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COMBINING RULES AND DISCRETION IN ECONOMIC DEVELOPMENT POLICY: EVIDENCE ON THE IMPACTS OF THE CALIFORNIA COMPETES TAX CREDIT

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Combining Rules and Discretion in Economic Development Policy: Evidence on the Impacts of the California Competes Tax Credit
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ABSTRACT

We evaluate the effects of one of a new generation of economic development programs, the California Competes Tax Credit (CCTC), on local job creation. Incorporating perceived best practices from previous initiatives, the CCTC combines explicit eligibility thresholds with some discretion on the part of program officials to select tax credit recipients. The structure and implementation of the program facilitates rigorous evaluation. We exploit detailed data on accepted and rejected applicants to the CCTC, including information on scoring of applicants with regard to program goals and funding decisions, together with restricted access American Community Survey (ACS) data on local economic conditions. Using a difference-in-differences approach, we find that each CCTC-incentivized job in a census tract increases the number of individuals working in that tract by over two – a significant local multiplier. We also explore the program's distributional implications and impacts by industry. We find that CCTC awards increase employment among workers residing in both high income and low income communities, and that the local multipliers are larger for non-manufacturing awards than for manufacturing awards.

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1. Introduction

State and local economic development programs have proliferated in recent decades. In an effort to stimulate local economic activity, subnational governments in the U.S. currently spend about $45 billion every year on business tax incentives alone, about three times the amount they spent in 1990 (Bartik, 2019). However, these incentives are controversial, and many question their effectiveness in attracting and retaining businesses. Indeed, it is hard to use existing research on one of the principal economic development tools in the U.S., place-based policies, to justify government expenditures on business incentives, as many studies point to only limited positive impacts of past programs (with some exceptions; see Neumark and Simpson, 2015).

In this paper, we evaluate the effects of the California Competes Tax Credit (CCTC) on the geographic areas (census tracts) in which credits are awarded. California adopted the CCTC in 2013, replacing its long-standing enterprise zone program. Like many economic development programs around the country, the CCTC aims to attract and retain businesses in the state. It also provides some preferential treatment for proposed economic development in distressed communities. However, in a departure from many of its predecessors, the CCTC combines explicit eligibility thresholds with some discretion on the part of program officials in selecting ultimate tax credit recipients. As such, the CCTC aimed to incorporate best practices in designing economic development programs. At the same time, the structure and implementation of the program facilitates rigorous evaluation.

To estimate the impact of the CCTC on local economic outcomes, we exploit fine-grained and detailed data on accepted and rejected applicants to the CCTC program together with restricted-access American Community Survey (ACS) data on local economic conditions. We use a difference-in-differences strategy that compares changes in outcomes in neighborhoods with winning vs. losing applicants. As part of this strategy, we control for total “proposed” jobs for an area among applicants, which helps to account for unobservable neighborhood characteristics that could be correlated both with demand for tax credits and with future economic conditions. In addition, we leverage detailed information on scores that applicants receive in the evaluation process to augment our difference-in-differences strategy in a manner that places more weight on locations where relatively more applicants were close to the threshold for eligibility for tax credits in each allocation round. This approach combines our difference-in-differences strategy with elements of a regression discontinuity (RD) design, as it more heavily exploits identifying variation in actual awards that comes from the pool of applicants with a better chance of winning.

Our main finding is that each CCTC-incentivized job in a census tract increases the number of employed individuals working in that tract by approximately two-and-a-half. In other words, we find evidence of a significant local multiplier on CCTC-incentivized jobs. The aggregate state-level multiplier might be larger or smaller due to spillovers to other areas, but our results point to meaningful direct employment impacts of the program in affected communities.

We also explore the CCTC’s distributional implications and impacts by industry. Taking advantage of information on workers’ places of residence, we find that CCTC awards increase employment among individuals residing in both high income and low income communities. We additionally find that local employment multipliers are larger for non-manufacturing awards than for manufacturing awards. The latter result is not inconsistent with expectations that location-based policies targeting firms in tradable sectors are more effective in expanding local employment, as many of the non-manufacturing firms that the CCTC incentivizes are in sectors that sell to national or global markets. All our estimates are robust to reweighting locations with winning and losing applicants to create even more comparable treatment and control groups.

Our findings speak to the efficacy of a new generation of economic development programs that have been refined to address deficiencies in earlier programs. One conjectured explanation for the modest estimated impacts of past economic development programs (often place-based programs) is that the incentives offered under such programs do not incentivize net new job creation (Patrick, 2016; Harger and Ross, 2016). The CCTC clearly creates such incentives. In addition, past research has suggested that tax incentives will be more effective when they have a discretionary component that allows program administrators to award the credits where they will have the largest impact (Neumark, 2013). The CCTC has a strong discretionary component (while still allowing a rigorous program evaluation, as discussed below). Finally, recent research shows that hiring credits can be more effective when the incentives can be recaptured if hiring goals are not met (Neumark and Grijalva, 2017). The CCTC builds in monitoring and recapture of incentives if employment, investment, or salary commitments are not met.

Our results also contribute to a broader literature on the effects of state and local economic development programs. Following many years of skepticism, there is increasing enthusiasm for using targeted incentives/subsidies to stimulate local economic activity and address regional disparities (Slattery and Zidar, 2020). Recent research has highlighted the extreme unevenness in economic conditions and opportunities (Chetty et al., 2014, Austin et al., 2018), and additionally how place-based transfers can provide important targeting benefits above and beyond person-based transfers (Gaubert et al., 2021). Given the resurgence in interest, and in recognition of the potential “windfalls” for firms and anti-competitive implications of crudely targeted and poorly structured economic development policies, effective design of the next generation of economic development programs is critical. We offer new evidence on the effects of programs that incorporate a variety of best practices from previous efforts. Implementing certain design features of the CCTC could help to improve job creation impacts of existing or future economic development programs.

2. The California Completes Tax Credit

2.1 CCTC Policy Design

Two main factors were influential in the design of the California Competes Tax Credit (CCTC) program and its choice of discretionary tools. First, three studies were heavily cited leading up to the dismantling of the California Enterprise Zone (EZ) program in 2013, which was fully supplanted by the CCTC by 2014.[1] Kolko and Neumark (2010) presented plant-level evidence showing that EZs had no effects on new job growth nor new business growth within the zones. Meanwhile, the California Budget Project (2013) documented that 20% to 30% of EZ hiring credits were in fact "retroactive vouchers" for workers hired over two years prior to receiving the incentive, and opened up the possibility that firms recouped windfall transfers for temporary hires. The California Legislative Analyst's Office (2003) further found that over 60% of the dollar amount of EZ tax credits claimed were by corporations with assets greater than $1 billion per year, and that the program was not targeting high distress areas nor the small and/or young businesses that are typically associated with stronger net job growth (Neumark et al., 2011; Haltiwanger et al., 2013). Together, this evidence suggested that the EZ program was "gameable," allocating credits for already hired (or temporary) workers at incumbent firms in the

[1] See California Budget Project (2013).

