Does Tax Complexity Discourage Entrepreneurship?

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ABSTRACT: We investigate claims that the complexity of the tax system discourages entrepreneurship. We use tax filing assistance centers, which help entrepreneurs file their taxes, as sources of plausibly exogenous variation in the tax complexity effectively facing potential entrepreneurs. We find that tax filing assistance centers significantly increase local entrepreneur entry and overall business income, suggesting that tax complexity significantly discourages entrepreneurship and small business creation.

Keywords: Entrepreneurship, tax complexity, taxation, new business formation

JEL classification: H23, H25, L26, M13

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1. Introduction

We examine whether tax complexity discourages entrepreneurship. We define entrepreneurship as the formation of new, typically small, businesses. We define tax complexity following Bradford (1986) as a multi-faceted concept that includes "*compliance complexity* (referring to the problems faced by the taxpayer in keeping records, choosing forms, making necessary calculations, and so on); *transactional complexity* (referring to the problems faced by taxpayers in organizing their affairs so as to minimize their taxes within the framework of the rules); and *rule complexity* (referring to the problems of interpreting the written and unwritten rules)."

In 1998, Congress heard arguments "toward simplifying the tax code … to allow entrepreneurs to concentrate on their businesses and not their tax returns" and that "small businesses face the brunt of [tax compliance] costs."[1] These arguments further noted that, "[f]or small business entrepreneurs, who represent 99.7% of employers, employ 53% of the private work force, contribute 47% of all sales and 50% of private gross domestic product to our nation's economy, tax complexity is a special burden." Despite these arguments, tax complexity has grown since 1998, leading small business owners to spend millions of hours each year attempting to adhere to tax code requirements and risking noncompliance (e.g., Time, 2016; Tax Foundation, 2022). Indeed, surveyed entrepreneurs rank setting up and paying taxes as the third and fourth most difficult factor in starting their business, surpassing even insuring and structuring their business (Kauffman Foundation, 2018).

Potential entrepreneurs may worry that if they launch a small business tax complexity will impose effort costs, create noncompliance risk, and cause them to forgo valuable deductions

[1] https://www.govinfo.gov/content/pkg/CHRG-105hhrg52037/html/CHRG-105hhrg52037.htm. Accessed November 16, 2022.

(Aghion et al., 2017; Zwick, 2021). Given the potentially severe penalties for noncompliance, the expense of outsourcing tax compliance to a third party, and the fact that outsourcing tax compliance does not eliminate all tax complexity, potential entrepreneurs may decide it is simpler and safer to stay at their current jobs. Consequently, tax complexity can discourage entrepreneurship and small business formation. However, others argue that tax complexity will not discourage entrepreneurship because it is not a salient issue for most potential entrepreneurs, that the complexity facing entrepreneurs is overstated, and that complexity is not a first-order concern for most entrepreneurs (e.g., Vox, 2017; Forbes, 2021). In total, whether tax complexity discourages entrepreneurship is an open empirical question.

To provide empirical evidence on tax complexity and entrepreneurship, we examine the impact of Internal Revenue Service (IRS) taxpayer assistance centers (TACs) on local entrepreneurship. The IRS does not operate TACs as part of its enforcement function. Instead, the IRS operates TACs to provide taxpayers, including entrepreneurs, in-person assistance navigating the tax system and filing their federal taxes. Tax assistance is in high demand, and much of this demand goes unmet by other federal services.[2] By providing entrepreneurs a free in-person resource to help navigate the federal tax system, TACs should reduce the tax complexity facing local entrepreneurs and reduce the burden of tax compliance requirements.

Our focus on a source of variation in the assistance available to potential entrepreneurs rather than in the underlying tax rules mirrors the IRS' recent focus on providing "[a] world-class

[2] For the 2022 filing season, the IRS received more than 72.8 million phone calls for filing help, but representatives answered only 10 percent of those calls; https://www.taxpayeradvocate.irs.gov/reports/2023-objectives-report-to-congress/full-report/. Accessed November 17, 2022. The IRS even lists tax topics that it will not assist with over the phone and notes that it, "can't offer line-by-line help with any form." https://www.irs.gov/help/find-information-on-complex-tax-topics. Accessed November 17, 2022. During the sample period taxpayers did not have to schedule TAC appointments via the IRS phone line (e.g., taxpayers could walk into TACs; this changed in 2017. https://www.taxpayeradvocate.irs.gov/wp-content/uploads/2020/10/ARC17_Volume1_MSP_010_TAC.pdf Accessed June 21, 2023).

customer service operation" that provides taxpayers help "navigating complex tax laws and accessing the credits they deserve."[3] Given that TACs provide assistance with tax forms and answer questions about tax law, we expect TACs to alleviate the burden of tax complexity by reducing both compliance and rule complexity. We obtain operating data for over 400 TACs using a Freedom of Information Act (FOIA) request to the IRS.

