The Impact of Publicly-Funded Business Advisory Services on Firm Performance: Evidence from the US Small Business Development Center Network*

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Abstract

This paper estimates the impact of publicly-funded advisory services offered to US small businesses on firm performance. We leverage a novel administrative dataset from the Northern California Small Business Development Center (SBDC) network covering all firm-center interactions from 2006–2023. To address endogeneity in firm engagement with centers, we exploit exogenous variation in proximity to centers generated by center closures, openings, and re-locations. We instrument for paired center-business consulting time with changes in distance resulting from these organizational shifts. A one standard deviation reduction in distance between a business and corresponding center (≈30 miles) increases average annual consulting time by 0.1 hours; each additional consulting hour raises average annual business revenue and employment by 6.4% and 3.3%, respectively. Back-of-the-envelope calculations suggest these advisory services are highly cost-effective. This study offers the first set of causal evidence on the effectiveness of small business advisory services on firm outcomes in the US. Our findings highlight the importance of accessibility and localized expertise in shaping small business outcomes, which may be particularly important in under-served industries and geographies.

JEL Codes: O38, M13, L26

Keywords: business advisory services, small business development center, entrepreneurship, revenue, employment

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1 Introduction

Economists and policy-makers have long been interested in identifying drivers of local economic development. One key factor is innovation (Schumpeter 1934); seminal research has shown that innovators and entrepreneurs are cornerstones in driving economic activity (Romer 1986). An important input for innovation has proven to be the geographic concentration of innovators themselves (Audretsch and Feldman 1996). A prime example of this was the surge in the number of privately-funded seed accelerators in California's Silicon Valley in the early 2000s. These accelerators were designed to partner with and provide important resources to entrepreneurs and startups to facilitate growth and financial gain. A key function of private accelerators, beyond offering direct access to capital, is provision of business advisory services that include assisting in securing external financing, navigating the legal and regulatory environment, and providing relevant knowledge and education. Research has shown the presence of accelerators has not only generated gains for participating businesses, but also large spillover effects across accelerator-targeted sectors in the local economy (Engel 2015; Hochberg and Fehder 2015; Bliemel et al. 2019; Madaleno et al. 2022).

However, private accelerators are generally concentrated in dense, tech-oriented urban ecosystems and select for high-growth, investor-facing ventures (Hathaway 2016). As a result, there are many other businesses and industries for which such a model is not profitable or even feasible. This gap in access has significant economic implications, as there may be large, unrealized social gains associated with additional growth and success of entrepreneurs and small businesses in these industries, particularly in under-served areas (Duranton 2011).[1] Hence, public resources may be necessary to deliver efficient levels of innovation.

The purpose of this study is to identify the impact of publicly-funded business advisory services on important economic outcomes of participating small businesses, and the extent to

[1] Rubinton (2021) finds that since 2018, business dynamism has been declining more rapidly in smaller cities versus larger cities. One hypothesized mechanism for this is that relatively higher concentrations of younger people, who are more likely to be entrepreneurs, are settling in larger cities (Engbom 2019).

which such investments are cost-effective. To do this, we leverage a comprehensive network of primarily publicly-funded small business advisory centers present across the US, known as America's Small Business Development Center (SBDC) Network. In the mid-1970s, The Small Business Administration (SBA) within the Department of Commerce established a national network of centers to provide management and technical assistance to entrepreneurs and small business owners.[2] The network has continued to expand—SBDCs are now found in all 50 states and provide assistance to over one million clients across the US per year, including new entrepreneurs and existing small business owners (SBDC: Our History 2024). Among the services offered are educational classes, marketing advice, financing opportunities, and consulting sessions with business advisors. In fact, nearly every other developed country offers partially or fully publicly-funded business advisory services (OECD 2021).

The specific empirical setting for this research consists of all SBDCs and associated businesses in the Northern California (NorCal) regional SBDC network. Established in 2006, the NorCal network now serves 36 counties, spanning from the California-Oregon border to as far south as Santa Cruz (80 miles south of San Francisco). As of 2024, the NorCal SBDC network employed over 500 individuals across 19 active centers, having served approximately 90,000 unique clients (businesses) over the last two decades.

We leverage a novel panel dataset from 2006-2023 that includes all businesses to ever work with at least one NorCal SBDC over this period. We observe a set of time-invariant information about each business, including location of operation, associated industry, and establishment date of the company. In addition, we observe a rich set of time-varying characteristics for each business, including revenue, employment, contact time (hours spent in consulting sessions between a center and client), preparation time (hours spent by a center to prepare for consulting sessions), and the specific center offering these services to each business. We observe each meeting between a business and corresponding center, allowing us to study the evolution of center resources provided to each business over time.

[2] The SBA offers an online portal providing information about the SBDC network for small businesses.

To measure the impact of public advisory services on business revenue and employment outcomes, we take advantage of an instrumental variables strategy. Firm engagement with SBDCs is endogenous; for instance, more motivated firms may work more closely with SBDC advisors, and certain centers may have more available resources to support firms. To address this, we leverage exogenous variation in the intensity with which small businesses may access SBDC resources, facilitated by conditionally random center closures, openings, and re-locations occurring between 2006-23. Over the nearly 20 year time-frame the NorCal SBDC Network has been in operation, there has been a significant number of changes to center operations and locations, regularly adjusting the spatial distribution of centers. The constructed instrument is the change in distance between a treated business and paired center induced by such changes; treated businesses constitute those that experience at least one change in distance with a paired center during their tenure with the network.[3] Section 3 provides a detailed overview of center movement and other relevant context for the construction of the instrument.

The empirical analysis generates two primary findings. First, a one standard deviation reduction in distance between a business and corresponding center ($\approx$30 miles) generates an expected increase of 0.1 consulting hours per year provided to a business, conditional on participation with the SBDC network. For context, the median firm in the data engages in 2 hours of consulting time annually. This suggests greater accessibility to a center enhances participation. The second finding highlights the impact of increased participation; we show that average annual revenue increases by approximately 6.4% while average employment increases approximately 3.3% for every 1 hour increase in annual consulting time between centers and firms. The median firm in the data has an annual revenue (employment) of \$86,488 (2 employees), thus one additional consulting hour (corresponding to a 50% increase) generates approximately \$5,500 in expected additional annual revenue and 0.07 expected

[3] In the event of a center closure, previous business clients of that center may be paired with an existing or newly-opened center. In the event of a center opening, previous business clients may move from existing or recently-closed center.

additional hires, respectively.

Our findings also indicate public business advisory services are highly cost-effective. In 2023, nearly 60,000 advisor-hours were spent on NorCal SBDC clients at an average cost of $230.60, only half of which is paid by federal tax dollars due to the SBDC matched funding model. The results suggest SBDCs can have significant impacts in facilitating entrepreneurship and small business growth, particularly for businesses that may be less competitive in accessing private resources. Moreover, this study likely underestimates the economic impacts of public business advisory services, since it does not consider the external benefits SBDC clients may provide to other businesses, particularly within the local region.

This research makes several important contributions. First, the findings in this paper are, to the best of our knowledge, the first to show the causal impact of primarily publicly-funded business advisory services in the US on firm performance. There exists a descriptive literature exploring the role of publicly-funded business development resources on entrepreneurship and firm outcomes, with some studies finding significant growth in employment, sales, and research productivity (Siegel, Westhead and Wright 2003; Hart and Roper 2003; Cumming and Fischer 2012), while others finding no effect (Lambrecht and Pirnay 2005; Roper and Hart 2005). A separate class of studies documents the impacts of a more general set of US policies targeting the growth and success of small businesses, including tax incentives (Gurley-Calvez and Bruce 2008; Carroll et al. 2000; DeLuca et al. 2007; Agrawal, Rosell and Simcoe 2020; Harju, Koivisto and Matikka 2022) and financing (Lerner 1996; Brown and Earle 2013; Granja et al. 2022). Our study also contributes to a more recent line of empirical research evaluating the impact of accelerators and accompanying services, including venture capital provision, on outcomes of participating businesses. However, existing work has primarily focused on private accelerators (Hallen, Bingham and Cohen 2014; Hallen, Cohen and Bingham 2020; Yu 2020) and capital investments (Lerner 2000; Belke, Fehr and Foster-McGregor 2004; Colombo and Grilli 2005; Kerr, Lerner and Schoar 2014), not publicly-funded business development resources.

Only a handful of existing studies, to the best of our knowledge, specifically look at the SBDC network in the US. Chrisman and Katrishen (1994) was the first to study the relationship between SBDCs and firm performance. Using a survey of long-term clients, they found receiving counseling in 1990 generated over $3.7 billion in new sales and 65,000 new employees hired in 1991, generating a return of $2.61 for each tax dollar spent on the SBDC program. Chrisman and McMullan (2004) and Chrisman, McMullan and Hall (2005) find a significant, predictive relationship between SBDC counseling resources and firm survival rates and long-term growth. Interestingly, while Chrisman, McMullan and Hall (2005) find diminishing returns to SBDC advisory services, Buffart et al. (2020) finds that center resources spent on clients receiving relatively high levels of advising generated much larger returns on investment than clients receiving low levels of advising, emphasizing the importance of "picking winners." Dunne, Toyoshima and Byrd (2021) provide a qualitative assessment of SBDCs in Idaho, arguing that centers play a pivotal role in offering accessible business development resources to large swaths of the population. Our study makes an important contribution to this literature by offering the first causal evaluation of SBDC services on firm outcomes.