EZs.

The second main factor that influenced the design of the CCTC was lessons learned from the Texas Enterprise Fund (TEF) (Parent, 2014). Texas had been one of the earlier states to experiment with discretionary tools, using a “deal-closing” cash grant negotiated between the state and firm as a legally binding job creation contract, with revenue clawback provisions for recipients that do not meet their obligations. However, a 2010 watchdog group reported that among a sample of 50 recipients, two thirds of TEF awardees had not met their job creation obligations (Kirkham, 2014). The same group also claimed that the TEF’s clawback provisions were not effective in returning revenue to the state in most failed contractual obligation cases.

The Texas program contains some of the elements that currently exist in the CCTC’s discretionary toolkit, including vetting for proof of consideration of other states and strategic consideration of innovative industries. However, the CCTC program departed from the Texas program in three important ways. First, the two-stage system California adopted had a clear formulaic component separate from its discretionary component. Second, benchmarks were not established as an aggregate contractual obligation, but as an annual obligation, which made it easier to pause tax credit certifications upon learning of failures to meet benchmarks. Last, the state chose to implement the program as a tax credit rather than a cash grant so that there would be no need to claw back revenue.

2.2 CCTC Program Structure and Rules

Any business that might locate in California or that might stay or grow in California can apply for tax credits under the CCTC program. Tax credits under the CCTC program are awarded based on a two-stage competitive process. The first stage relies on a quantitative evaluation of the projected costs and benefits of the tax credit allocation to an applicant. For each application, a cost-benefit ratio is calculated by dividing the amount of tax credit requested by the sum of total new employee compensation and total capital investment in the state. Program administrators rank the applications by cost-benefit ratios, from lowest to highest. They then impose a cutoff for the first stage of the process by moving up the cost-benefit distribution until the total costs of all included applications is two times the budgeted amount for that wave of applications. Importantly, a few critical exceptions can be made that advance applicants to the second stage even if they do not meet the cutoff (discussed below).

The second stage involves a more comprehensive evaluation of each application that makes the first-stage cutoff (including exceptions), with program administrators selecting among these applications those that are most consistent with program goals. This is accompanied by the negotiation of agreements with applicants about specific requirements or milestones that must be met to receive the credits by the Governor's Office of Business and Economic Development (GO-Biz). In these agreements, businesses commit to meeting annual milestones for full-time employment, salary levels, and project investment. These agreements are then either approved or rejected by the CCTC Committee in a public meeting. If approved, businesses have five years to meet their milestones.

Between \$150 and \$200 million per year was budgeted for tax credit allocation for fiscal years 2014-15 to 2017-18.[2] Each fiscal year, there are three allocation rounds with application deadlines in August, January, and March. There is no fee for applying for the credit, and it typically takes approximately three months for applicants to be notified about their award.

The tax credits provided under the CCTC are fairly large. The mean winning applicant in

[2] The funding is based on fiscal years. For the empirical analysis that follows, we use four years of applications: 2014-15, 2015-16, 2016-17, and 2017-2018. We do not use the (single) funding round from 2013-14 because the applicant data are missing project location as well as information on proposed job creation; only \$30 million was available for allocation in 2013-14. Unallocated and recaptured credits can be rolled over from one year to the next.

our data was allocated roughly $865,000 in tax credits. The interquartile range among winners is between $100,000 and $875,000. The minimum amount a business can request is $20,000. Tax credits for a single applicant are capped at 20% of the total amount of credits allocated in a given fiscal year (approximately $30 million during our sample period). However, only about 20% of winners receive more than $1 million in credits.[3]

In the period covered by our data, there are on average 284 applicants in each allocation round (i.e., in each phase of funding in a fiscal year, of which there are three). On average, 82 are awarded in each round. The average of the cumulative total pledged jobs over the five-year contract terms for awarded projects is about 101; the median is 31.[4]

Any business can apply to the CCTC program. However, GO-Biz, which administers the CCTC, categorizes applicants across four types: (1) California growth projects for firms already located in the state; (2) out-of-state applicants proposing to come to California; (3) California retention for projects threatening to leave the state; and (4) projects relocating within California. Until 2018, GO-Biz also made a distinction between "small" and "large" businesses; the latter included firms that had more than $2 million in revenue in the previous tax year. The set-aside that existed for small businesses was eliminated in 2018. However, until then, in many allocation rounds there was no relevant cutoff score for small businesses because there were more funds available than were requested by small businesses in the state. In our weighted difference-in-

[3] The tax credits are not refundable, but have a six-year carryforward. Credits can be recaptured if businesses fail to meet job creation, average salary, or investment milestones within the five-year timeframe of the contract. Contracts can also be cancelled and credits recaptured if businesses fail to satisfy annual reporting requirements. Job creation milestones are subject to a three-year maintenance requirement; if employment totals fall below milestones within three years, businesses must pay back the amount of any prior credits claimed.

[4] In addition to proposed job creation, our data include proposed capital investment and salary levels as recorded in businesses' applications to the CCTC program. Average capital investment per awarded project is approximately $17.4 million. Pledged salaries for newly created jobs in the applications for the first year average around $63,000. Proposed job creation, capital investment, and salary levels in businesses' CCTC applications may differ from final contract terms for winning applicants in some cases.

differences analysis, we therefore use only large business scores for constructing the weights. However, we retain the information on jobs awarded (or proposed) from all applicants.

While the CCTC aims to increase competitiveness across all sectors of the state economy, in the discretionary stage of awarding credits (stage 2), the strategic importance of certain industries is considered, with a particular focus on attracting and retaining "high-value employers in California in industries with high economic multipliers and that provide their employees good wages and benefits."[5] Notably, at the tail end of our sample period, and when the CCTC had originally been set to end (in July 2018), the California State Legislature extended the program and also made several changes intended to improve targeting of the incentives toward firms that would otherwise locate outside California (LAO, 2020).[6]

The CCTC retains an element of place-based policymaking. Businesses anywhere in the state can receive tax credits under the program, but applicants that indicate that 75% of their proposed net increase of new full-time employees work at least 75% of the time in an area of high unemployment or high poverty receive priority in the review process.[7] As part of the online application, the CCTC provides a list of high-unemployment/high-poverty cities and counties that qualify.[8] GO-Biz may also advance an application to stage 2 of the review process regardless of the cost-benefit ratio if the applicant certifies that absent the award of the credit, the

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[5] See Governor's Office of Business and Economic Development (2020a).
[6] The Legislature's 2018 budget allocated $180 million for CCTC awards for each fiscal year between 2018-2019 and 2022-2023. It also added a requirement that applicants demonstrate that the credit will affect their ability or willingness to create jobs in the state that might not otherwise be created in the state, added job training opportunities as a factor GO-Biz can consider in awarding credits, and eliminated the set-aside for small business (LAO, 2020).
[7] Through the first allocation round of fiscal year 2016-2017 (i.e., for seven of the allocation rounds in our data), locating in an area of high unemployment or high poverty did not automatically advance an applicant to the second stage of evaluation. For the remaining five allocation rounds in our data, locating in an area of high unemployment or high poverty allowed an applicant to automatically advance to the second stage of evaluation (regardless of cost-benefit ratio).
[8] See Governor's Office of Business and Economic Development (2020b).

applicant's project could occur in another state or that the applicant could terminate or relocate all or a fraction of its employees to another state.