We examine the impact of TAC operations on entrepreneurship within the same zip code. We expect TACs to particularly impact entrepreneurship within the same zip code because TACs mostly provide in-person services and because local potential entrepreneurs are the most likely to be aware of local offices.[4] To control for local business conditions, demographics, and state-level factors such as state tax rates, we separately include metropolitan statistical area (MSA)-year and county-year fixed effects, along with a host of controls for demographic characteristics the IRS uses to select TAC locations. We measure entrepreneurship using data on new business registrations collected by the Startup Cartography Project (e.g., Barrios et al., 2021; Andrews et al., 2022; Barrios et al., 2022). These new businesses are almost all small business ventures, which account for approximately 44% of US GDP (Kobe and Schwinn, 2018). Despite their economic importance in the aggregate, small businesses may be particularly sensitive to tax complexity due to their small individual sizes.

Consistent with assistance with tax complexity significantly discouraging small business formation, differences-in-differences estimates suggest that TACs significantly increase local

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[3] https://www.irs.gov/newsroom/written-testimony-of-daniel-werfel-commissioner-internal-revenue-service-before-the-hoac-subcommittees-on-government-operations-and-the-federal-workforce-and-health-care-and-financial-services-and-irs-operations. Accessed November 14th, 2023. These sources of help include operating more TAC locations.

[4] Zip codes cover a relatively small geographic area. In subsequent analyses we examine spillovers from TACs to nearby zip codes and find that TAC effects rapidly dissipate. This rapid dissipation suggests that TACs are mainly salient to potential entrepreneurs that live or work in the same zip code as the TAC and/or that potential entrepreneurs' travel costs are quite high (we speculate that the former explanation is more likely).

entrepreneur entry. The 90% confidence interval of the estimate in the most stringent specification suggests that TACs increase entrepreneurship by about 4 to 13%; 9% at the midpoint. A 9% increase is about double the effect of gig economies on entrepreneurship within cities documented by Barrios et al. (2022). Starting from the median of entrepreneur entry of 114, a 9% increase corresponds to the creation of about 10 businesses within the zip code. In total, assistance with tax complexity increases business creation, consistent with tax complexity significantly affecting entrepreneurship.

One potential concern with using TACs as a source of variation is the possibility that the IRS opens or closes TACs based on omitted characteristics that vary across zip codes and within county- and MSA-years in a way that biases the results. Addressing concerns that the IRS endogenously selects locations based on contemporaneous changes in business activity, IRS materials are clear that the IRS considers historical workload when selecting TAC locations.[5] Alleviating broader endogeneity concerns, IRS materials are clear that the IRS partially selects TAC locations based on many unobservable characteristics, such as furniture costs, which are plausibly exogenous with respect to contemporaneous entrepreneurship.

Further alleviating endogeneity concerns, IRS materials are also clear that the IRS considers historical location demographics when selecting TAC locations and that it takes several years to open or close a TAC. For example, in 2005 the IRS used 2004 operating and demographic data to select TACs to close and began closing these TACs in earnest in 2011 (see Section 2.1 for more). Consequently, any endogenous variable considered by the IRS should result in differential trends in entrepreneurship several years prior to the opening or closing of a TAC. Inconsistent with endogeneity driving the results, we find no evidence that entrepreneurship varies in the years prior

[5] https://www.irs.gov/pub/irs-news/tac-criteria.pdf. Accessed June 21, 2023.

to changes in TAC activity (i.e., we find no evidence of pre-existing differential trends in entrepreneurship within a zip code prior to changes in TAC activity).

We estimate several other extensions of the main results. We first examine whether TACs additionally affect entrepreneurship in nearby zip codes. Consistent with spillovers from TACs to nearby zip codes, we find that TACs affect entrepreneurship in nearby zip codes by approximately $1/4^{th}$ as much as they as affect entrepreneurship in the same zip code. The relatively small magnitude of these spillovers supports examining the impact of TACs at the zip code level.

We next examine the robustness of the inferences to various econometric modelling choices. A potential concern with the traditional staggered differences-in-differences design is that the staggering of TAC treatments biases estimates due to heterogeneous treatment effects (e.g., Chaisemartin and D'Haultfœuille, 2020; Barrios, 2021; Baker et al., 2022). To address this concern, we estimate a "stacked" differences-in-differences regression (Gormley and Matsa, 2011). We find similar results using a stacked differences-in-differences regression, which is unsurprising because of the large number of never-treated control observations in the sample and relatively short panel (Chaisemartin and D'Haultfœuille, 2020).

Finally, we examine the robustness of the inferences to changes in the independent variable. The main tests examine the inverse hyperbolic sine of entrepreneur entry because we expect entrepreneurship to respond proportionally to TAC operation. In robustness tests, we find similar results when instead taking the shifted natural logarithm of entrepreneur entry. We also examine how TAC activity relates to an alternative measure of business activity, business income. We find that the presence of a TAC increases business income by approximately 7%, which further suggests TACs affect real business activity.

