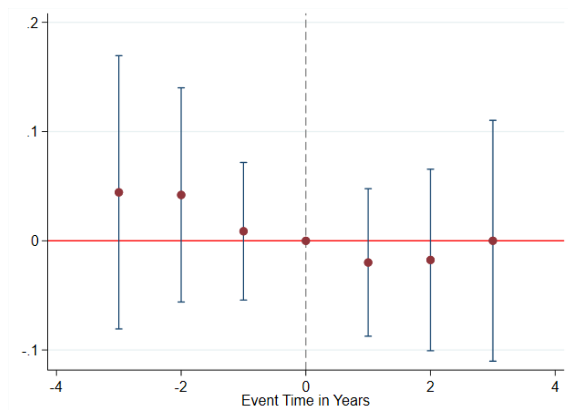
E.1 More on Education, Experience and Wages

First, looking at the lack of change in number of postings post MDP entry and the small but insignificant increase in number of establishments, it is reasonable to wonder what happens to these variables' growth rate. Figure E1 below suggests the answer is no change. Second, looking at the effect of MDP entry on the wage distribution, one might ask did MDP entry affect employers' probability of listing wages on their job ads in the first place? In answer to this question, Figure E2 shows the effect of MDP entry on the probability of listed wages at the posting level.

Figure E1: The Effect of MDP Entry on Postings and Firms' Growth Rage.



A. Postings

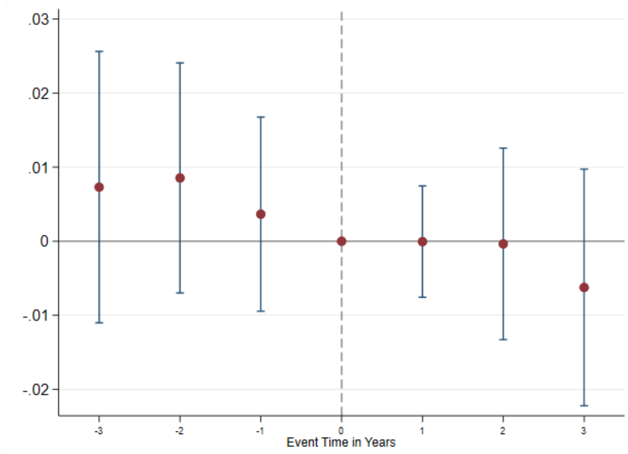


B. Firms

Notes: This figure plots the regression coefficients on the interaction between MDP and post-treatment indicators using a 3 year observation window. Observations are indexed at the year of MDP opening. County and year fixed effects are included. Sample is restricted to non-MDP employers' postings with valid county and employer name. 95% confidence intervals shown. Growth rates are measured by taking the natural logarithms of number of postings and firms respectively. *Sources*: Lightcast Vacancy Data.

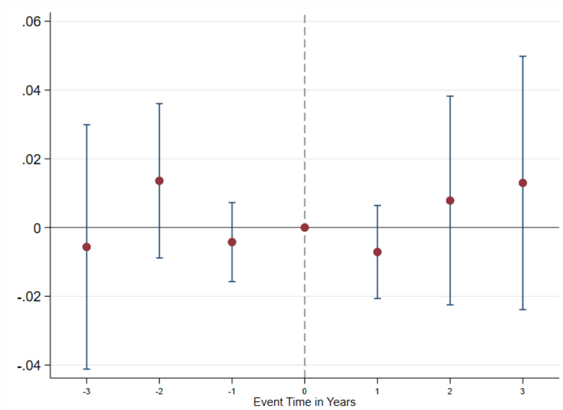
The listing of education, and experience requirement has been an outcome of interest in earlier work like Hershbein and Kahn (2018). Therefore, Figure E3 presents the dynamic effect of MDP entry on listing of education and experience. In Figure E4, we present the effect of MDP entry on education and experience distribution when the denominator is restricted to postings that list each respective variable. This is different from our main figures, where we categorize postings that don't list education as requiring no education and postings that don't list experience as requiring no experience. I.e., whereas our main figures consider absence of listing as the lowest category, Figure E4 doesn't consider them part of the universe. Nonetheless, we still see downskilling in both education and experience, but now the drop of demand for professional degrees is significant instead of Bachelor's.