3. Data

Our data come from several sources. First, we obtained comprehensive information from the California Governor's Office of Business and Economic Development (GO-Biz) on applicants to the CCTC program. We use data from the twelve allocation rounds that occurred between mid-2014 and mid-2018. The application data contain a range of information on each business that applies for the tax credits. Most importantly, we have information on the number of jobs proposed to be created for each of the five years that an applicant may secure tax credits under the program. Additionally, we have information on total proposed new employee compensation and capital investment in the state as well as the amount of tax credits requested; together, these form the basis for the applicant score that determines whether the applicant makes it to stage 2 of the evaluation process in a given round. We also observe which applicants make it to each stage of the evaluation process for all the allocation rounds. Finally, in addition to their industry, we have details on the location of each applicant's proposed job creation; this allows us to match most applicants (93%) to census tracts.

We derive our outcome data from the restricted-access American Community Survey (ACS) for 2013-2018, which we accessed at a Federal Statistical Research Data Center (FSRDC). The ACS provides detailed population and housing information for the entire United States. However, for confidentiality reasons, in public-use versions of the ACS, data for highly geographically disaggregated levels (for example, the tract level) are calculated based on surveys conducted over multiple years. Therefore, the public-use data do not permit us to characterize higher frequency changes in employment and other outcomes that might be attributable to CCTC incentives. In addition, the public-use files only provide coarse information on respondents' place of work (e.g., whether a person works in the same or a different county or PUMA than where they live). In order to calculate the effects of the CCTC on the number of people working in the targeted location, we need respondents' place of work at more granular levels. The restricted-access ACS provides us with information on the tract of work for most respondents who are employed.[9] We use this information to create measures of employment by tract, which we use as our primary outcome. Leveraging information on tract of residence for respondents, we also construct measures that distinguish effects for residents of, for example, higher poverty vs. lower poverty tracts.

A drawback of our data is that, because of confidentiality restrictions, we are limited in our ability to test for heterogeneous effects across areas with different initial conditions or to examine effects separately by year (as doing so would create different implicit samples). However, we are able to use multiple approaches to identify the effects of the CCTC from reliable comparison tracts, mitigating bias from selection into the tracts chosen for CCTC incentives (and the intensity of these incentives). The robustness of the findings across these approaches bolsters our confidence in a causal interpretation of our findings.

4. Methods

In this section, we discuss our empirical approaches to estimating the effects of the

[9] Isenberg et al. (2013), Graham et al. (2014), and Green et al. (2017) provide details on ACS place of work and place of residence information and describe how they compare with workplace and residence information sourced from administrative records. The Census Bureau's ACS place of work geocoding uses survey respondents' answers to questions regarding the work location address (number and street name), work location city/town/post office, work location county, work location state, work location zip code, whether the work location is inside or outside town/city limits, and employer name (Freedman et al., 2008; U.S. Census Bureau, 2014).

CCTC on job creation in the neighborhoods that receive incentives under the program. To study the direct effects of CCTC incentives on recipient neighborhoods, we use two complementary approaches. First, using data for all rounds of CCTC funding between fiscal 2014-2015 and 2017-2018, we study the extent to which jobs pledged by funded businesses translate into actual employment gains in a given tract. We conduct this analysis in a generalized difference-in-differences framework, comparing employment gains in tracts with tax credit awards to gains in tracts without awards but that received applications.

Second, we build on the difference-in-differences design to incorporate information on applicants' scores. Doing so permits us to refine the treatment and control groups in ways that further improve the credibility of our empirical approach and estimates. Specifically, for tracts that received at least one scored applicant, we weight the tracts in our difference-in-differences analysis based on businesses' average distance from the cost-benefit ratio cutoff. The intuition is that applicants with scores far from the cutoff are likely located in places that could be different along not only observed, but also unobserved dimensions. Thus, we obtain estimates that place more weight on the effects of CCTC incentives in tracts where most applicants had scores close to the cutoff for their respective funding allocation round.

Importantly, with both of our approaches, we do not rely strictly on geographically proximate tracts to build control groups; a key concern in using proximate tracts as controls is that estimates might be biased by potential positive spillovers (agglomeration effects) or negative spillovers (business-stealing effects). Prior work on different economic development programs suggests that spillovers tend to be small or negative (Freedman, 2012; Freedman, 2013; Hanson and Rohlin, 2013; Einio and Overman, 2020). Because we do not use proximate tracts as controls, our estimated tract-level multipliers are not upward biased due to the comparison to nearby tracts that lose jobs. However, there could be negative spillovers at a more aggregate level if the CCTC redirects some job creation that would have occurred elsewhere in the state into areas where the credit is awarded; in that case, our tract-level multiplier estimate would overstate the overall multiplier for the state. Conversely, incentivizing businesses to locate or expand in one part of the state might induce other firms, such as upstream suppliers, to create additional jobs elsewhere in the state; in that case, our tract-level multiplier estimate might understate the overall multiplier for the state.

4.1 Generalized Difference-in-Differences

For our first approach, we consider the degree to which jobs promised by funded business translate into actual employment gains in a given tract. Given our focus on the location of jobs, we measure employment in a tract based on place of work, rather than residence.

Our basic specification is

$$y_{it} = \alpha + \beta AWARD_{it} + \gamma PROPOSED_{it} + S_i\mu + R_t\eta + \sum_{d=2}^{10}\{D^{y}{}_{i0}\, R_t\theta_{dt}\} + \varepsilon_{it} \quad (1)$$

where y_{it} is employment in tract *i* in year *t* as measured in the ACS, $AWARD_{it}$ is the number of jobs promised by CCTC-supported businesses in tract *i* in year *t*, $PROPOSED_{it}$ is the total number of jobs proposed by CCTC applicants (including both those who did and did not receive tax credits) in tract *i* in year *t*, S_i are tract fixed effects, R_t are year fixed effects, and ε_{it} is the error term.[10] The $D^{y}{}_{i0}$ are dummy variables for the deciles of employment (*y*) at baseline (2013, the earliest year in our data); these are interacted with the year dummy variables to allow for arbitrary changes in employment across time for tracts with different initial employment levels. We cluster standard errors at the tract level, which allows for arbitrary patterns of heteroskedasticity across tracts and serial correlation within tracts.

[10] To be clear, we are studying the effects of CCTC-incentivized *jobs* on the number of *employed workers*.