We contribute to the academic literature and policy debates by documenting how a source of assistance with navigating tax complexity affects entrepreneurship. Advocates for simplifying the tax code have long argued that tax complexity creates significant costs that discourage entrepreneurship and business creation. Yet there is little direct evidence in support of or against, the argument that tax complexity discourages entrepreneurship. This lack of direct evidence is presumably because the federal tax code covers all potential taxpayers equally and only creates cross-sectional variation in complexity based on endogenous differences in business models and compliance decisions. We sidestep this issue by using the staggered implementation of TACs in different zip codes at different times as a source of plausibly exogenous variation.

We also contribute to the literature by answering the call of Lester (2021) for more research on taxes and employment. Prior studies in this literature document how tax rates affect employment.[6] In contrast, we document how assistance with tax complexity affects entrepreneur entry. Understanding entrepreneur entry is particularly important because small businesses produce almost half of US GDP (Kobe and Schwinn, 2018). Understanding the effects of tax complexity is particularly important given recent proposals in the European Union and the United States to simplify the tax code and reduce compliance costs (e.g., the Fair Tax Act of 2023; Forbes, 2023). Understanding the effects of tax complexity is also particularly important given the IRS' renewed focus on providing taxpayers with additional tools to "navigate the complexity of our tax laws."[7]

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[6] E.g., Bruce (2000), Djankov et al. (2010), Akcigit et al. (2016, 2019), Williams (2018), Chen et al. (2019), Lester (2019), Zidar (2019), and Glaeser et al. (2023a,b). Amberger et al. (2023) and Denes et al. (2023) are the mostly closely related studies. Amberger et al. (2023) examine how country level tax complexity, as measured by the time surveyed medium-sized firms indicate they spend preparing, filing, and paying taxes, relates to firm-level investment. Denes et al. (2023) find that angel investor tax credits do not relate to entrepreneurial activity as measured by startup outcomes (e.g., venture capital funding).

[7] https://www.congress.gov/bill/118th-congress/house-bill/25. Accessed August 28th, 2023. https://ec.europa.eu/commission/presscorner/detail/pl/ip_23_4405. Accessed September 21st, 2023.

We organize the rest of the paper as follows. Section 2 provides background and institutional details. Section 3 discusses the empirical approach and results. Section 4 concludes.

2. Institutional Detail and Prior Literature

2.1 Taxpayer assistance centers

A key challenge in documenting the effect of tax complexity on entrepreneurship is that tax complexity is a byproduct of rules that can otherwise affect business creation (Slemrod, 2005; Hoppe et al., 2018; Hoppe et al., 2023). Consequently, any correlation between entrepreneurship and tax complexity may partially reflect the effect of the underlying rules that create the complexity. For example, complex capital depreciation rules reduce the tax burden on business investment, and hence encourage business creation, independently of their effect on tax complexity. We overcome this by using TACs as a source of variation in the ease with which potential entrepreneurs can navigate the tax system.

As noted by IRS commissioner Danny Werfel tax laws are complex, and taxpayers may need assistance "navigating complex tax laws and accessing the credits they deserve." To ensure the IRS can help taxpayers, the IRS is dedicating its recent budget increase to "ensuring taxpayers can easily reach the IRS," including in person at TACs. We mirror the IRS' focus on taxpayer accessibility by using TACs as a source of variation in the assistance available to local taxpayers with tax complexity, rather than in the underlying tax rules.

TACs help taxpayers, including small businesses, with tax forms, questions about tax law, navigating issues with the IRS, recommending changes to avoid issues with the IRS, receiving all

https://www.irs.gov/newsroom/written-testimony-of-daniel-werfel-commissioner-internal-revenue-service-before-the-hoac-subcommittees-on-government-operations-and-the-federal-workforce-and-health-care-and-financial-services-and-irs-operations. Accessed November 14th, 2023.

eligible deductions and refunds, etc.[8] Based on help codes for a random sample of TACs provided by the IRS, general questions about accounts and payments are the most common, while questions about tax forms, individual returns, and business returns are also common. As noted by Bradford (1986, p. 270-271), "The hardest [tax] problems have to do with financial affairs and directly owned businesses…. one of the irritations in life is determining which outlays are eligible for deduction…consider a classic problem of tax administration: the office at home. Are all or any of the expenses deductible? …Home computers and automobiles used partly for business purposes are further examples…The complexity involved in the tax treatment of such transactions is largely the result of the narrow line dividing expenses for purposes of earning a return and those for direct personal benefit. The necessary distinctions create headaches for taxpayer." TACs can assist individuals navigating these and other potential tax complexities and thereby encourage marginal potential entrepreneurs to start a business either by providing help *ex ante* or by providing them the knowledge that they will receive help *ex post*.