The set of studies most closely aligned with this work focuses on other countries, where there has been extensive research examining policy interventions that spur entrepreneurial activity and small business performance (McKenzie 2017; Anderson et al. 2021; Anderson and McKenzie 2022; Hussam, Rigol and Roth 2022; Bryan, Karlan and Osman 2024). Gonzalez-Uribe and Leatherbee (2017) study outcomes for Chilean firms engaging with the accelerator *Start-up Chile*. Using a fuzzy regression discontinuity design that exploits "just accepted" versus "just rejected" firms, they find that firms receiving a combination of basic services and formal entrepreneurial schooling through the accelerator were 21% more likely to receive additional financing and increase their venture size from 0.9 to 1.8 employees on average. Bloom et al. (2013) conducts a field experiment providing free management consulting to large Indian textile firms, finding adoption of improved practices raised productivity 17% in the first year and facilitated the opening of more production plants within three years.[4] Bruhn, Karlan and Schoar (2018) and Iacovone, Maloney and McKenzie (2022) conduct randomized controlled trials on small and medium enterprises (SMEs) in Mexico and Colombia, respectively, where they provided a subset of firms with intensive management consulting and mentoring services. Bruhn, Karlan and Schoar (2018) finds these services boosted short-run productivity, return on assets, and profits of treated SMEs, and in the longer-run, treated firms experienced a 57% increase in employment and 72% in their total wage bill. Iacovone, Maloney and McKenzie (2022) implement both individual- and group-based consulting interventions, finding that each approach led to relatively large improvements in general management practices. The group-based intervention also facilitated significant growth in both sales and number of employees in treated firms.

The rest of the paper proceeds as follows. First, we provide background on the SBDC network and pertinent institutional context. Next, we describe the data and offer relevant descriptive statistics. We then detail the empirical strategy to evaluate firm outcomes and discuss the identifying assumptions necessary to interpret the findings. We present the results of the analyses, followed by a discussion and policy implications. The final section provides concluding remarks and suggests opportunities for future research.

2 Background and Institutional Context

2.1 History of SBDCs

SBDCs provide assistance to over one million clients across the US each year, including new entrepreneurs and existing small business owners (SBDC: Our History 2024). The program

[4] A follow-up study nine years later found that not only was there still a significant gap in practices and performance between treated and control plants, but spillovers in practices occurred both within and between experimental and non-experimental firms (Bloom et al. 2020).

is described by the Small Business Administration (SBA) as the "Federal Government's largest and most successful technical assistance program for small businesses." According to a report published by America's SBDC Association, long-term SBDC clients generated approximately $6.6 billion in sales and added 80,995 new full-time jobs between 2022-23. In addition, each federal dollar spent on SBDC services generated $23.91 in new capital to help businesses grow, $1.59 in federal revenues, and $2.40 in state revenues (Chrisman 2024).[5]

The SBDC program was founded in the early 1970s by William Flewellen and Reed Powell, both university educators and members of the SBA's national advisory board. Flewellen and Powell believed the US would benefit from public investment in small businesses and partnerships between businesses, universities, and government (SBDC: Our History 2024). The first SBDC was established in 1976 at California State Polytechnic University at Pomona, where Powell was an instructor. This flagship center was announced under SBA's University Business Development Center Program, whose goal was to utilize the resources and innovative atmosphere of higher education settings in small business development. In the subsequent months, seven additional universities across the U.S. established a similar program.[6]

The success of these initial programs eventually led to the Small Business Development Act of 1980, which authorized federal funding to be matched one-for-one with non-federal funds (U.S. Congress 1980).[7] By 1991, as the network continued to expand outside of universities, every state in the nation operated an SBDC program. The US SBDC Network now consists of numerous state and regional conglomerates (like the NorCal SBDC Network) that receive federal, state, and private funding. It supports an infrastructure of

[5] America's SBDC is a non-profit organization that represents America's nationwide network of SBDCs. They work jointly with the SBA and United States Congress to ensure continued support for the SBDC program. Additionally, America's SBDC is responsible for a accrediting SBDC programs across the nation.

[6] These initial participating universities included California State University at Chico, The University of Georgia, The University of Missouri at St. Louis, The University of Nebraska at Omaha, Rutgers University, The University of Southern Maine and the University of West Florida.

[7] The federal funds authorized for SBDCs are no longer matched one-for-one with non-federal funds. Federal funds are distributed on a *pro rata* basis among the states. These funds are typically authorized through an Appropriations Act every 2-3 years (Levin 2023).

approximately 1,000 centers and over 5,000 employees.

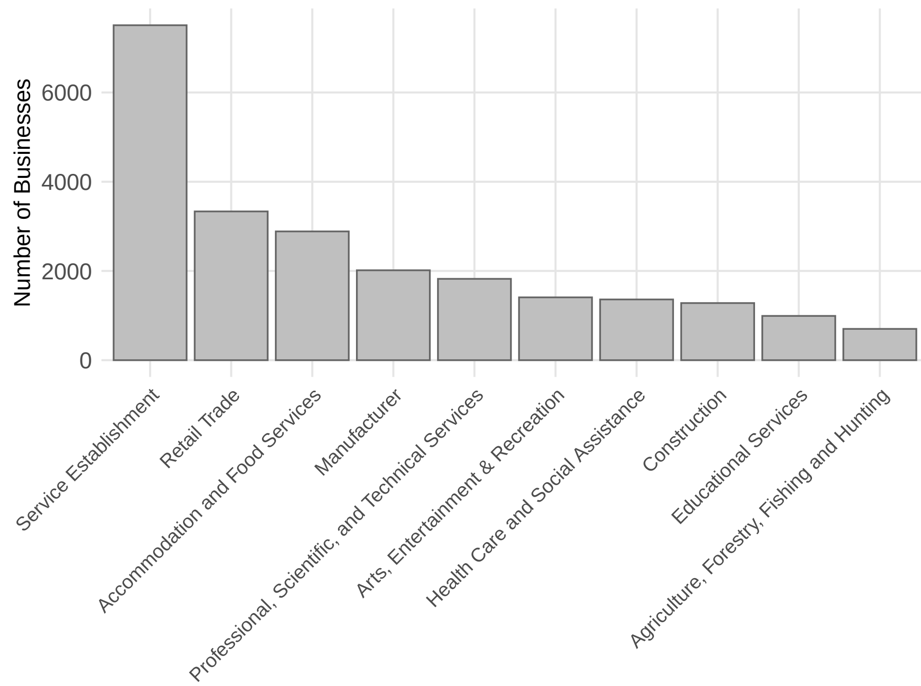
2.2 The Northern California SBDC Network

This study examines the Northern California (NorCal) regional SBDC network, which covers nearly 12,000 square miles and 36 counties in the upper half of the state (American Association of Small Business Development Centers 2024). The network has experienced major growth since 2006 when it was first established; as of 2018, it made up the 3rd largest SBDC program in the US and operated 19 active centers with over 500 employees.[8] According to the NorCal SBDC Network, in 2021 alone it provided one-on-one advising to 20,317 businesses, leading to over 10,000 new jobs created and nearly $242 million in taxable revenue (American Association of Small Business Development Centers 2024). Figure 1 documents the variety of industries the NorCal SBDC Network has served over its existence. One can see that unlike a typical private accelerator, firms working with NorCal SBDCs tend to come from a wide range of sectors, including services, manufacturing and construction, and health and education.

Each center in the NorCal SBDC network is responsible for a geographic area, typically encompassing 2-3 counties depending on whether the center is serving a more rural or urban area. Each center has a fiscal host, examples of which include state universities, local chambers of commerce, and business councils, among others. Hosts establish the SBDC program under their management, typically in conjunction with other business services they offer. They are in charge of providing facilities and fiscal management of centers. In particular, hosts manage grants and other funding received for the SBDC program. They are required to reach a certain threshold of funding to receive matched funds from the NorCal SBDC Network. Furthermore, each center (and its accompanying host) is responsible for hiring business advisors to consult with small business clients. Advisors are

[8] Previously, California had been broken into 6 different regions. In 2018, the Northwest SBDC region absorbed the Northeast region, adding new centers to the the NorCal SBDC Network we study, greatly expanding its size.

Figure 1: Top 10 Industries by Number of Businesses



hired on a contract basis and typically consist of local business executives and leaders in the region who work for the centers on a part-time basis.[9]

Advisors play a critical role in center services; their primary responsibility is to facilitate consulting sessions with business clients associated with the center. Each consulting session is tailored to the specific business' needs and goals; more comprehensive needs and goals of businesses often require more consulting time. Crucially, advisors are typically hired from the community where the center is located. When centers are reorganized, advisor-business pairings may or may not persist depending on feasibility.[10]

Oversight and coordination of this decentralized structure is managed by the NorCal SBDC lead center, which is hosted by California State Polytechnic University at Humboldt in Arcata, California. They are responsible for maintaining standard practices across centers, expanding the network, and managing the local centers in cooperation with their respective

[9] It should be noted that contracted advisors are atypical for an SBDC Network. Advisors in the majority of SBDC conglomerates around the country are full-time employees.

[10] This information was provided by informational discussions with several executives located at the NorCal SBDC Lead Center.

host. The lead center also operates a centralized intake process: when a business engages with the NorCal SBDC Network for the first time, it is typically through an online form processed by the lead center, who then matches businesses with appropriate hosts.