We construct $AWARD_{it}$ by summing all promised jobs by each CCTC awardee for each year in each tract. We similarly construct $PROPOSED_{it}$ by summing all promised and proposed jobs for all CCTC applicants (whether they received an award or not). We include the latter measure to help control for possible selection in the types of locations CCTC applicants target; higher growth areas might be those that receive more applications and, by extension, more awards. The tract fixed effects subsume all possible time-invariant observable and unobservable tract characteristics that might be correlated with CCTC incentives, and that also might independently affect outcomes. Meanwhile, the year fixed effects control for all time-varying factors that affect all tracts in California in the same way, accounting in particular for the fact that employment was trending upward generally in the state in years following the rollout of the CCTC. With the inclusion of the baseline employment decile-by-year fixed effects, we additionally control for potentially different employment trajectories across tracts with varying initial levels of employment.

The sample covers 2013-2018, encompassing two years prior to nearly all pledged job creation under the CCTC and up to five years after the first pledged job creation.[11] For the generalized difference-in-differences approach, we use the full sample of tracts that ever received an application for tax credits under the program, which in effect excludes many tracts with very little commercial activity and ensures greater comparability between tracts with and without winning projects in a given time period.

The coefficient of interest in equation (1) is β, which, in a regression for ACS-measured employment in levels, provides an estimate of the degree to which subsidized (proposed and awarded) jobs translate into actual employment gains in a tract. An estimate of β equal to 0

[11] There is a very small number of jobs pledged in 2014 from the first allocation round of the 2014-2015 fiscal year.

would imply that there is no net job creation associated with awarded jobs in a tract. In that case, insofar as we have estimated the causal effect of the CCTC, we would conclude that the program is a windfall – subsidizing jobs in a tract that would have been created in that tract anyway. An estimate of β between 0 and 1 would imply that each CCTC-incentivized job led to less than 1 additional employee in the tract, which would suggest that there is still some windfall, with positive net job creation but by fewer jobs than the number of incentivized jobs – possibly from crowd-out of unsubsidized jobs. An estimate of β equal to 1 would imply that each incentivized job led to 1 new employed worker in the tract. Meanwhile, an estimate of β greater than 1 would imply a positive local multiplier effect associated with CCTC-incentivized jobs, or a greater increase in employment associated with CCTC incentives than the number of jobs that the CCTC directly incentivized in a tract.

4.2 Locally Weighted Difference-in-Differences

As a second approach, we incorporate information on the scores of CCTC applicants into a weighting scheme that effectively places more weight on the impacts of CCTC incentives in tracts where applicants on average have scores closer to the threshold for their funding allocation round. The motivation is that tracts with applicants whose scores are very far from the threshold for first-stage CCTC eligibility determination could be different types of areas than those with applicants whose scores are closer to the cutoff. To the extent that our controls cannot fully capture unobserved or unmeasured differences across tracts that might be leading to differential changes in employment growth, and that those differences may be more pronounced among tracts where applicants requested very large or very small amounts of tax credits relative to their projected capital and payroll investment, placing more weight on tracts closer to the cutoff will mitigate any resulting bias in our estimates of the impacts of CCTC incentives.

This approach effectively combines elements of an RD design into our generalized difference-in-differences strategy. However, for our locally weighted difference-in-differences regressions, we must limit the sample to tracts with at least one large applicant such that we can consistently calculate scores relative to the cutoff for advancing to stage 2 of the evaluation process.

We present estimates from two weighting schemes, both of which are triangular with peaks of one at the threshold score. To define weights, we begin by calculating the absolute distance of the investment score for each proposed project from the cutoff declared for that funding round. This measure is then averaged over all projects in a given tract. This tract score is then normalized by subtracting it from the largest value and then dividing by the largest value, such that tracts with smaller absolute re-centered scores (or smaller deviations between their scores and the cutoff) have weights that are close to one, and tracts with greater absolute re-centered scores have weights very close to zero. Based on this weighting scheme, over 90% of tracts with scored applicants receive weights between 0.9 and 1, while only a small fraction receive lower weights. Therefore, in addition to this first scheme, we use a second weighting scheme that effectively linearizes the weights (in terms of the distance from the score) by raising the original weights to the 64^{th} power. Figure 1 displays the empirical CDFs of the weights.

5. Results

We begin with descriptive statistics, and then discuss in detail our main results from the generalized difference-in-differences analysis. We then turn to our analyses of the CCTC's distributional effects and impacts by industry. Finally, we describe the results from our locally weighted difference-in-differences, which takes further advantage of applicant score information.

5.1 Descriptive Statistics

The first row of Table 1 shows the average number of jobs awarded by tract, by year, under the CCTC using information on the annual milestones specified in businesses' applications. The table covers tracts with any CCTC applications. The first year (2013) shows a zero because no awards were granted that year. After 2014 (a year for which there was only one funding round in our data), these averages are in the range of 7-42. The next row shows CCTC jobs proposed by applicants; these numbers are somewhat larger. The third row shows awards conditional on an award being granted, which are considerably larger (by definition); across all years, the average number of jobs awarded per tract conditional on their being an award is approximately 75.[12]

The fourth row of Table 1 shows average tract employment for those tracts with CCTC applicants. Recall that we define tract employment using place-of-work information available in the restricted-access ACS; it is not based on the employment status of residents of tracts with CCTC applicants. Mean tract-level employment is high relative to the usual tract size, but the means are pulled up substantially by some tracts with very high employment, and by the restriction of the sample to tracts where there was at least one CCTC application (which tend to be tracts with high employment).[13] The comparisons between CCTC jobs awarded and overall tract employment among tracts that generated at least one application show that the CCTC-incentivized jobs are not large relative to the total.

[12] Note that, in contrast to the job figures discussed in Section 2.2, these represent tract-level as opposed to project-level averages. In addition, instead of cumulative job creation over entire five-year contracts, the statistics in Table 1 reflect the annual milestones for all applicants corresponding to a particular calendar year. In our sample, the average number of awarded projects per tract (calculated over tracts that ever received awards) is 1.5 (median = 1, 75th percentile = 2, 90th percentile = 3, 99th percentile = 7, and maximum = 17). The average number of applicants per tract (calculated over tracts that ever received applications) is 2.4 (median = 1, 75th percentile = 3, 90th percentile = 5, 99th percentile = 15, and maximum = 45).

[13] The variation in tract employment levels represents one motivation for inclusion of the baseline employment decile-by-year fixed effects.

Some of our analyses focus on the effects of CCTC awards on employment of individuals who live in lower income vs. higher income tracts, defined as having below- vs. above-median poverty rates, as well as who live in lower vs. higher education tracts, defined as having below- vs. above-median share of residents with a bachelor's degree. Some also focus on manufacturing vs. non-manufacturing employment. The employment levels for each of these breakdowns, averaged over all years, are reported in column 7 of Table 1.[14]

Our locally weighted difference-in-differences sample is restricted to tracts that have at least one large applicant. Not surprisingly, as shown in column 8 of Table 1, all employment averages are larger for tracts with at least one large applicant relative to the broader sample of tracts in which there were any applicants.