TAC location decisions are generally a slow-moving, bureaucratic process. For example, in 2005 the Government Accountability Office (GAO) assessed the 2006 IRS budget request and advised that, "In light of the current budget environment and IRS's improvements in taxpayer service over the last several years, this is an opportune time to reconsider the menu of services it provides. It may be possible to maintain the overall level of assistance to taxpayers by changing the menu of services offered, offsetting reductions in some areas with new and improved service in other areas."[9] In response to the GAO's assessment, then IRS commissioner Mark W. Everson released a statement on the expected closure of 68 TACs, a process that began in earnest in 2011

[8] https://www.irs.gov/pub/irs-pdf/p334.pdf. Accessed June 26, 2023.
[9] https://www.gao.gov/assets/gao-05-566.pdf; https://www.taxpayeradvocate.irs.gov/wp-content/uploads/2020/08/ARC17_ExecSummary.pdf Accessed June 25, 2023.

and even then took several years.[10] In selecting which TACs to close, Everson noted that the IRS' methodology relied on fiscal year 2004 TAC operating and Census data.

The IRS' methodology for closing TACs highlights four important institutional details for the research design. First, it suggests that the IRS does not randomly operate TACs and that we must exercise caution with respect to potential selection effects and correlated omitted variables. Second, the IRS' methodology suggests that the IRS selects TAC locations based on historical characteristics, rather than concurrent changes in activity. Because the IRS does not select TAC locations based on concurrent changes in activity, selection is unlikely to drive any correlation between changes in TACs and contemporaneous entrepreneurship. Third, the slow-moving nature of TAC location decisions suggests that any endogeneity between TAC location decisions and entrepreneurship is likely to manifest prior to changes in TAC locations. Fourth, many of the TAC operation characteristics considered by the IRS are largely orthogonal to entrepreneurship outside of their effect on TAC operations (e.g., furniture costs), suggesting that there is a large degree of exogeneity in TAC locations.[11]

During the sample period, individuals could schedule TAC help in advance or receive walk-in assistance, including with tax law. TACs are well trafficked, suggesting that they materially affect constituents. In 2014, 389 TACs received 5,449,445 visits, in 2015 378 TACs received 5,434,144 visits, and in 2016 376 TACs received 4,426,918 visits; over the three year period TACs received a yearly average of 13,395 visits.[12] TAC visits began declining in 2016 due

[10] https://www.irs.gov/pub/irs-news/tac-statement.pdf. Accessed June 21, 2023.
[11] https://www.irs.gov/pub/irs-news/tac-statement.pdf. Accessed June 21, 2023. Unfortunately, we cannot observe these orthogonal characteristics and the IRS was unable to provide data on them.
[12] https://www.taxpayeradvocate.irs.gov/wp-content/uploads/2020/10/ARC17_Volume1_MSP_010_TAC.pdf. Accessed June 25, 2023.

to changes in IRS policy such as requiring advance appointments, and for this reason we end the sample in 2015.

Although TACs are not geographically constrained in who they assist, we expect them to particularly impact geographically proximate individuals who are most likely to be aware of the TAC and have the shortest travel time to the TAC. To our knowledge, TAC openings and closings are not well-advertised, so the effect of TACs is likely primarily driven by individuals seeing the TAC and or hearing about it via word of mouth. To the extent that TACs affect non-proximate individuals, and therefore outcomes at control observations, the resulting estimates will underestimate the benefits of TACs. We model these potential spillovers and find evidence that they lead to marginally conservative estimates.

2.2 Prior literature on tax complexity

As noted in Section 1, we define tax complexity as including compliance complexity, transactional complexity, and rule complexity (Bradford, 1986). Closely related to compliance complexity are tax compliance costs, which are the "…costs incurred by taxpayers, or third parties such as businesses, in meeting the requirements laid upon them in complying with a given structure and level of tax" (Sandford et al., 1989). Compliance complexity generates tax compliance costs due to effort costs, the costs of tax risk, the costs of hiring accountants to navigate tax complexity, etc. However, not all tax compliance costs are the result of tax complexity (e.g., fixed filing fees).

Tax complexity is an arguably understudied topic (Ulph, 2015). To aid research on tax complexity, Lawless (2012) and Hoppe et al. (2023) develop measures of tax complexity based on cross-country surveys and Slemrod (2005) develops measures of tax complexity based on the length of state tax forms and instruction booklets. Amberger et al. (2023) measure tax complexity by the time medium-sized firms indicate they spend preparing, filing, and paying taxes according to the World Bank's Doing Business survey, and find that country-level complexity negatively relates to firm-level investment. Although these measures of tax complexity can yield important insights, they unfortunately cannot speak to US federal tax complexity because they do not vary across US federal taxpayers. Moreover, these measures of tax complexity do not readily allow one to separate the effects of tax complexity from the effect of the underlying rules that generate the complexity. To separate the effect of tax complexity from the effect of the underlying rules and to generate cross sectional variation across federal taxpayers, we use TAC locations as sources of plausibly exogenous variation. Consequently, the design varies the assistance available to a subset of potential entrepreneurs to navigate tax complexity, but holds the rules themselves fixed, as federal tax rules apply to all members of the population.