Of particular importance for this study, the lead center generally oversees center movements, openings, and closures. These changes typically occur on a case-by-case basis, and are often due to fluctuations in funding or expiring leases.[11] One common mechanism for host changes is difficulty obtaining matching funds. If a host cannot reach the threshold of funds necessary for matching by the NorCal SBDC Network, a new host is sought out. According to discussions with NorCal SBDC network executives, when host changes occur, the lead center engages in a Request for Proposal (RFP) process to identify new potential hosts to facilitate the relocation or opening of a center. This process does not target specific communities or cities, rather it identifies hosts who can offer the most resources and best fit for SBDC clients.[12]

To introduce additional structure to the process of matching centers and hosts, the NorCal SBDC Network developed a regular Request for Proposals (RFP) process in 2020. In addition to case-by-case host changes, the network implemented the RFP process to be repeated every five years across all centers. This allows existing hosts to either renew or end their relationships with the network, and prospective hosts to submit proposals. The stated goal of this procedure is to ensure that each center host continues to serve as a strong and valuable partner.[13] The first network-wide RFP cycle in the NorCal SBDC Network, held in 2020, led to major restructuring: 8 centers closed in 2021, and 8 new centers opened in 2022. This marked one of the largest shifts in the network's configuration since its inception in 2006.

These structural changes in the network's composition are noteworthy given the unique role each center plays in serving the specific needs of the local business community.

[11] Some hosts opt not to renew their lease agreements due to the increasing demands of managing a center.

[12] When a center closure or relocation occurs, the lead center will continue to pay the contracted advisors at the previous center to continue working with business owners until the new center is established.

[13] The RFP process was recommended by America's SBDC, the nonprofit organization responsible for the NorCal Network's accreditation.

Differences in business needs across regions stems from a range of factors, including the makeup of local industries, regulatory landscape, access to capital, infrastructure, and broader socioeconomic conditions. While many forces contribute to these varying conditions, a consistent and impactful driver is the urban-rural divide. This geographic and socioeconomic consideration is particularly important in the Northern California region, which features both highly urban and highly rural areas. Such an environment underscores the importance of place-based business support models like the SBDC network, which can deliver services tailored to the differing needs of both urban and rural entrepreneurs.

3 Data

We leverage a novel panel dataset provided by the NorCal SBDC network. Each observation examines a business i in year t matched with one of 50 possible center locations spanning the NorCal network and active at some point between 2006-2023.[14] Table 1 provides general information about the structure of the dataset. Each business is assigned a unique client ID by the NorCal network.[15] Treated clients include any business that experienced a closure, opening, or movement of a center they were matched with.[16] Centers are uniquely identified by their specific location (address). Businesses are classified under 190 possible industries, each one defined by a North American Industry Classification System (NAICS) code. Other business-specific characteristics include business zip code, business entity type (LLC, Corp, etc.), and establishment date of the company.[17]

We also observe several time-varying characteristics at the business level; Table 2 displays

[14]Centers may retain the same host when changing locations, but any change in host will necessarily be associated with a change in location. For simplicity and accuracy, we treat each location change as a new center. Figure 5 provides a map of active NorCal SBDC centers as of 2023.

[15]There were a small number of businesses with addresses outside of the Northern California region; we remove these businesses from the sample.

[16]This does not include clients who were initially (or at some point) matched with the NorCal SBDC lead center.

[17]To leverage rich variation in categorization of businesses, the last column of Table 1 displays a variable that combines the NAICS code with the business entity type, denoted as "industry x entity type." However, for the sake of simplicity, we refer to this combined industry x entity type as industry in the paper.

Table 1: Unique Counts of Key Panel Characteristics

Years	Client IDs	Treated Clients	Industries	Centers
18	89,269	3,365	190	50

summary statistics for these variables. Firms engage in an average of 3.49 consulting sessions per year with centers. Contact and preparation time are reported when a center and business engage in a session. Contact time measures the hours spent between a center and a client during a consultation, while preparation time measures the hours spent by a center to prepare for consultation. These variables allow us to observe (1) different sessions for businesses and (2) the center responsible for facilitating each session. As Table 2 shows, businesses spend an average of 3.74 hours annually in consulting sessions with centers, while centers spend nearly 1.5 hours annually in preparation per business. Since there are relatively few hours a business spends with a center, each hour is plausibly quite meaningful to a business.

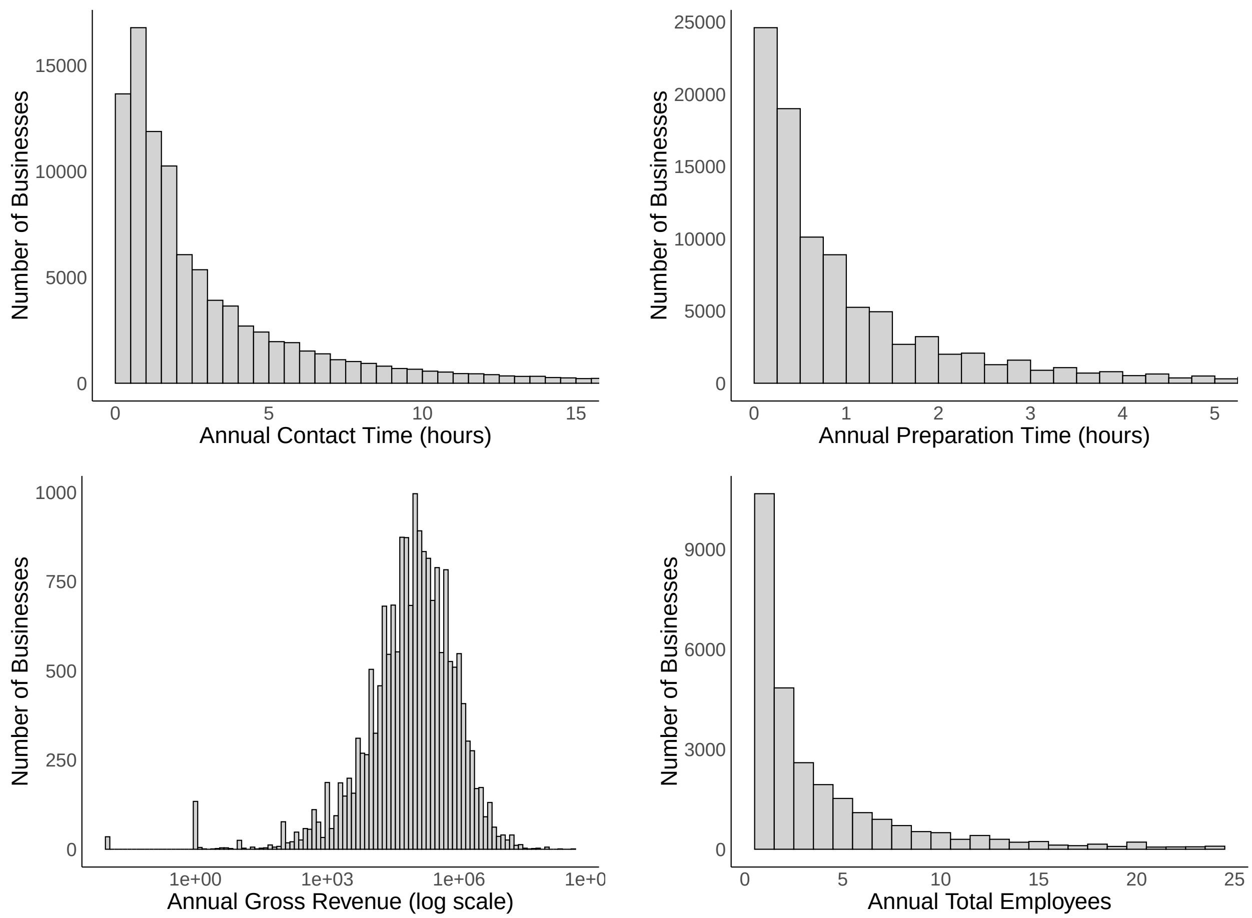
Table 2: Summary Statistics of SBDCs and Participating Businesses

Variable	Number of Observations	Mean	SD	Median	5^{th} Percentile	95^{th} Percentile
# of Sessions	96,064	3.49	4.09	2	1	10
Contact Time (hours)	96,064	3.74	8.20	2	0.25	13
Preparation Time (hours)	96,064	1.45	2.36	0.75	0	5.25
Distance (miles)	48,880	15.5	28.6	7.3	0.9	55.4
Δ in Distance (miles)*	4,178	10.8	73.9	-0.08	-81.3	174.0
Annual Revenue ($1000s)	9,198	679.6	7,839.2	86.5	1.0	2,000.0
Employees	16,666	6.49	79.4	2	1	20

Note: These statistics omit all businesses that engaged with the NorCal SBDC lead center. The lead center is often responsible for on-boarding businesses into the network, thus logging contact time not associated with the primary business advisory services.
*The number of observations for the "Δ in Distance" variable consists of every unique change in business-center pairing, resulting from center openings, closures, or re-locations. Comparing this value to the number of treated businesses in Table 1 shows there are businesses who have experienced > 1 changes in the center pairing.

Figure 2, which depicts the individual distributions of contact time, preparation time, revenue, and employment, reinforces this relationship. One can see that the distributions for both contact and preparation time are heavily right-skewed. This is intuitive, given most consultations occur every few months and last approximately 1 hour. We also observe

Figure 2: Distribution of Contact Time, Preparation Time, Revenue, and Employment



Note: This figure illustrates the distributions of the four labeled variables. The vertical axis displays the number of businesses that register a value for contact time, preparation time, total employees, or revenue in a given year.