5.2 Main Results: Generalized Difference-in-Differences Analysis

Our main analysis of the impacts of awards under the CCTC program begins with Table 2. In column 1, we report results for a parsimonious model that includes tract and year fixed effects, but does not include either the control for total proposed CCTC jobs or the baseline employment-by-year interactions. The estimated coefficient of CCTC Jobs Awarded (β in equation (1)) is 4.035, significant at the 1% level. This estimate suggests a significant positive local multiplier associated with CCTC-incentivized jobs, with each incentivized job awarded resulting in approximately 4 additional individuals working in the tract. Put differently, for each job incentivized directly by the CCTC, an additional approximately 3 workers appear in the tract. We cannot distinguish whether these additional workers are in the same firm or in different firms located in the same tract. However, our results broken out by industry will address the question

[14] Confidentiality restrictions prevent reporting these by year. Also, the means for the higher income or higher education tracts, or for non-manufacturing employment, can be calculated as the differences relative to the total. Appendix Table A1 provides additional detail on CCTC jobs awarded and proposed for manufacturing and non-manufacturing.

of how large within- vs. across-firm multipliers are to some extent.

In column 2, we add the control CCTC Jobs Proposed. As noted earlier, this controls for underlying economic conditions that might have prompted applicants to request the CCTC, which could otherwise be confounded with the actual effects of the CCTC. The estimated coefficient on this control variable is 0.683 and strongly significant, suggesting that the number of CCTC jobs proposed is positively correlated with subsequent tract employment growth. Including jobs proposed also attenuates our estimate of the effect of jobs awarded on subsequent employment growth in the tract. However, the estimated effect of CCTC Jobs Awarded is still large; the estimate is 2.986 and strongly significant, again implying a sizable positive local multiplier. In column 3, we add the baseline employment-by-year controls. The estimated effect of CCTC Jobs Awarded declines some, but remains above 2.5 (2.695) and is still significant at the 1% level. Therefore, the evidence thus far points to a significant positive employment multiplier associated with CCTC incentives at the tract level.

Our estimated local multiplier is similar to, albeit at the high end of, multipliers estimated elsewhere in the literature (e.g., Greenstone et al., 2010; Moretti, 2010; Moretti and Thulin, 2013; van Dijk, 2017). Bartik and Sotherland (2019) note that plausible state multipliers for firms subsidized by state economic development programs are in the range of 1.7 to 2.0; that is, for every 100 jobs created as a direct result of state incentives, 70-100 additional jobs are indirectly created in that state. Notably, however, our estimates are more granular, reflecting multiplier effects within census tracts. To the extent that there are positive spillovers on job growth in other parts of the state, they may understate the statewide multiplier. On the other hand, some of the jobs created within tracts at subsidized firms may have been created in other areas in the absence of CCTC incentives; in that case, our estimate of the local multiplier will overstate the statewide multiplier.

One aim of the CCTC program, paralleling many other economic development programs, is to encourage job creation in disadvantaged parts of the state, and thereby improve employment opportunities for residents of those areas.[15] In Table 3, we decompose the overall employment effects into effects for workers *living* in tracts with above- vs. below-median poverty rates as well as for workers *living* in tracts with above- vs. below-median share with a bachelor's degree (where the median is defined over all tracts in California). In these regressions, we continue to include tract as well as baseline employment decile-by-year fixed effects. We also continue to include the total number of jobs that firms proposed in that tract (such that the specification matches that in column 3 of Table 2).

The regression estimates in Table 3 suggest that employment gains attributable to CCTC incentives are larger for workers living in more affluent and more highly educated tracts. At the same time, though, there are increases in the numbers of workers residing in higher poverty and less educated tracts as a result of CCTC incentives that are also statistically significant. The ratio statistics in columns 1 and 3 show the baseline fractions of workers who reside in above- vs. below-median poverty tracts as well as below- vs. above-median education tracts. Comparing these ratios to the differential effects by the poverty and education levels of workers' residential tracts suggests that the program is increasing employment among workers living in high vs. low poverty tracts roughly proportionately to baseline levels, and if anything, perhaps increasing employment among workers living in high education tracts more than employment among workers living in low education tracts.[16] This echoes previous findings for programs in which

[15] Recall that the program gives some preference to applicants whose investments occur in high unemployment and high poverty parts of the state.

[16] At baseline, there were 25% fewer workers living in lower income areas than higher income areas in tracts that receive CCTC applications. The increase in the number of workers from lower income areas as a result of CCTC

subsidized businesses have scope to hire workers living outside the immediate area (Freedman, 2015).

We next turn to differential effects by sector. A frequent criticism of many economic development programs is that they subsidize activity among services firms that rely predominantly on local demand. To the extent that such firms are subsidized, their growth is likely to come at the expense of other firms in the same area. In principle, subsidizing activity in tradable goods and services sectors may be more effective because their market is geographically larger and the overall scale of the industry is not likely to be constrained by local demand. California's Legislative Analyst's Office raised this concern in regard to the CCTC program in light of its propensity to incentivize firms in the non-tradable sector (LAO, 2017).

Table 4 breaks out the separate effects of CCTC-incentivized manufacturing and non-manufacturing jobs on total tract employment, as well as on manufacturing and non-manufacturing tract employment. Again, the regressions include tract and baseline employment decile-by-year fixed effects as well as the number of jobs that CCTC applicants proposed in that tract (now separating manufacturing and non-manufacturing applicants). In column 1, we find that the local multiplier associated with non-manufacturing jobs is substantially larger than that for manufacturing jobs (4.8 vs. 1.1); we cannot rule out that the effect of incentivizing manufacturing jobs is zero, although the point estimate slightly exceeds 1 (and recall that a value of 1 is consistent not with windfalls, but rather with each incentivized job leading to one new worker in the tract). Meanwhile, there is a relatively large estimated effect for the number of manufacturing jobs proposed, consistent with the tax credit being a windfall for many firms in

awards is similarly 28% lower than the increase in the number of workers from higher income areas. At baseline, there were 32% fewer workers living in lower educated areas than higher educated areas in tracts that receive CCTC applications. The increase in the number of workers from lower educated areas as a result of CCTC awards is 55% lower than the increase in the number of workers from higher educated areas.

the sector.

To shed further light on the mechanisms underlying these results, we split total employment in the tract into manufacturing employment and non-manufacturing employment in columns 2 and 3 of Table 4. We find no effect of either incentivized manufacturing or non-manufacturing jobs on total manufacturing employment in a tract. This not only corroborates the estimates in column 1, but also provides a check on the credibility our results more broadly since we would generally not expect incentivizing non-manufacturing jobs to have multipliers in the local manufacturing sector. We also see in column 2 evidence of windfalls for incentivizing manufacturing jobs, as the estimated effect of these jobs on local manufacturing employment is close to zero (0.116). In column 3, meanwhile, we find that, consistent with expectations, growth in employment in the non-manufacturing sector is driven by jobs incentivized in that same sector. There is also evidence that at least some non-manufacturing applicants proceed to hire locally even without the tax credits, but windfalls at the local level appears to be less severe for non-manufacturing than for manufacturing.