Several studies find that individuals and firms pay compliance costs due to tax complexity. Aghion et al. (2017) find that self-employed individuals "leave money on the table" due to tax complexity and value tax simplicity by up to 650 euros a year. Benzarti (2020) finds that individuals forgo large tax savings to avoid tax complexity. Zwick (2021) finds that most eligible firms do not claim refunds for tax losses, suggesting that tax complexity causes businesses to forgo valuable deductions. Feldman et al. (2016) find that individuals reduce their reported wage income when losing a child tax credit, suggesting individuals do not understand the tax system. Cowx (2021) finds that firms respond less to R&D tax credits when enforcement uncertainty is greater. Collectively, these studies suggest that potential entrepreneurs may be particularly sensitive to tax complexity and that tax complexity imposes significant compliance costs.

3. Empirical approach and results

3.1 Regression model, sample, and descriptive statistics

We examine how local entrepreneurship varies as a function of TAC presence using the following staggered differences-in-differences model:

$$ihs(Startups_{i,t}) = \beta_0 + \beta_1 TAC_{i,t} + \gamma' X_{i,t} + Y_i + Z_{j,t} + \varepsilon_{i,t} \tag{1}$$

where i indexes zip codes, t indexes calendar years, and j indexes counties or MSAs. *Startups* is the number of for-profit business registrations recorded by the Startup Cartography Project in zip code i at time t (Barrios et al., 2021; Andrews et al., 2022; Barrios et al., 2022).

The Startup Cartography Project measures startups using state business registrations. All corporations, partnerships, and limited liability companies register with the Secretary of State or equivalent to enjoy the legal benefits of business creation. While it is possible to operate as a sole proprietorship and forgo registration, doing so also forgoes the legal benefits. Given that single-member LLCs have the same default treatment as sole proprietors and TAC personnel are not supposed to provide nontax advice, exposure to TACs should not affect business registrations outside of their effect on real business activity (we further validate this assumption in subsequent tests).

We take the inverse hyperbolic sine (ihs) of *Startups* because we expect TACs to affect new business creation proportionally (e.g., by 10%) rather than absolutely (e.g., by 10 business registrations). The ihs transformation leads to similar interpretations, and similarly reduces the influences of outliers and skew, as the natural logarithm transformation (e.g., Johnson, 1949; Burbidge et al., 1988; Glaeser and Omartian, 2022). The relative benefit of the ihs transformation is that it is defined for nonpositive values (e.g., zero). Although the Startup Cartography Project does not record zeros, we interpolate them for observations bookended by positive values (e.g., if for a given zip code the Startup Cartography Project records one new business registration in 2013, nothing for 2014, and two new business registrations in 2015, we assume the zip code experienced zero new business registrations in 2014).

TAC is an indicator equal to one if the IRS operates a TAC in zip code *i* at time *t*. Zip codes cover relatively small geographic areas, suggesting that selecting a larger geographic footprint to measure the effects of TACs may increase power. However, in subsequent tests we find that that the effect of TACs rapidly dissipates with distance, suggesting that TACs primarily affect local zip codes where travel costs are lower and, especially, salience is greater.

We use a FOIA request to the IRS to obtain TAC operating data. In reposed to our request, the IRS provided a list of every operational TAC as of January 1st of each year but could not provide exact opening and closing dates. Consequently, we cannot determine whether a closed TAC operated for most of the last year in which it is included on the IRS' list. For example, we cannot determine whether a TAC on the 2013 list but not the 2014 list was last operational as of the beginning or the end of 2013, or sometime in between. Anecdotally, our understanding is that the IRS tries to operate closing TACs through April 15 due to tax season but closes them shortly thereafter. Since April 15 is only 3.5 months into the year, we set *TAC* equal to 0 for TACs in their last year on the list.

Figure 1 provides a map of TAC locations during the sample period. Black dots denote TACs that operated throughout the sample period. Red boxes denote TACs that closed during the sample period. Green pluses denote TACs that opened during the sample period. Blue diamonds denote the 12 TACs that both opened and closed during the sample period. Including these 12, 35 TACs opened and 69 TACs closed during the sample period. Figure 1 highlights that the IRS operates TACs in high-population areas, but also broadly geographically due to quasi-exogenous political requirements (e.g., a requirement that two TACs operate in every state). Figure 1 also highlights that some TAC openings and closings occur in proximate zip codes. These proximate events may attenuate estimates to the extent that there are spillovers between proximate zip codes (e.g., because the negative effect of a TAC closing in one zip code is sometimes partially offset by the positive spillover of a TAC opening in an adjacent zip code). We explore how the exclusion of proximate events affects estimates in Table 8.