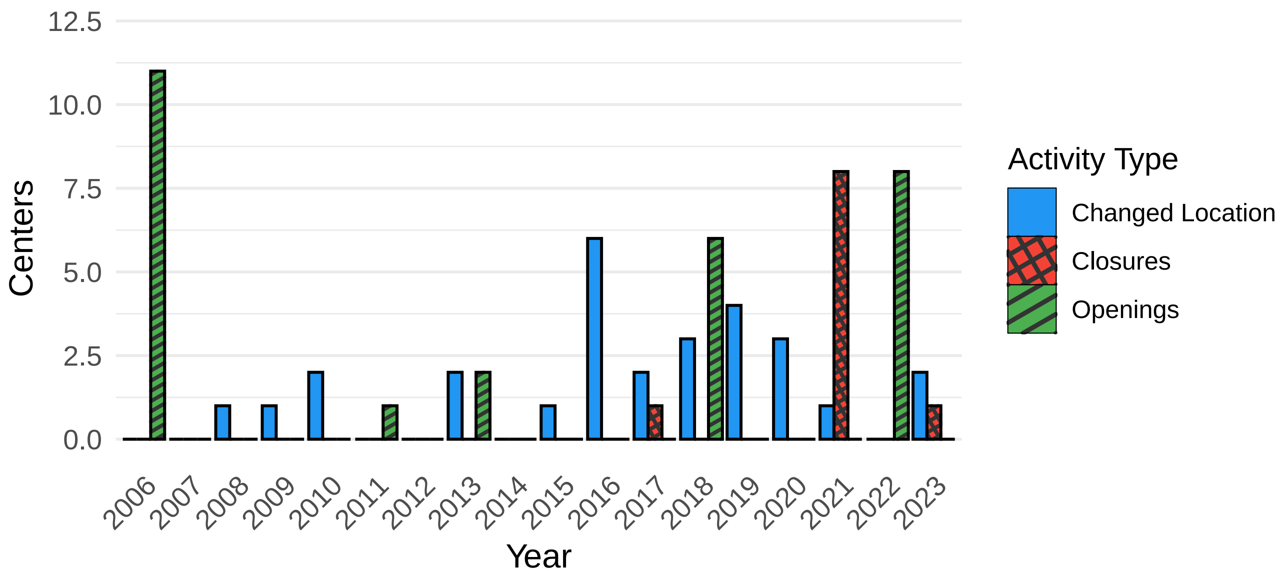
business-level revenue and employment. The data collected and provided to us by the NorCal SBDC network only includes the most recent revenue and employment observation collected for each business. One can see business revenues are distributed log-normally and employment is right-skewed.[18] This is also appropriate, given the clientele the SBDC Network serves which includes small businesses typically employing only a few individuals.

Distances between businesses and their corresponding centers are computed using location data for each. To maintain confidentiality, business locations are provided at the

[18]The long right-tails of both employment and annual revenue inform the large standard deviation estimates found in Table 2.

5-digit USPS zip code level, while center coordinates are geocoded from their full addresses. Using locations of centers and businesses at each encounter, we compute a straight-line measure of distance between a business and its corresponding center.[19]

Figure 3: Center Closures, Openings, and Location Changes



A key source of variation in our data is the evolution of business-center pairings over time and space. There are three possible changes a pairing can experience, which we observe: a center closure, opening, or change in location. If a center closes, an associated business is typically re-assigned to the closest open center. If a center opens, certain businesses may switch from an existing center to this new center. If a center changes location, businesses may choose to move with the center, or be re-assigned to a different center. The data captures all business-center adjustments between 2006-2023. Figure 3 illustrates the overall variation observed, indicating annual openings (green), closures (red), and location changes (blue). One can see that in almost every year there is at least one center that moves locations. Center openings and closures happen less frequently and in larger bunches, particularly in 2021 for closures and 2018 and 2022 for openings.[20]

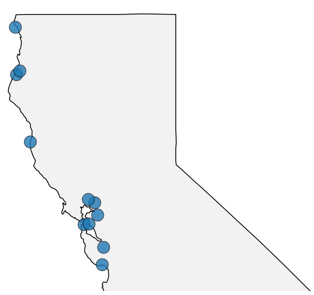
[19]Distance is calculated using the Haversine Formula. There are alternative ways to calculate distance; for example, one could calculate distance between centers according to the typical commuter route.

[20]The 11 openings in 2006 represent the initial centers established when the NorCal SBDC Network was developed and introduced in 2006. In 2018, the NorCal SBDC network we study expanded by absorbing the

Figure 4 shows how the geographic makeup of the NorCal SBDC network has evolved over time. It shows four key time periods: 2006, 2013, 2018, and 2023.[21] Each new shape introduced in a subsequent period indicates either a relocated or newly-established center compared to the previous period. The figure highlights the network's substantial growth over the past 18 years, reflecting both re-locations and expansions. This evolving spatial distribution generates important variation in the proximity of businesses to paired centers.

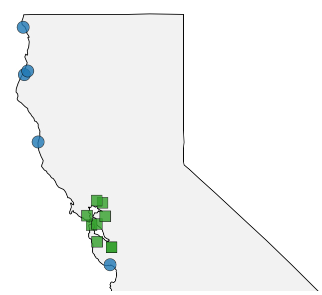
Figure 4: Timeline of NorCal SBDC Center Movement

2006



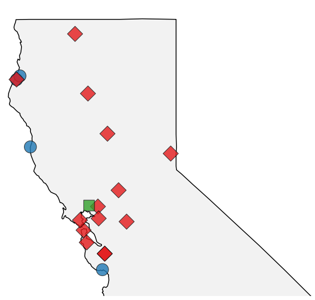
Active Centers: 11

2013



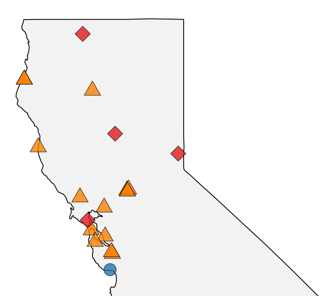
Active Centers: 14

2018



Active Centers: 19

2023



Active Centers: 19

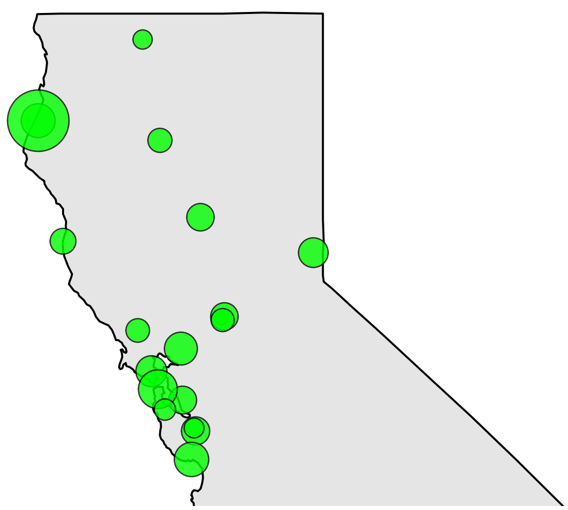
Note: The four symbols include a blue circle (2006), green square (2010), red diamond (2018), or an orange triangle (2023). A new symbol appearing on the map indicates a center either changed location or was newly established in comparison to the previous period. Note that some centers visually overlap with one another on the map; this is due to multiple centers located in the same city or in close geographic proximity.

Northeast regional network of California; we classify these newly introduced centers as openings.

[21] These four distinct periods account for over 90 percent of all center closures and openings between 2006-2023.

While businesses are generally paired with geographically proximal centers, many businesses' first interaction with the SBDC network begins through an online form. This often means that initial consultations are reported by the lead center SBDC in Arcata, CA. Figure 5 shows the geographic location of all active centers as of 2023; a larger circle indicates a greater number of clients a center works with. The NorCal lead center is represented by the largest circle, given their role in processing many new clients and serving as the administrative focal point for the NorCal SBDC network.[22]

Figure 5: Active SBDC Centers



Active Centers: 19

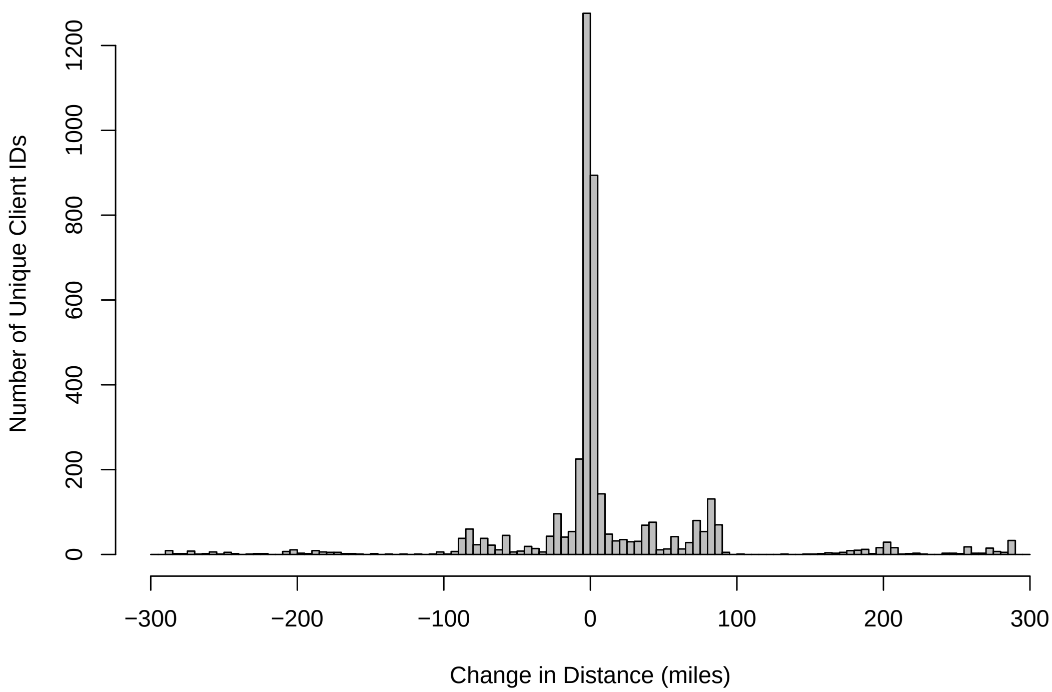
Note: This figure maps the number of active centers in the NorCal SBDC Network in 2023. Each center is identified by a green circle. The larger the circle, the greater number of clients that the center has served. Note that some centers overlap with one another on the map, as indicated by instances of circles falling within other, larger circles.