These findings might be surprising to the extent that one thinks of manufacturing as corresponding more closely to the tradeable goods sector. However, many non-manufacturing firms incentivized by the CCTC might produce tradable goods and services, or those that do not rely strictly on local demand.[17] In addition, discussions with CCTC program staff indicate that some of the CCTC incentives in manufacturing go to highly specialized R&D activities that are heavily concentrated in job markets that already have high employment (like the Bay Area).

[17] As evidence, we considered two classifications of industries from Mian and Sufi (2014), one based on trade data and one based on geographic concentration. They use four groupings: tradable, non-tradable, construction, and "other" ("other" representing by far the largest category, with 59% of employment as they measure it). Using either classification, most of the non-manufacturing awards (measured as a percentage of awards, or of jobs) are in the "other" sector (about two-thirds to three-quarters), rather than non-tradables or construction. (Calculations available from the authors upon request.)

Keeping these high paying, knowledge intensive jobs in California may have important benefits, including in the longer run if and when some of this work leads to production jobs. However, these particular incentives are unlikely to have large, local multiplier effects.

5.3 Locally Weighted Generalized Difference-in-Differences Results

A concern with our baseline generalized difference-in-difference results is that there may still be some unobserved differences in employment trajectories across tracts with vs. without CCTC awards. To help address this concern, we take advantage of the rich detail we have on applicants, and in particular their scores from the first stage of the application review process. We reweight tracts based on the average scores of applicants in those tracts, putting more weight on those closer to the threshold for their funding allocation round. The motivation is that tracts with applicants whose scores are very far from the threshold for first-stage CCTC eligibility determination could be different types of areas than those with applicants whose scores are closer to the cutoff. Proposed benefits and credits requested by businesses are more likely to be similar if they come from tracts with more similar underlying economic conditions.

One limitation of this approach is that we must have at least one large applicant in a tract in order to calculate a score relative to the cutoff for the round consistently. This restriction shrinks our sample of tracts by about 30%. In order to verify that changes in sample composition owing to this restriction alone do not affect the main findings, we show in Table 5 results for this sample using the same specifications as in Tables 2-4. These results are nearly identical to those for our full sample of tracts, indicating that tracts with at least one large applicant are not substantially different from those with any applicants, at least in terms of estimated effects of the CCTC.

In Tables 6 and 7, we show results using two different weighting schemes, both of which are triangular with peaks of 1 at the threshold score for the relevant funding round. The first weighting scheme uses weights calculated as the largest cutoff-normalized score across all tracts minus each individual tract's cutoff-normalized score, divided by the largest normalized score. In this scheme, tracts with average normalized scores close to zero will have weights close to one, whereas those with average normalized scores far from the cutoff will have weights closer to zero. As shown in Figure 1, this simple weighting scheme heavily downweights a small number of tracts whose average scores are far from the relevant threshold.

The results from using this first weighting scheme applied to our generalized difference-in-differences regressions appear in Table 6. The estimates do not differ substantially from the unweighted results in Table 5 nor from the baseline difference-in-differences results in Tables 2-4. We continue to see an overall local multiplier close to 2.5. We also continue to find that most of the effects arise from incentivizing non-manufacturing establishments.

We experimented with an alternative weighting scheme that effectively linearizes the weights applied to tracts. We do so by raising the weights generated in the first scheme to the 64^{th} power (see Figure 1). The results using this alternative weighting scheme appear in Table 7, and again are qualitatively similar to the unweighted results (Table 5) as well as our baseline results (Tables 2-4).

6. Conclusion

There is a new wave of interest in economic development programs (Austin et al., 2018; Bartik, 2019). However, the track record of such policies is mixed (Neumark and Simpson, 2015; Slattery and Zidar, 2020). The California Competes Tax Credit is a relatively new program that incorporates best practices from previous initiatives by combining explicit eligibility thresholds with some discretion on the part of program officials to select tax credit recipients. At the same time, the structure and implementation of the program facilitates rigorous evaluation.

We study the effects of the CCTC on the census tracts in which credits are awarded. We exploit detailed data on accepted and rejected applicants to the CCTC, including information on scoring of applicants with respect to program goals and funding decisions, together with restricted access American Community Survey (ACS) data on local economic conditions. We use a difference-in-differences approach, and supplement this by employing weighting schemes based on businesses' average distance from an objective eligibility cutoff to better account for unobservable factors.

Our key finding is that each CCTC-incentivized job in a census tract increases the number of employed individuals working in that tract by around two-and-a-half. In other words, we find evidence of a significant local multiplier on CCTC-incentivized jobs. We also explore the program's distributional effects and impacts by industry. We find that CCTC awards increase employment among workers residing in both high income and low income communities. We additionally find that the local job creation effects are driven largely by awards to non-manufacturing establishments. The results from our difference-in-differences strategy are robust to placing more weight on locations with relatively more applicants close to the threshold for advancement to the discretionary stage of the evaluation process, which creates even more comparable treatment and control groups.

Thus far, the CCTC program has allocated $1.23 billion in tax credits to businesses. Pledged jobs by awarded businesses during this period totaled 124,000, which implies a direct cost per incentivized job of $9,900. Applying our estimate of the multiplier associated with these jobs, the total incentive per job created in recipient tracts is approximately $3,960.[18] This may overstate or understate the total cost per job statewide, as there may be negative or positive spillovers of CCTC-incentivized job creation across tracts. Given that the CCTC program is relatively new, the permanence of jobs created as a result of the CCTC is also unclear. Nonetheless, in terms of the rough magnitude, this cost per job estimate compares very favorably to other place-based programs such as EZs and the New Markets Tax Credit (Neumark and Kolko, 2010; Freedman, 2012), to other hiring credit programs (especially once one accounts for windfalls, based on nearly all estimates), and to the EITC (Neumark, 2013; Neumark and Grijalva, 2017).[19]

Overall, our results speak to the efficacy of newer economic development programs that have been refined to address perceived shortcomings of previous initiatives. They also have important policy implications. While we find little evidence that the CCTC disproportionately benefits individuals living in lower income areas, implementing design features of the CCTC could help to improve job creation impacts of current or future economic development programs that focus on economically distressed areas.

[18] The corresponding numbers for our sample period are about $8,400 and $3,360. These numbers may overstate the actual cost per job because some awardees may not claim the full amount of the tax credits allocated to them. Given that the timing of tax credit claims can differ from when jobs are created (the credit has a six-year carryforward), and the fact that many awardees in our data have not reached the end of their contract terms, we do not know with certainty what fraction of allocated credits will go unclaimed.

[19] We are currently engaged in additional research studying the establishment-level effects of the CCTC using business microdata (Hyman et al., in progress).