Eq. (1) includes controls for demographic characteristics that the IRS considers when making TAC operating decisions (see Appendix A for variable definitions). To control for population size and wealth in a zip-code year, we include the number of returns that claim the earned income tax credit (*Number of EITC*), the total number of exemptions filed (*Number of exemptions*), the total number of tax returns (*Number of returns*), the number of tax returns that report unemployment compensation (*Number unemployed*), total population (*Population*), and total reported taxable income (*Taxable income*). To further control for population effects, we require a minimum population of 10,000 for inclusion in the final sample (Barrios et al., 2022). To control for racial representation, we include the populations of the Equal Employment Opportunity commission racial groups (e.g., *Population Asian*; the omitted category is two or more races). Finally, we control for the population 65 years of age or older (*Population 65+*). We obtain all demographic controls from Census.gov and individual income tax controls from the IRS Statistics of Income. Lastly, we examine the effect of TACs on *Business income* (the total Schedule C income reported in a zip code), which we also obtain from the IRS Statistics of Income.

To control for time invariant differences across zip codes, Eq. (1) includes a vector of zip code effects, *Y*. These zip code fixed effects isolate time-series variation in business formation and TAC operation. Isolating time-series variation is important because the discussion in Section 2.1 highlights that endogenous selection is unlikely to bias the time-series relation between TACs and contemporaneous entrepreneurship. Eq. (1) also separately includes vectors of county-year and MSA-year fixed effects, *Z*, to control for time-varying local conditions and factors that may also affect entrepreneurship (e.g., local economic booms and state tax rates; see Gentry and Hubbard, 2000).[13] County-year fixed effects control for variation more proximate to the TAC zip code on average, which could increase the precision of estimates but could also attenuate estimates due to spillovers from TACs to nearby zip codes within the county. Any such attenuation should be less pronounced when using the broader MSA-year fixed effects. We cluster standard errors by zip code to account for serial dependence within zip codes over time.

Our final sample spans 2010 to 2015. Many TAC institutional details changed in 2016, such as no longer allowing walk-in visits and otherwise limiting TAC services, suggesting ending the sample in 2015 is appropriate. However, we note that the changing institutional details also suggest that the results do not perfectly generalize to the effects of TACs today, and hence the results mainly speak to how assistance with tax complexity affect entrepreneurship (Glaeser and Guay, 2017).

Table 1 reports descriptive statistics for the sample. Panel A reports statistics for untransformed variables and Panel B reports statistics for variables after the ihs transformation. TACs are uncommon; they operate in 3.2% of sample zip code-year observations. On average, 168 new startups register in a given zip code each year, although there is significant variation in startup activity (standard deviation of 172). The large number of average startups in each zip code suggests that the inverse hyperbolic sine transformation is appropriate (Bellemare and Wichman, 2020).

3.2 Determinants of TAC operation

We begin by examining the determinants of TAC operation to explore the validity of the identification strategy. To do so, we estimate Eq. (1) after removing *TAC* as an independent

[13] If a zip code spans multiple counties, we assign that zip code to the county that contains the highest percentage of the zip code's population.

variable and replacing *Startups* with *TAC* as the dependent variable. We report results in Table 2. Column (1) reports results when including only year fixed effects. Consequently, cross-sectional differences in demographics across zip codes are the main source of identifying variation in column (1). In the cross-section, most zip code demographics statistically significantly relate to *TAC*, which is unsurprising given the IRS explicitly considers these demographics when making TAC operation decisions. However, the adjusted R-squared in column (1) is about 2%, confirming the discussion in Section 2.1 that the IRS considers many idiosyncratic factors when making TAC operation decisions.

We next explore potential sources of bias for the main test by estimating the time-series relation between TAC operation and zip code demographics. To do so, we include zip code fixed effects, and report results in column (2) of Table 2. In column (2), only one of the 13 demographic characteristics statistically significantly relates to TAC operation, which is about what one would expect by chance. We continue to find little relation between TAC operation and zip code demographics when including MSA-year and county-year fixed effects in columns (3) and (4). The lack of a significant relation between time-series variation in demographic characteristics and TAC operation confirms the discussion in Section 2.1 that the IRS does not consider contemporaneous zip code characteristics when locating TACs. Consequently, endogenous selection is unlikely to drive any correlation between TAC operation and contemporaneous entrepreneurship.