The geographic redistribution of centers over time is central to our identification strategy. When a center closes or relocates, affected businesses are reassigned to the next closest center, introducing variation in distances between businesses and paired centers. We exploit such variation to estimate the effect of proximity on intensity of business advising services. Figure 6 depicts the distribution of change in distance values between treated businesses and

[22]Despite not being located in geographic proximity, many businesses will register contact time with the lead center in the first year observed as a result of the on-boarding process. Due to this administrative structure and because of the localized geographic variation we seek to exploit, we omit all businesses who register contact time with the lead center and subsequently experience a change in associated center.

matched centers.[23] The average (standard deviation) change in distance is approximately 10.8 miles (73.9 miles) (Table 2). Figure 6 shows notable variation in change in distance, including substantial density among both positive (further distance between a business and center) and negative values. Most change in distance values range between -100 and 100 miles. The significant density near 0 is due to many instances of small change in distances experienced for closures, openings, and location changes that occurred within the same city.[24]

Figure 6: Distribution of Change in Distance



Note: This figure calculates the change in distance between a business its corresponding, but closed, center and the new distance between a business and its corresponding, but open, center in the following year. This means that negative change in distance values is associated with a center moving closer to a client, while positive change in distance values indicates a center moving farther away. For each subsequent year after treatment, the change in distance value remains the same. Notably, this figure cuts off any change in distance values greater than 300 miles or less than -300 miles.

[23] Note that untreated businesses are simply businesses who do not experience a change in distance associated with a business-center pairing adjustment.

[24] There are also some small outlier clusters in the 200-mile range. These outliers are mostly due to transitory changes that occurred between a center closing and opening. That is, a small number of businesses logged consulting hours with a different center while they had no other options during the transition period. Each bin represents a 5 mile change in distance.

4 Empirical Strategy

We are interested in measuring the impact of publicly-funded business advisory services on small business outcomes. We leverage variation in the number of annual consulting hours between a business and associated SBDC to determine changes in firm-level outcomes, principally revenue and employment. Due to unobserved confounders affecting business-center engagement and business outcomes, we employ an instrumental variables (IV) approach. Firm engagement with centers is endogenous; for instance, highly motivated firms are more likely to engage with centers and also have stronger performance outcomes. The IV approach leverages exogenous changes in distance between businesses and paired centers resulting from conditionally random center closures, openings, and re-locations. We hypothesize that changes in physical proximity influences business engagement levels (as measured by consulting time), which in turn affects business outcomes (as measured by revenue and employment).

The first-stage estimating equation leverages panel data at the business-year level and takes the following form:

$$\text{ContactTime}_{ijct} = \alpha_0 + \alpha_1 \Delta\text{Distance}_{ijct} + \gamma_i + \sigma_c + \delta_t + \varepsilon_{ijct} \tag{1}$$

where $\text{Contacttime}_{ijct}$ is the number of contact (consulting) hours received by firm i, classified in industry j, from center c during year t. γ_i, σ_c, and δ_t indicate firm-, center-, and year-fixed effects, respectively. The instrument, $\Delta\text{Distance}_{ijct}$, also varies at the business-year level. The coefficient α_1 indicates the average impact of changes in distance between a business and paired center on predicted annual consulting hours the business receives.

The second-stage estimating equation measures changes in firm outcomes due to changes in predicted contact time values estimated from the first-stage. We define two separate firm outcomes $y_{ijt} = \{\text{Revenue}_{ijt}, \text{Employment}_{ijt}\}$. As mentioned previously, we only observe the most recent revenue and employment value recorded for each business, and thus do not directly observe within-business changes in revenue and employment. To continue leveraging both spatial and temporal variation in the second-stage, we average outcomes across businesses within the same industry each year. The average outcome is calculated as follows:

$$\frac{1}{n}\sum_{i=1}^{n} y_{ijt} = \bar{y}_{jt} \tag{2}$$

where $\bar{y}_{jt}$ is the average revenue (employment) for businesses in industry j and year t.

We prefer this approach over a business-level cross-sectional estimation for two primary reasons. First, businesses accumulate different amounts of consulting time with a paired center each year. Depending on when a business' most recent revenue or employment value is recorded, it may not account for the total accumulated consulting time shared between a business and center, thus generating a misleading relationship between consulting time and business outcomes. Second, leveraging industry-year data in the second-stage accommodates the inclusion of industry-fixed effects, which helps further account for possible endogeneity in the relationship between business-center consulting time and firm outcomes.

As a result of using industry-year variation in outcomes in the second-stage, we calculate average predicted contact time at the industry-year level using business-year predicted values generated from the first-stage:

$$\frac{1}{n}\sum_{i=1}^{n} \widehat{\text{ContactTime}}_{ijt} = \overline{\text{ContactTime}}_{jt} \tag{3}$$

where $\overline{\text{ContactTime}}_{jt}$ is the average number of consulting hours for businesses in a given industry j and year t generated from the predicted business-year contact time estimates from Equation 1.

The second-stage estimating equation takes the following structure:

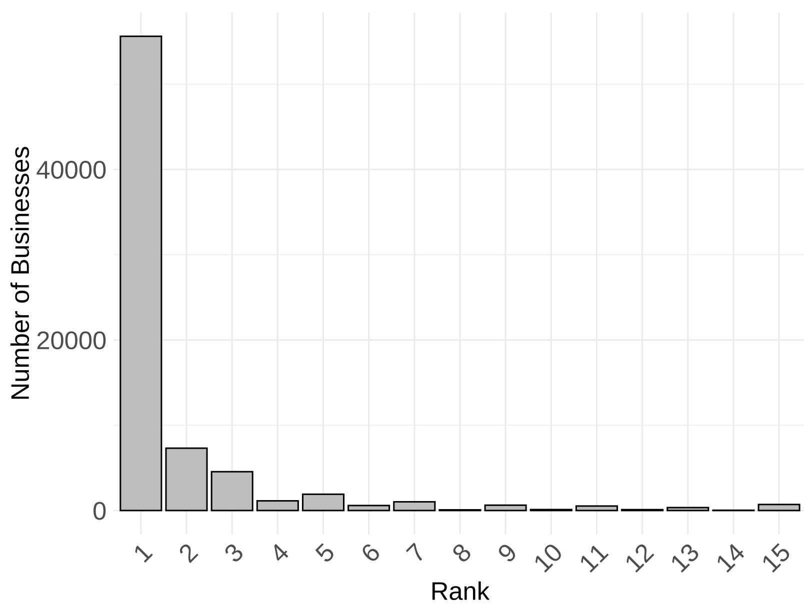
$$\ln(\bar{y}_{jt} + 1) = \beta_0 + \beta_1 \overline{\text{ContactTime}}_{jt} + \phi_j + \lambda_t + u_{jt} \tag{4}$$

where $\bar{y}_{jt}$ represents average business-level outcomes in industry j during year t, and ϕ_j and λ_t indicate the industry- and year-fixed effects, respectively. β_1 measures the average impact of changes in predicted average business-center contact time on proportional changes in average business outcomes.[25]

4.1 Identifying Assumptions

Here we discuss the validity of the IV approach in achieving identification. The instrument, change in distance, is expected to be predictive of consulting hours spent between a business and its corresponding SBDC. While we provide evidence of relevance in the first-stage estimation results in Table 3 in Section 5, Figure 7 offers additional supporting context that businesses generally choose to work with the center geographically closest to them.[26] This pattern further motivates change in distance as a highly relevant instrument.

Figure 7: Count of Business-Center Pairings Based on Order of Geographic Proximity



Note: For each business-year observation, we rank all potential centers from closest to furthest in distance and identify the center with which the business engaged. A rank of 1 indicates the business worked with its closest center, 2 indicates the second closest, and so on.

[25] Because some average business outcomes at the industry-year level take on a value of 0, we add a value of one to each observation to ensure the second-stage specification can be estimated.

[26] While physical distance is certainly relevant in facilitating consulting time between a business and corresponding SBDC, it may also be important in terms of local knowledge and regulation a center can offer a business.

Second, change in distance should be uncorrelated with unobserved factors affecting revenue and employment. While fundamentally untestable, we believe this condition is plausibly met. Observed change in distance between a business and accompanying center is the result of three possible shocks: center closures, openings, and re-locations. In instances where closures and openings were related (i.e. a business moved from a closed center to a newly open center), new centers generally served the same geographic region of businesses while operating from new locations. And while businesses may have experienced other temporal shocks correlated with SBDC network reorganization (e.g. the COVID-19 pandemic), the extent to which these shocks were common to all businesses in the network is accounted for by time-fixed effects. We discuss specific, outstanding threats to exogeneity in Section 4.2.

Finally, it is unlikely that change in distance impacts revenues and employment directly. That is, variation in change in distance is driven by movements of centers themselves, and the resulting physical change in proximity should only impact firm outcomes through changes in the availability and utilization of center resources. Put differently, if a business never receives services from a center, then their revenue and employment should be unaffected by the change in proximity between a business and associated center.