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Table 1: Descriptive Statistics, Tracts with Any CCTC Applicants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2013	2014	2015	2016	2017	2018	All Years (Full Sample)	All Years (Tracts with ≥ 1 Large Applicant)
CCTC Jobs Awarded	0	0.36	7.71	17.48	30.17	42.13	16.31	22.96
	(0)	(4.05)	(63.03)	(107.10)	(154.60)	(194.47)	(114.44)	(137.59)
CCTC Jobs Proposed	0	4.618	23.82	52.65	91.90	138.32	51.88	72.13
	(0)	(39.86)	(124.02)	(209.25)	(315.26)	(456.40)	(252.65)	(296.45)
CCTC Jobs Awarded	0	10.60	45.78	64.03	74.68	99.11	75.03	92.60
(Conditional on Award)	(0)	(19.74)	(148.06)	(197.77)	(236.34)	(288.80)	(236.4)	(264.48)
Employment	4164	4306	4411	4575	4713	4849	4503	5628
	(6535)	(6951)	(7202)	(7439)	(7642)	(7934)	(7299)	(8466)
Employment Lower Income							1964	2435
							(2882)	(3315)
Employment Lower Education							1849	2289
							(2500)	(2854)
Employment Manufacturing							664.2	920.4
							(1775)	(2095)
N	1300	1300	1300	1300	1300	1300	7800	5400

Notes: The table presents means and standard deviations (in parentheses) for the variables listed in the first column. The sample sizes in the last row are approximate (rounded to the nearest 100). The statistics for the third row are for the subsample of tracts that had non-zero awards for each year.

Table 2: Difference-in-Differences Results

	(1)	(2)	(3)
	Tract Employment		
CCTC Jobs Awarded	4.035***	2.986***	2.695***
	(0.960)	(0.958)	(0.811)
CCTC Jobs Proposed		0.683***	0.476**
		(0.265)	(0.214)
Tract Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	No
Baseline Employment Deciles × Year Fixed Effects	No	No	Yes
Tracts	1300	1300	1300
Observations	7800	7800	7800

Notes: The outcome for each regression is tract employment. Baseline employment deciles are measured using 2013 values of the outcome variable. The baseline employment deciles × year fixed effects subsume the year fixed effects. The sample sizes (tracts and observations) are approximate (rounded to the nearest 100). Standard errors are clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Difference-in-Differences Results, by Characteristics of Workers' Residence Tracts

	(1)	(2)	(3)	(4)
	Lower Income	Higher Income	Lower Education	Higher Education
CCTC Jobs Awarded	1.127***	1.575***	0.847***	1.877**
	(0.324)	(0.541)	(0.211)	(0.790)
CCTC Jobs Proposed (Not Shown)	Yes	Yes	Yes	Yes
Tract Fixed Effects	Yes	Yes	Yes	Yes
Baseline Employment Deciles × Year Fixed Effects	Yes	Yes	Yes	Yes
Ratio (Column 1/2, 3/4 Dep. Var.)	0.747		0.684	
Tracts	1300	1300	1300	1300
Observations	7800	7800	7800	7800

Notes: Column 1 outcome is employment among individuals whose tract of residence had a poverty rate in 2013 above the statewide median, and column 2 is below median. Column 3 outcome is employment among individuals whose tract of residence had a share of workers with a bachelor's degree or more in 2013 below the statewide median, and column 4 is above median. Baseline employment deciles are measured using 2013 values of the outcome variable. The baseline employment deciles × year fixed effects subsume the year fixed effects. The sample sizes (tracts and observations) are approximate (rounded to the nearest 100). The ratio statistic in column 1 refers to the average ratio of the outcomes in column 1 to column 2 measured in 2013 in the sample tracts. The ratio statistic in column 3 refers to the average ratio of the outcomes in column 3 to column 4 measured in 2013 in the sample tracts. Standard errors are clustered at the tract level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Difference-in-Differences Results, by Industry

	(1)	(2)	(3)
	Total Employment	Manufacturing Employment	Non-Manufacturing Employment
CCTC Manufacturing Jobs Awarded	1.126	0.116	0.821
	(0.814)	(0.436)	(0.735)
CCTC Non-Manufacturing Jobs Awarded	4.785***	0.529	4.273**
	(1.669)	(0.343)	(1.667)
CCTC Manufacturing Jobs Proposed	0.919	0.825***	0.323
	(0.591)	(0.242)	(0.530)
CCTC Non-Manufacturing Jobs Proposed	0.397**	-0.0785	0.501**
	(0.201)	(0.0507)	(0.208)
Tract Fixed Effects	Yes	Yes	Yes
Baseline Employment Deciles × Year Fixed Effects	Yes	Yes	Yes
Ratio (Column 2/3 Dep. Var.)		0.184	
Tracts	1300	1300	1300
Observations	7800	7800	7800

Notes: Column 1 outcome is total employment, column 2 outcome is manufacturing employment, and column 3 outcome is non-manufacturing employment. Baseline employment deciles are measured based on 2013 values of the outcome variable. The baseline employment deciles × year fixed effects subsume the year fixed effects. The sample sizes (tracts and observations) are approximate (rounded to the nearest 100). The ratio statistic in column 2 refers to the average ratio of the outcomes in column 2 to column 3 measured in 2013 in the sample tracts. Standard errors are clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Difference-in-Differences Results, Locally Weighted Regression Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Empl.	Empl., Lower Income Tracts	Empl., Higher Income Tracts	Empl., Lower Education Tracts	Empl., Higher Education Tracts	Manu. Empl.	Non-Manu. Empl.
CCTC Jobs Awarded	2.575***	1.049***	1.540***	0.782***	1.778**		
	(0.804)	(0.331)	(0.540)	(0.224)	(0.774)		
CCTC Manufacturing Jobs Awarded						0.133	0.853
						(0.440)	(0.731)
CCTC Non-Manufacturing Jobs Awarded						0.547	4.107**
						(0.356)	(1.663)
CCTC Jobs Proposed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract Fixed Effects.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Employment Deciles × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ratio (Column 2/3, 4/5, 6/7 Dep. Var.)		0.736		0.675		0.210	
Tracts	900	900	900	900	900	900	900
Observations	5400	5400	5400	5400	5400	5400	5400

Notes: See notes to Tables 2-4. CCTC Jobs Proposed consists of two separate controls for manufacturing and non-manufacturing in columns 6 and 7. Sample is restricted to tracts with at least 1 large applicant. Standard errors are clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Locally Weighted Difference-in-Differences Results, Weighting Scheme 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Empl.	Empl., Lower Income Tracts	Empl., Higher Income Tracts	Empl., Lower Education Tracts	Empl., Higher Education Tracts	Manu. Empl.	Non-Manu. Empl.
CCTC Jobs Awarded	2.584***	1.055***	1.546***	0.784***	1.786**		
	(0.809)	(0.332)	(0.544)	(0.225)	(0.780)		
CCTC Manufacturing Jobs Awarded						0.129	0.838
						(0.442)	(0.726)
CCTC Non-Manufacturing Jobs Awarded						0.551	4.148**
						(0.359)	(1.673)
CCTC Jobs Proposed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Employment Deciles × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ratio (Column 2/3, 4/5, 6/7 Dep. Var.)		0.732		0.671		0.210	
Tracts	900	900	900	900	900	900	900
Observations	5400	5400	5400	5400	5400	5400	5400