3.3 Tax complexity and entrepreneurship

Having found support for the validity of the identification strategy, we turn to the main research question; how does tax complexity affect entrepreneurship? Table 3 reports the results of estimating Eq. (1). In odd-numbered columns we include MSA-year fixed effects and in evennumbered columns we include the more granular county-year fixed effects. We report results without including controls in columns (1) and (2) to assess how the inclusion of controls affect inferences and to address concerns about potential "bad controls" (Angrist and Pischke, 2009).

Across all four columns of Table 3 we find that TACs increase entrepreneurship, suggesting that plausibly exogenous assistance navigating tax complexity increases entrepreneurship (*t*-statistics of 3.02 to 3.73).[14] In terms of economic magnitudes, the results suggest that the ability to use a TAC increases entrepreneur entry by about 9-16%, consistent with tax complexity significantly discouraging entrepreneurship. The 90% confidence interval on *TAC* in the most stringent specification reported in column (4) suggest that TACs increase entrepreneur entry by 4 to 13%. Starting from the median of *Startups*, this corresponds to the creation of 5 to 15 new businesses (recall from Section 2.1 that the average TAC receives over 13,000 visits each year). Inconsistent with correlated and omitted variables driving these results, we find that the inclusion of controls for demographic characteristics that the IRS explicitly considers when making TAC operation decisions does not meaningfully affect the coefficient on *TAC*.

The coefficient on *TAC* does attenuate when including more granular county-year fixed effects (column 4) in place of less granular MSA-year fixed effects (column 3). One explanation for the attenuated coefficient is that the county-year fixed effects "over control" for TAC operations by including a greater proportion of control observations nearby the TAC that receive positive spillovers from the TAC. A second explanation for the attenuated coefficient is that the county-year fixed effects control for an omitted variable that positively varies with both *TAC* and *Startups* at the MSA-year level, but not at the county-year level. While we cannot easily envision

[14] An alternative mechanism may be that TACs do not directly affect marginal potential entrepreneurs, but instead only indirectly affect them by providing existing businesses with more time to focus on their core business models, spurring demand for new startups. This alternative mechanism is another way in which TACs can cause new business creation by reducing tax complexity.

such a variable, in Sections 3.4 and 3.5 we explore these two explanations for why including more granular county-year fixed effects attenuates the coefficient on *TAC*.

3.4 Tax complexity and entrepreneurship, parallel trends

We next examine how the relation between TAC operations and entrepreneurship evolves over time. As discussed in Section 2.1, the IRS considers historical TAC characteristics and location demographics when making TAC operation decisions. Because the IRS uses historical information to select TAC locations, any correlated and omitted variable driving the relation between TACs and contemporaneous entrepreneurship would likely bias the relation several years prior to changes in TAC operation. To explore whether such a correlated and omitted variable drives the results, we estimate examines whether entrepreneurship varies prior to changes in TAC operation decisions.

We re-estimate Eq. (1) after replacing the dependent variable with the inverse hyperbolic sine of the number of startups in the current year and each of the last three years (i.e., ihs(*Startups*), ihs($Startups_{t-1}$), ihs($Startups_{t-2}$), and ihs($Startups_{t-3}$)). We report results in Table 4. We summarize the results in Figure 2, which plots the *TAC* coefficient estimate and its 90% confidence interval along the y-axis against the year in which startup activity was measured along the x-axis. Panel A of Table 4 and Figure 2 reports results with MSA-year fixed effects and Panel B of Table 4 and Figure 2 reports results with county-year fixed effects. In all panels we find no evidence that startup activity varies as a function of TAC activity, prior to changes in TAC activity (i.e., we find consistent evidence of parallel trends in entrepreneurship prior to *TAC*; *t*-statistics on the pre-trend coefficients of -1.46 to 0.65).

The evidence in Figure 2 and Table 4 that entrepreneurship does not vary prior to changes in TAC operation provides strong evidence that the empirical approach in Table 3 captures the causal effect of assistance navigating tax complexity on entrepreneurship. As discussed in Section 2.1, the IRS considers historical operations and location demographics when making TAC operation decisions and hence any correlated and omitted variable that biases the relation between TAC activity and entrepreneurship should therefore manifest several years prior to changes in TAC activity. The lack of any changes in entrepreneurship prior to changes in TAC activity suggest that correlated and omitted variables do not bias the Table 3 results. Moreover, the lack of any pre-trends in entrepreneurship address concerns that TAC operation decisions are driven by differential trends in entrepreneurship that would have persisted even in the absence of changes in TAC operation.

3.5 Tax complexity and entrepreneurship, spillover analysis

Having documented evidence that correlated and omitted variables are unlikely to bias the coefficient on *TAC* when including less granular MSA-year fixed effects, we next examine whether the larger coefficient on *TAC* when including MSA-year fixed effects is due to spillovers from TACs to nearby zip codes. To do so, we re-estimate Eq. (1) after including the number of TACs in zip codes within 10 miles of zip code *i* (*TAC nearby*).[15] To maximize the ability to detect spillovers we focus on the MSA-year specification.[16] Table 5 reports the results of estimating the modified Eq. (1).