4.2 Threats to Identification

The primary threat to identification of the IV strategy is the existence of location-time specific shocks that are likely to impact business outcomes and also correlated with center re-locations, closures, and openings.[27] In other words, the validity of change in distance as an instrument is threatened if center movements systematically coincide with local economic upturns or downturns.

For example, consider a center that relocates from an economically stagnant or declining

[27] Time-invariant, location-specific shocks are accounted for with the inclusion of center and business fixed effects in the first-stage. Time-varying shocks affecting all units identically are controlled for with year fixed effects.

region to one that is expanding, which facilitates a reduction in distance for some businesses while improving their business environment. In this case, we are unable to identify to what extent changes in center accessibility versus location-time specific changes in broader economic conditions are generating improved business outcomes. It is important to note the extent to which changing economic conditions affect regions differently is not a threat to identification perse. This is only concerning if region-specific changes in economic conditions are systematically correlated with patterns of center closures and openings. Figure A.1 in the Appendix visually illustrates a hypothetical manifestation of this concern.

We believe this pathway is unlikely, as the NorCal SBDC Network does not target specific communities or cities based on their economic forecast; the primary determinant of center movements is matching them with hosts that can maximize their impact. Of course, hosts are likely to feature unobservable characteristics that may be correlated with changes in distance to clients (i.e. changes in host quality resulting from center movements may be systematically correlated with changes in distance to client businesses). However, the first-stage specification accounts for time-invariant, host-specific characteristics through the inclusion of center-fixed effects, and so a threat to identification through this channel must result from time-varying, center-specific confounders. Specifically, centers would need to systematically relocate according to location-specific changing economic conditions within Northern California that are correlated with changes in distance experienced by client firms. This point clearly demonstrates that, while plausible, it is unlikely there is endogeneity biasing the IV estimates through this channel.

5 Results

This section provides results from the empirical analysis. Table 3 presents five specifications; specifications 1 and 2 feature results from an OLS estimation examining the effect of consulting hours on revenue and employment averaged across businesses at the industry-year level. Specification 3 presents results from the first-stage estimating equation, measuring the effect of change in distance on predicted consulting hours at the business-year level. Specifications 4 and 5 present the second-stage estimation results, examining the effect of average predicted contact time on average revenue and employment, respectively. Section 5.3 presents results estimating heterogeneity in the impact of change-in-distance on contact time.

Table 3: OLS and IV Estimation Results

	OLS		First-Stage	Second-Stage	
	Log (Avg Rev)	Log (Avg Emp)	Contact Time	Log (Avg Rev)	Log (Avg Emp)
Avg Contact Time	0.026 (0.031)	0.022^{*} (0.013)			
Δ in Distance			-0.0035^{***} (0.0009)		
Avg Predicted Contact Time				0.064^{**} (0.031)	0.033^{**} (0.015)
Observations	1,226	1,308	95,448	1,226	1,308
Business-Fixed Effects			X		
Center-Fixed Effects			X		
Industry-Fixed Effects	X	X		X	X
Year-Fixed Effects	X	X	X	X	X
Clustered Robust SEs	X	X	X		
Bootstrapped SEs				X	X
R^2	0.429	0.398	0.655	0.433	0.400
F-Statistic			14.4		

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note: This table presents the coefficients (standard errors) of the OLS and IV first- and second-stage estimations. Information regarding fixed effects and estimation of standard errors is provided in the bottom panel of the table. All standard errors are clustered at the industry level. When bootstrapping standard errors, we cluster by industry with 1,000 iterations.

5.1 First-Stage Results

The first-stage results present the estimates of the impact of change in distance on number of consulting hours, leveraging panel data at the business-year level. We find that for every one standard deviation increase in distance between a business and matched center (approximately 30 miles), predicted consulting time between them decreases by approximately 0.1 hours each year. The estimate is highly statistically significant and the F-statistic is moderately strong. While the F-statistic is stronger in the first-stage estimation using industry-fixed effects (Table A.1), it is intuitive that variation in change in distance and consulting hours is more appropriate at the business- rather than industry-level.[28] The first-stage coefficients are very similar in both specifications.

We estimate two additional specifications employing (1) center preparation time and (2) combined consulting and preparation time as outcome variables in the first-stage. The first specification in Table A.2 shows the effect of change in distance on preparation time; these values remain statistically significant but are approximately one-third the magnitude of the estimates in Table 3. While reasonable, we believe these results to be less relevant, as preparation time is logged by the center consultant and does not measure actual interaction time between a center and a business. The second specification in Table A.2 shows the effect of change in distance on the sum of preparation and contact time; these results are consistent with (and slightly larger in magnitude than) the results in Table 3, reinforcing the relative importance of business-center contact time vs. center preparation time.

5.2 Second-Stage Results

The second-stage results deliver the impact of changes in number of consulting hours on expected business-level revenue and employment, estimated at the industry-year level. The results suggest average revenue increases by approximately 6.4% for every 1 additional consulting hour, while average employment increases by 3.3% for every 1 additional consulting hour.[29] For added context, the median firm engages in 2 hours of consulting time annually and has an annual revenue (employment) of $86,488 (2 employees). So, one additional consulting hour generates $5,534 in expected additional annual revenue and

[28]The strength of the first-stage F-statistic is affected by the number of fixed effects, due to the estimation occurring at the business-year level.

[29]Due to the difference in the structure of the residuals between the first- and second-stage estimations, we compute cluster bootstrapped standard errors by industry in the second-stage estimations (Freedman 1984, Glaser and Rahman 2016).

0.066 expected additional hires, respectively. Note that these estimates should be interpreted on the intensive margin, namely the effect of increases in consulting time for firms already apart of the SBDC network. Importantly, when comparing the IV and OLS estimates, one can see the OLS estimates appear to be biased downward, underestimating the impact of consulting time between businesses and centers on revenue and employment.

5.3 Heterogeneity by Change in Distance

The first-stage results depict the marginal impact of a change in distance between firms and corresponding centers on expected contact time, leveraging the entire sample of firm-center observations. However, there is substantial variation among treated firms with respect to the magnitude of changes in distances experienced. The absolute change in distance experienced by a firm may lead to differently-sized marginal effects on expected contact time. This may be due to physical travel considerations when meeting with center advisors, center and advisor time and scheduling constraints, and possible diminishing returns to advisory services.

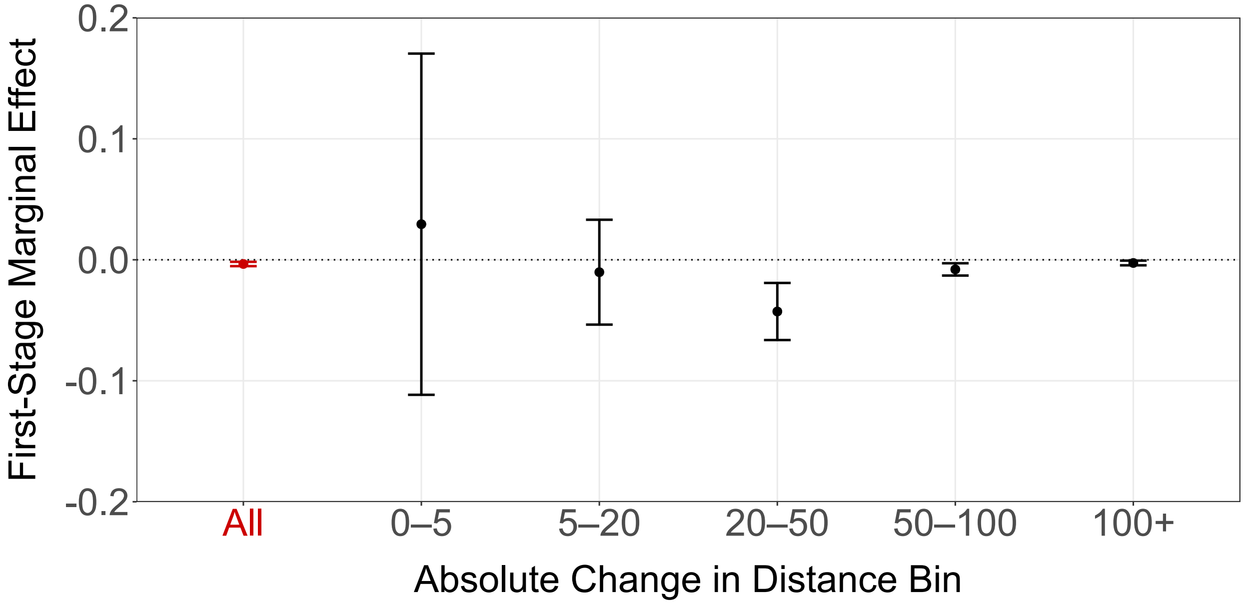
To test for such heterogeneity, we subset the data into several change-in-distance bins and estimate separate IV specifications for each. Figure 8 depicts results associated with the first-stage specification.[30] Each bin contains observations of treated businesses that experience a change in distance with their corresponding center falling within the bounds of the bin, as well as observations of all businesses never experiencing a change in distance.[31] Thus, bins simply differ by the composition of treated businesses they include. The "All" estimation refers to the specification in column 3 of Table 3, which includes the full sample of firms used in the primary estimation.

One can see there is significant heterogeneity in the marginal effect of change-in-distance on predicted contact time by magnitude of change-in-distance experienced between a firm and

[30] A more detailed set of numeric results is contained in Table A.3.

[31] Treated businesses that experience multiple changes in distances due to >1 corresponding center adjustments are assigned to the bin associated with the largest magnitude change in distance experienced. Robustness of findings to this assignment mechanism is included in the Appendix in Figure A.2 and Table A.4. The qualitative nature of the findings is unchanged.