Figure E2: The Effect of MDP Entry on Posted Wages

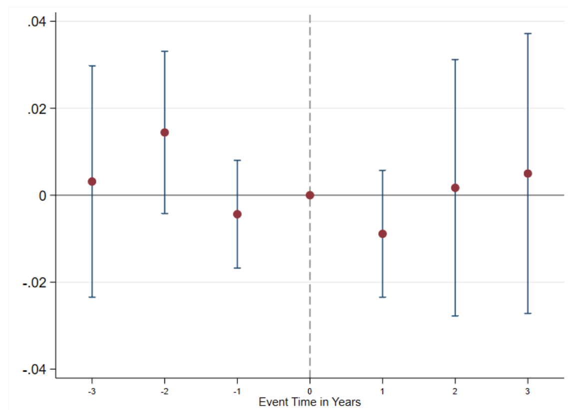


Notes: This figure plots the coefficients on the interaction between MDP and post-treatment indicator. Observations are indexed at the year of MDP opening. Case, year, and county fixed effects are included. Estimates are clustered at county level. 95% confidence intervals shown. *Source*: Lightcast vacancy data.

Figure E3: The Effect of MDP Entry on Demand for Education and Experience



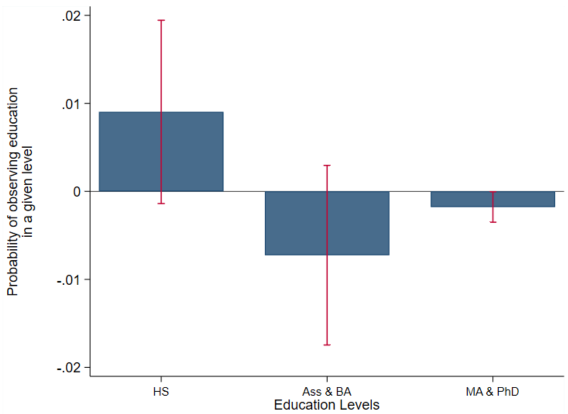
A. Education



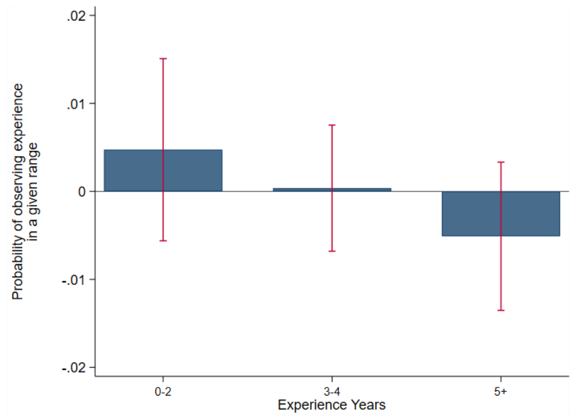
B. Experience

Notes: This figure plots the regression coefficients on the interaction between MDP and post-treatment indicators using a 3 year observation window. Observations are indexed at the year of MDP opening. Case, year, state, 2-digit NAICS and industry-year fixed effects are included. Sample is restricted to non-MDP employers' postings with valid county, employer name and 2-digit NAICS. Estimates are clustered at county level. 95% confidence intervals shown. *Sources*: Lightcast Vacancy Data.

Figure E4: The Effect of MDP Entry on Demand for Education and Experience



A. Education



B. Experience

Notes: This figure plots the coefficients from linear probability regressions of education (left panel) and experience (right panel) being in a given bin on the interaction between job-level exposure to a million dollar project and an indicator for MDP opening. Case, year, state, 2-digit NAICS, 2-digit occupation and industry-year fixed effects are included. Sample is restricted to non-MDP employers' postings with employer name, county, industry and occupation. Estimates are clustered at county level. The denominator for both panels are postings that have an education and experience listed respectively. For experience, bins are binned for 5 years and above, which together represent about 13% of the distribution. 95% confidence intervals shown. *Source*: Lightcast vacancy data.