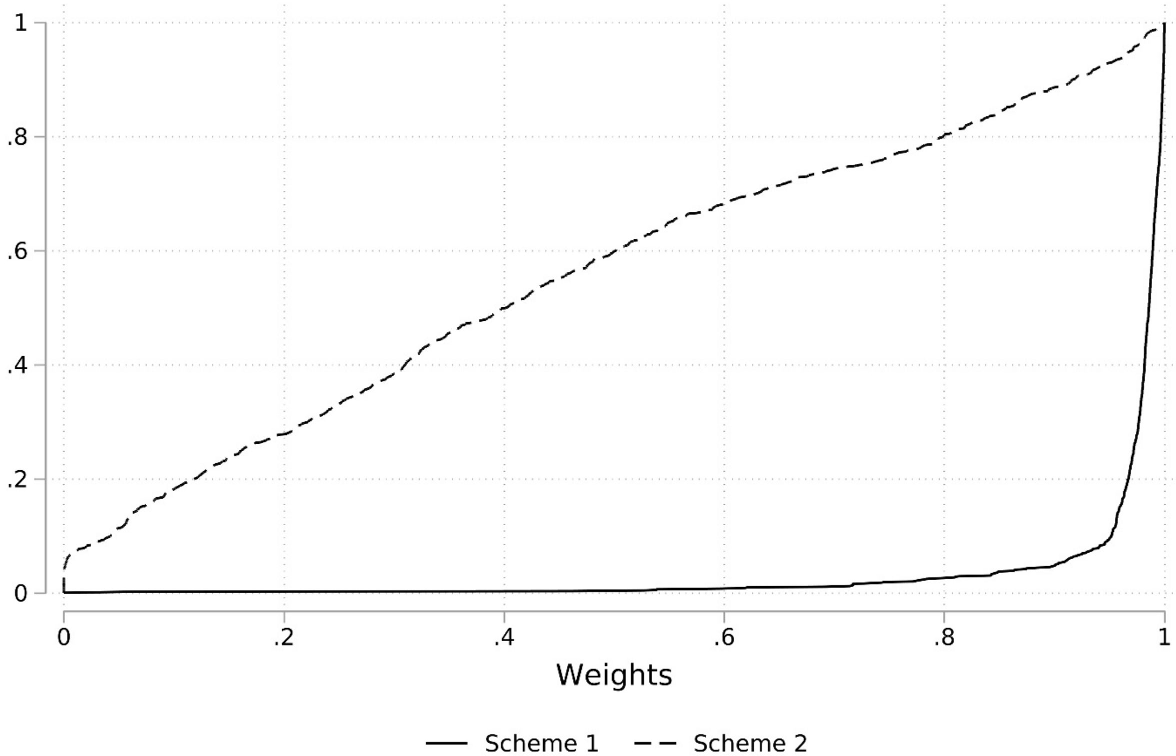
Notes: See notes to Tables 2-4. CCTC Jobs Proposed consists of two separate controls for manufacturing and non-manufacturing in columns 6 and 7. Sample is restricted to tracts with at least 1 large applicant. The regressions are weighted by average absolute values of score minus the cutoff. See text and Figure 1 for more information on the weighting. Standard errors are clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Locally Weighted Difference-in-Differences Results, Weighting Scheme 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Empl.	Empl., Lower Income Tracts	Empl., Higher Income Tracts	Empl., Lower Education Tracts	Empl., Higher Education Tracts	Manu. Empl.	Non-Manu. Empl.
CCTC Jobs Awarded	2.948***	1.186***	1.785***	0.772**	2.131**		
	(0.984)	(0.409)	(0.652)	(0.308)	(0.946)		
CCTC Manufacturing Jobs Awarded						-0.0695	0.652
						(0.527)	(0.772)
CCTC Non-Manufacturing Jobs Awarded						0.568*	4.416***
						(0.332)	(1.642)
CCTC Jobs Proposed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Employment Deciles × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ratio (Column 2/3, 4/5, 6/7 Dep. Var.)		0.697		0.646		0.203	
Tracts	900	900	900	900	900	900	900
Observations	5400	5400	5400	5400	5400	5400	5400

Notes: See notes to Tables 2-4. CCTC Jobs Proposed consists of two separate controls for manufacturing and non-manufacturing in columns 6 and 7. Sample is restricted to tracts with at least 1 large applicant. The regressions are weighted by average absolute values of score minus the cutoff raised to 64^{th} power. See text and Figure 1 for more information on the weighting. Standard errors are clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1

Figure 1: Empirical CDFs for Weighting Schemes



Note: This figure shows the empirical CDFs for the weights created among the sample of tracts with at least 1 large applicant. The horizontal axis represents the weights that lie between 0 and 1, and the vertical axis is the proportion between 0 and 1. The empirical CDFs of two weighting schemes (corresponding to Table 6 and Table 7, respectively) are shown on the figure, one solid and another dashed.

Appendix Table A1: Descriptive Statistics for CCTC Manufacturing and Non-Manufacturing jobs, Awarded and Proposed

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2013	2014	2015	2016	2017	2018	All Years (Full Sample)	All Years (Tracts with ≥ 1 Large Applicant)
Jobs Awarded: Manufacturing	0	0.31	4.61	8.49	13.69	18.52	7.60	10.74
	(0)	(3.98)	(58.43)	(92.50)	(127.83)	(154.72)	(93.55)	(112.63)
Jobs Awarded: Non-Manufacturing	0	0.04	2.84	8.63	15.94	22.96	8.40	11.77
	(0)	(0.99)	(20.91)	(50.31)	(78.79)	(106.59)	(59.11)	(71.19)
Jobs Proposed: Manufacturing	0	2.49	10.32	17.47	27.10	36.94	15.72	22.52
	(0)	(33.87)	(100.47)	(139.37)	(181.17)	(214.66)	(135.72)	(163.56)
Jobs Proposed: Non-Manufacturing	0	2.11	13.15	34.72	63.94	100.33	35.71	48.94
	(0)	(21.06)	(68.43)	(142.93)	(237.52)	(379.59)	(197.40)	(228.60)
Jobs Awarded: Manufacturing (Conditional on Award)	0	15.42	56.81	72.15	79.78	99.36	79.06	82.24
	(0)	(23.81)	(198.67)	(261.63)	(300.47)	(347.53)	(292.27)	(302.25)
Jobs Awarded: Non-Manufacturing (Conditional on Award)	0	3.03	28.67	46.34	57.42	78.72	57.99	77.58
	(0)	(7.77)	(60.82)	(108.96)	(141.47)	(186.06)	(145.77)	(168.27)
N	1300	1300	1300	1300	1300	1300	7800	5400

Notes: The sample sizes in the last row are approximate (rounded to the nearest 100). The statistics in the last two rows are for the subsample of tracts that had non-zero awards for manufacturing and non-manufacturing, respectively, for that year.