Figure 8: First-Stage IV Estimates by Change-in-Distance Bin



Note: Points represent coefficient estimates from the first-stage specification for each change-in-distance bin grouping treated businesses. Confidence intervals are estimated using clustered-robust standard errors. Treated clients with multiple change-in-distance instances are assigned to the bin corresponding to their largest (in magnitude) Δ in distance.

corresponding center. Interestingly, the results suggest that a one-mile change in distance is most impactful on contact time among firms experiencing *moderate* changes in distance with corresponding centers. Smaller and larger and changes-in-distance deliver lower magnitude (and in the case of smaller changes, statistically insignificant) marginal impacts.

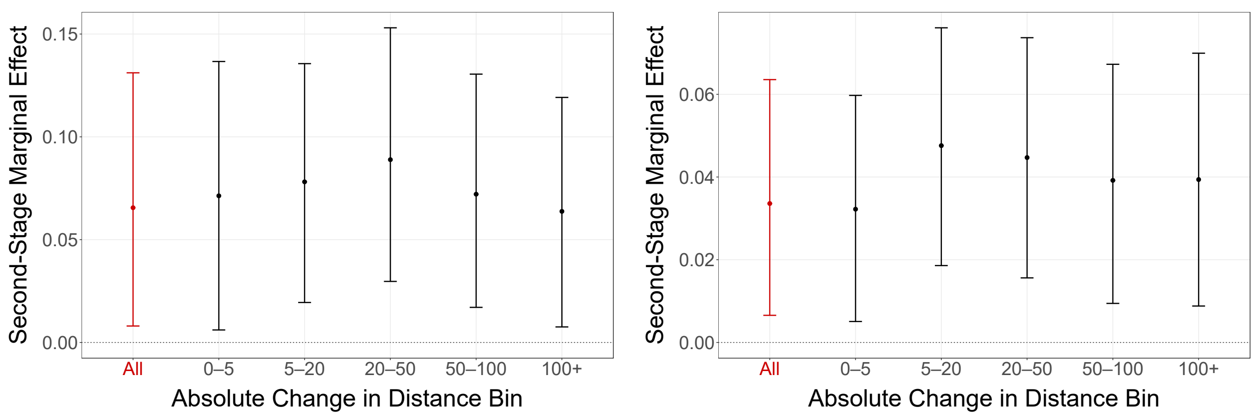
These findings are intuitive; firms experiencing small changes tend to be close in proximity to their corresponding centers, and therefore may already optimize over the amount of annual consulting time spent with center advisors (subject to center- or advisor-specific constraints on the number of consulting hours that can be offered on an annual basis). Moreover, small changes in distance also preserve the regional context for firm-center interactions. For firms experiencing relatively large changes, the marginal impact is expected to be small either because of constraints on availability of consulting hours, or because at some point there are significant diminishing returns to additional consulting time. Even in the case where a firm's annual consulting time does meaningfully change in response to a large adjustment in distance, a small *marginal* effect is intuitive due to the substantial change in distance. Firms experiencing moderate changes in distance balance these considerations and therefore face larger marginal adjustments in the amount of contact time spent with a center.

Figure 9 depicts the second-stage results for annual revenue (panel a) and employment (panel b) under each change-in-distance bin first-stage specification. One can see the point estimates and significance are stable and similar to the primary estimation results found in columns 4 and 5 of Table 3. This suggests the effect of contact time on annual revenue and employment outcomes is not sensitive to the source of variation in change-in-distance from the first-stage estimation.

Figure 9: Second-Stage Estimates by Change-in-Distance Bin

Panel A: Annual Revenue

Panel B: Employment



Note: Points represent coefficient estimates from the second-stage specification for each change-in-distance bin, using predicted contact time from the first-stage regressions. Confidence intervals are estimated using bootstrapped standard errors. Treated clients with multiple change-in-distance instances are assigned to the bin corresponding to their largest (in magnitude) Δ in distance.

6 Discussion

Our findings suggest that increased accessibility facilitates more consulting time between businesses and advisors, which causes significant increases in annual firm revenue and employment. There are several important implications of these findings. First, physical proximity to advisory services remains a relevant factor in the business environment, even in an increasingly digital age. Results from the first-stage estimation indicate small businesses are increasing consulting time with centers when they are closer geographically. The heterogeneity analysis offers additional insight, namely that firms facing moderate changes in proximity to corresponding centers (rather than relatively small or large changes) experience larger marginal impacts on consulting time. A plausible mechanism for this is that firms experiencing small changes in proximity may already be optimizing over the number of consulting hours, while the marginal impact of large changes in proximity is depressed either by center- or advisor-specific constraints on availability of consulting hours, or due to diminishing returns to additional consulting time at a certain point.

At the same time, the broader takeaway of the importance of physical proximity likely depends on the nature of advisor-client meetings; we do not observe whether a specific consulting session is held virtually or in-person. A traditional interpretation would suggest shorter distances reduce costs associated with physical meetings, directly increasing participation. Thus, the physical closeness of the center to a business is the primary driver behind higher consulting time. Yet, the relevance of distance may also imply that small business owners value proximity as it pertains to the local knowledge that comes from engaging with regionally embedded advisors. Supporting this idea, Jaffe, Trajtenberg and Henderson (1993) examines the geographic locations of patent development and citations of those patents, finding that citations are more concentrated in areas proximal to where patents are developed. Jara-Figueroa et al. (2018) found that hiring workers with location-specific knowledge significantly improves the growth and survival of pioneer firms, reinforcing that regional expertise is a valuable asset.[32] Our findings indicate that physical access could be a proxy for informational access and relevant advisory expertise.[33]

The second primary set of findings suggests that increased consulting time with advisors leads to higher average revenues and employment. Specifically, each additional

[32] Jara-Figueroa et al. (2018) define pioneer firms as "firms operating in an industry that was not present in a region."

[33] Such expertise is also critical in creating a more even playing field between smaller and larger firms operating in heavily bureaucratic policy environments. Large firms tend to have more internal resources to navigate "red tape" as well as identify and take advantage of favorable policy loopholes (Welsh and White 1981).

hour of consulting annually is associated with an approximately 6.4% and 3.3% increase in average annual business revenue and employment, respectively. Since the average number of consulting hours for a business is approximately 4 hours annually (2 hours for the median firm in the data), even modest increases in engagement can have a significant effect on business outcomes. Importantly, while consulting hours may facilitate direct benefits to firms (e.g. goal-setting, financial planning, overview of relevant regulation, etc.), there may be significant complementary, indirect benefits associated with more time spent with center advisors. For instance, more consulting time may facilitate introductions to separate professional networks or financing opportunities, which in turn provide direct benefits to firms. Additional hours spent with advisors generally facilitates a stronger economic environment for small businesses owners and entrepreneurs to exchange ideas, leverage resources, and find support within the local community.

From a policy perspective, these findings suggest public advisory services can significantly impact entrepreneurship and small business growth, particularly for businesses that may be less competitive in accessing private resources. Moreover, the size of the impacts we estimate suggest these advisory services are highly cost-effective. The 2023-24 operating budget for the NorCal SBDC network was $10.5 million, and according to our data, delivered 59,408 total hours of advisor preparation and consulting time to clients. This suggests each advisor-hour costed $230.60 on average, while our findings indicate that each consulting hour delivered an additional $5,534 in expected additional annual revenue and 0.066 expected additional hires. In fact, due to the SBDC network funding model requiring matching donor funds for each federal dollar, the taxpayer funded cost for each advisor-hour was $115.30 on average.

The costs associated with maintaining the network of SBDCs appear to deliver significant benefits in the form of higher revenues and employment of participating small businesses, suggesting public investments in advisory services may ultimately benefit the broader economy through tax revenue and job creation. In fact, this study likely underestimates the economic impacts of these investments, since it does not consider the external benefits SBDC clients may provide to businesses that do not work directly with SBDCs. The findings also indicate the importance of both a dense network of centers and locating centers in under-served areas. A denser center network facilitates more geographically localized expertise, allowing businesses to select into the most topically relevant center. Increased accessibility of centers, particularly in under-served areas, is expected to enhance and create less costly interactions between centers and businesses.

7 Conclusion

This study offers two key findings regarding the impact of public advisory services on firm performance outcomes. First, we find that closer geographic proximity between advising centers and businesses increases consulting time facilitated. Second, for every additional consulting hour between a business and advisor annually, average annual business revenue and employment increase by approximately 6.4% and 3.3%, respectively.

The results suggest that while shorter distances may facilitate greater physical interactions and information exchange, the local expertise that SBDC consultants provide small business owners is likely an important driver of successful business outcomes. The findings in this paper are, to the best of our knowledge, the first attempt at identifying the causal impact of publicly-funded business advisory services in the US on business performance. Previous research examining small business advisory services in the US has used survey methodologies and estimated correlations. This study performs a rigorous assessment of the impact of publicly-funded advisory resources, particularly time spent between advisors and business, on business revenues and employment. SBDC advisors also provide important, localized expertise, and policymakers may benefit from expanding centers to under-served areas.

Beyond the findings of this study, there are several avenues for future research that could enhance our understanding of the efficacy of SBDCs and publicly-funded small business development resources in general. First, richer data on business outcomes over time will allow closer study of the impacts of public investment in small business advisory services across various economic dimensions. For example, observing costs businesses incur as well as financing applied for and received would further enhance our understanding of the impacts of these services. In addition, further investigation of heterogeneous effects of advising across businesses in different industries would offer insight into which industries benefit most from public advisory resources. Finally, assessing the impacts of SBDCs on the local economy more generally may shed light on the external benefits public advisory services offer communities in addition to the direct benefits experienced by clients.