F Tables Corresponding to Figures in the Text

Table F1: The Effect of Large Firm Entry on Firms and Postings

	(1)	(2)
Number of	Postings	Firms
lead 3	8,334.519	352.427
	(6,222.338)	(221.314)
lead 2	6,668.822	293.609
	(4,404.216)	(183.225)
lead 1	3,741.859	159.855
	(2,382.271)	(120.257)
lag 1	-1,340.511	-19.458
	(2,446.040)	(131.158)
lag 2	-544.295	105.059
	(3,992.023)	(220.716)
lag 3	-1,097.886	116.514
	(4,905.672)	(288.680)
R-squared	0.927	0.904

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: All the above regressions are estimated at county level and include county and year fixed effects. Data balanced three years before and after MDP entry for each case. Sample is restricted to non-MDP employers' postings with valid county, and employer name. Regression are clustered at county level. 95% confidence intervals shown. Dashed *Sources*: Lightcast Vacancy Data.

Table F2: The Effect of Large Firm Entry on Degree Requirement and Skill Demand

	(1) Any Degree	(2) STEM Degree	(3) Computer	(4) Cognitive	(5) Social	(6) Management
Lead 3	-0.004	-0.002	-0.000	-0.012*	-0.003	-0.006
	(0.008)	(0.008)	(0.007)	(0.007)	(0.011)	(0.011)
Lead 2	-0.001	-0.014*	-0.005	-0.008	-0.004	-0.004
	(0.005)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
Lead 1	-0.000	-0.008	0.001	-0.002	-0.004	-0.005
	(0.007)	(0.005)	(0.007)	(0.004)	(0.006)	(0.006)
Lag 1	-0.009*	-0.003	-0.004	-0.001	-0.000	-0.001
	(0.006)	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)
Lag 2	-0.007	-0.003	-0.001	-0.001	0.004	-0.001
	(0.008)	(0.007)	(0.006)	(0.007)	(0.010)	(0.010)
Lag 3	0.001	-0.002	0.006	0.005	0.009	0.001
	(0.008)	(0.008)	(0.006)	(0.006)	(0.010)	(0.011)
Observations	12,759,944	4,103,926	12,759,944	12,759,944	12,759,944	12,759,944

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: All the above regressions are estimated at posting firm and include the following fixed effects: case, year, county, 2-digit NAICS and industry-year. Sample is restricted to non-MDP employers' postings with valid county, employer name and 2-digit NAICS. All estimates are clustered at county level. Data balanced three years before and after MDP entry for each case. 95% confidence intervals shown. *Sources*: Lightcast Vacancy Data.

Table F3: Comparison Between Incumbent Firms and MDP's Requirements

	Incumbent Firms	MDP	T-Stat
Education requirements			
Any	0.57	0.80	0.23
BA or more, conditional on any	0.57	0.73	0.17
Major specified	0.32	0.55	0.23
STEM, conditional on major	0.32	0.68	0.36
Experience requirements			
Any	0.52	0.72	0.20
Years, conditional on any	3.55	5.16	1.61
3+ years	0.57	0.79	0.22
Skill requirements			
Cognitive	0.36	0.62	0.26
Computer/Software	0.39	0.61	0.22
Customer Service	0.43	0.31	-0.11
Financial	0.17	0.20	0.03
Management	0.53	0.75	0.22
Social	0.49	0.65	0.16
Writing	0.14	0.27	0.12

Notes: Incumbent firms' average is calculated using postings by firms in winner and runner-up counties in the three years prior to MDP entry for each pair. MDP is estimated using postings by million dollar establishments aggregated in table 1. BA or more is the share of postings requiring a minimum of a bachelor's degree conditional on any educational level being listed. Similarly, STEM degree is conditional on a degree being listed and *3+ years* is conditional on any experience being listed. STEM is defined as postings listing degrees in the following fields: natural sciences, engineering, computer science, and air space. More specifically, Lightcast assigns each degree a Classification of Instructional Program (CIP) code, which we then use to identify STEM degrees. For keywords used to identify each skill see table 2. All differences are statistically significant at the 1 percent level. *Source*: Lightcast Vacancy Data.