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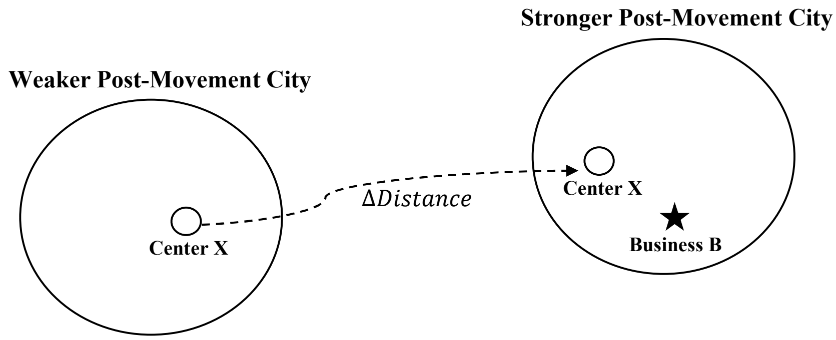
Appendix

Figure A.1: Place-Specific Shocks Correlated with Center Movement



Note: This figure displays the movement of Center X from a city that is economically declining to one that is improving. Business B, located in the economically improving city, experiences both a decrease in distance to Center X and a stronger post-movement economic environment compared to its peers.

Table A.1: First-Stage Estimation Results (Industry- vs. Business-Fixed Effects)

	First-Stage	
	Contact Time	Contact Time
Δ in Distance	-0.0035^{***}	-0.0027^{***}
	(0.0009)	(0.0006)
Observations	95,448	95,448
Business-Fixed Effects	X	
Industry-Fixed Effects		X
Center-Fixed Effects	X	X
Year-Fixed Effects	X	X
Clustered Robust SEs	X	X
R^2	0.656	0.019
F-Statistic	14.4	23.3

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note: This table presents the coefficients (standard errors in parentheses) of the first-stage estimations of change in distance on contact time. Column headers indicate the dependent variable for each specification. Specification 1 estimates with business-fixed effects while specification 2 estimates with industry-fixed effects. Further information regarding fixed effects and estimation of standard errors is provided in the bottom panel of the table.

Table A.2: First-Stage Estimation Results (Preparation Time vs. Combined Preparation and Contact Time)

	First-Stage	
	Preparation Time	Preparation + Contact Time
Δ in Distance	-0.0013^{***}	-0.0046^{***}
	(0.0005)	(0.0013)
Observations	$86,900$	$96,064$
Business-Fixed Effects	X	X
Center-Fixed Effects	X	X
Year-Fixed Effects	X	X
Clustered Robust SEs	X	X
R^2	0.615	0.640
F-Statistic	8.64	11.95

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

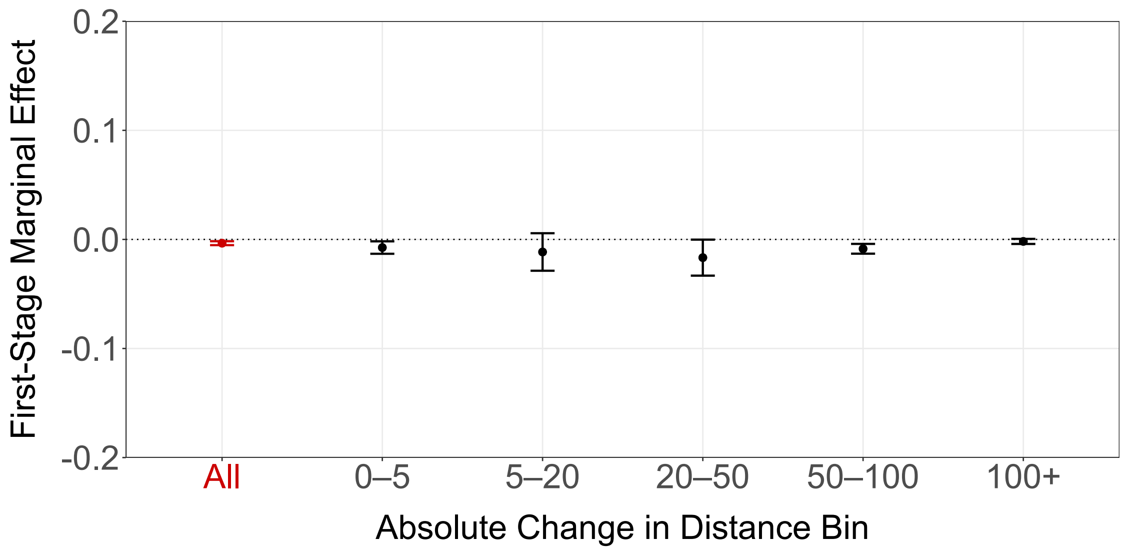
Note: This table presents the coefficients (standard errors in parentheses) of the first-stage estimations where the outcome variable is preparation time (specification 1) and combined preparation and contact time (specification 2). Column headers indicate the dependent variable for each specification. Information regarding fixed effects and estimation of standard errors is provided in the bottom panel of the table.

Table A.3: First-Stage Estimates by Change-in-Distance Bin

Bin	**Coefficient**	**95% CI**	R^2	F**-stat**	N	**# Treated Clients**	**# Total Clients**
All	-0.0035	[-0.0053, -0.0017]	0.656	14.40	95,448	3,365	60,469
0–5	0.0294	[-0.1116, 0.1704]	0.664	0.17	89,976	1,789	58,893
5–20	-0.0102	[-0.0536, 0.0331]	0.675	0.21	85,495	475	57,579
20–50	-0.0427	[-0.0664, -0.0191]	0.675	12.59	85,208	390	57,494
50–100	-0.0080	[-0.0130, -0.0029]	0.674	9.40	85,552	465	57,569
$\geq$ 100	-0.0026	[-0.0046, -0.0007]	0.676	7.09	84,825	246	57,350

Notes: Estimates are generated from the first-stage specification for each change-in-distance bin grouping treated businesses. Confidence intervals are estimated using clustered-robust standard errors. The column "# Treated Clients" counts the number of businesses with at least one non-zero change in distance in each bin; treated clients with multiple change-in-distance instances are assigned to the bin corresponding to their largest (in magnitude) change-in-distance. There are 57,104 clients that never change distance and are included in every specification.

Figure A.2: Graphical First-Stage Estimates by Change-in-Distance Bin (Smallest Δ in Distance Assignment)



Note: Points represent coefficient estimates from the first-stage specification for each change-in-distance bin grouping treated businesses. Confidence intervals are estimated using clustered-robust standard errors. Treated clients with multiple change-in-in distance instances are assigned to the bin corresponding to their smallest (in magnitude) change-in-in distance.

Table A.4: Numeric First-Stage Estimates by Change-in-Distance Bin (Smallest Δ in Distance Assignment)

Bin	**Coefficient**	**95% CI**	R^2	F**-stat**	N	**# Treated Clients**	**# Total Clients**
All	-0.0035	[-0.0053, -0.0017]	0.656	14.40	95,448	3,365	60,469
0–5	-0.0075	[-0.0132, -0.0018]	0.661	6.59	90,924	1,946	59,050
5–20	-0.0115	[-0.0287, 0.0057]	0.676	1.72	85,270	442	57,546
20–50	-0.0167	[-0.0332, -0.0002]	0.676	3.93	84,872	335	57,439
50–100	-0.0086	[-0.0131, -0.0041]	0.675	14.08	85,340	428	57,532
$\geq$ 100	-0.0018	[-0.0042, 0.0005]	0.676	2.40	84,650	214	57,318

Notes: Estimates are generated from the first-stage specification for each change-in-distance bin grouping treated businesses. Confidence intervals are estimated using clustered-robust standard errors. The column "# Treated Clients" counts the number of businesses with at least one non-zero change in distance in each bin; treated clients with multiple change-in-distance instances are assigned to the bin corresponding to their smallest (in magnitude) change-in-in distance. There are 57,104 clients that never change distance and are included in every specification.

Table A.5: Numeric Second-Stage Results by First-Stage Change-in-Distance Bin Specifications (Annual Revenue)

Bin	**Coefficient**	**95% CI**	R^2	N
All	0.0655	[0.0080, 0.1311]	0.433	1,226
0–5	0.0713	[0.0061, 0.1367]	0.432	1,200
5–20	0.0781	[0.0194, 0.1356]	0.469	1,154
20–50	0.0889	[0.0297, 0.1530]	0.467	1,151
50–100	0.0721	[0.0171, 0.1305]	0.473	1,153
$\geq$ 100	0.0638	[0.0075, 0.1192]	0.469	1,151

Notes: Estimates are generated for the second-stage specification examining annual revenue, using predicted contact time estimates generated from the first-stage specifications in Table A.3 for each corresponding change-in-distance bin. Confidence intervals are estimated using bootstrapped standard errors.

Table A.6: Numeric Second-Stage Results by First-Stage Change-in-Distance Bin Specifications (Total Employment)

Bin	**Coefficient**	**95% CI**	R^2	N
All	0.0336	[0.0066, 0.0636]	0.400	1,308
0–5	0.0322	[0.0051, 0.0597]	0.409	1,279
5–20	0.0476	[0.0186, 0.0761]	0.390	1,232
20–50	0.0447	[0.0156, 0.0737]	0.374	1,231
50–100	0.0392	[0.0094, 0.0673]	0.382	1,234
$\geq$ 100	0.0394	[0.0088, 0.0699]	0.384	1,229

Notes: Estimates are generated for the second-stage specification examining total employment, using predicted contact time estimates from the first-stage specifications in Table A.3 for each corresponding Δ in distance bin. Confidence intervals are estimated using bootstrapped standard errors.