The results in Table 5 provide consistent evidence that TACs increase entrepreneurship in nearby zip codes. In particular, the coefficient on *TAC nearby* suggests that TACs increase entrepreneur entry in nearby zip codes by about 4%, or about 1/4th the effect of having a TAC

[15] Modelling spillovers requires selecting a boundary within which spillovers are expected and outside which spillovers are not expected. We select 10 miles but note that the results in Table 5 are robust to measuring *TAC nearby* using zip copes within 15 or 20 miles, zip codes that share borders, and zip codes in the same county.

[16] In the county-year specification the coefficient on *TAC nearby* is small (0.007) and statistically insignificant (*t*-statistic of 0.46), consistent with reduced power to detect spillovers because most zip codes in a county with a TAC are within 10 miles of that TAC's zip code (i.e., *TAC Nearby* = 1 for most observations, reducing power to detect spillovers).

within the same zip code. The coefficient on *TAC* in Table 5 is also slightly larger than its counterpart in Table 3, suggesting that un-modeled spillovers slightly attenuate estimates in Table 3.

The evidence in Table 5 that the effect of TACs shrinks by 3/4^{ths} even for zip codes within 10 miles of the TAC's home zip code highlights that the effect of TACs rapidly dissipates over relatively short distances. This rapid dissipation suggests that TACs are particularly salient for potential entrepreneurs that live or work in the TAC's home zip code, or that potential entrepreneurs face particularly high travel costs. While we speculate the former explanation is more likely, in either case the rapid dissipation of TAC effects suggests that the choice to use zip codes to measure *TAC* introduces limited measurement error.

3.6 Tax complexity and entrepreneurship, stacked differences-in-differences

A potential concern with the staggered differences-in-differences results is that the staggering of treatments can bias treatment estimates due to the use of previously treated observations as controls for currently treated observations (e.g., Chaisemartin and D'Haultføeuille, 2020; Barrios, 2021; Baker et al., 2022). We expect this bias to be minimized in this setting due to the large number of never-treated control observations in the sample and the relatively short panel (Chaisemartin and D'Haultføeuille, 2020). Nonetheless, we estimate an additional "stacked" differences-in-differences specification to further rule out the possibility that the staggered differences-in-differences estimates are biased (Gormley and Matsa, 2011).

To estimate a stacked differences-in-differences model, we first remove the 12 zip codes in the sample that receive multiple treatments and the 226 zip codes that are always treated (i.e., where *TAC* is collinear with the zip code fixed effect). We then create datasets in which we pair each zip code that experiences a treatment event in year *t* with a cohort of control observations that are not yet treated by year *t* or that are never treated. We then interact the various fixed effects with a cohort indicator that denotes the year of treatment events for each dataset (Baker et al., 2022). Finally, we "stack" the datasets so they form a single sample for which re-estimate Eq. (1) updated to include the modified fixed effects.

Table 6 reports the result of estimating the updated Eq. (1). The coefficient estimates on *TAC* in columns (1) and (2) are similar to their counterparts in Table 3 (estimates of 0.199 and 0.101 compared to 0.159 and 0.086 in Table 3). Moreover, the coefficient estimates are statistically significant (*t*-statistics of 3.57 and 2.78). We conclude that the traditional staggered differences-in-differences estimates are not meaningfully biased.

3.7 Tax complexity and entrepreneurship, shifted natural logarithm transformation

In equation (1), we transform the dependent variable because we expect entrepreneurship to respond proportionally, rather than absolutely, to assistance with tax complexity. For example, we expect business creation to increase by 10% in response to TACs as opposed to by 10 units (e.g., in a zip code where 100 business are created each year on average and in a zip code where 10 are created each year on average, we expect TACs to increase business creation to 110 and 11, as opposed to 110 and 20). Consequently, we take the inverse hyperbolic sine of the dependent variable. Although the mean of startups in the sample of 168 is well above the rule of thumb of 10 suggested by Bellemare and Wichman (2020), we nonetheless examine the robustness of the main results to an alternative transformation of the dependent variable. We re-estimate Eq. (1) after taking the shifted natural logarithm (i.e., ln[1 + *variable*]) of all continuous variables, as opposed to taking the inverse hyperbolic sine. Table 7 reports the results, which are similar to their counterparts in Table 3 (*t*-statistics of the coefficient estimate for *TAC* of 3.69 and 2.94 in Table 7 compared to 3.69 and 3.02 in Table 3).

3.8 Tax complexity and entrepreneurship, excluding proximate treatments

Figure 1 highlights that some TAC treatment events occur in proximate zip codes and Table 5 demonstrates that TAC activity affects entrepreneurship in proximate zip codes. Taken together, Figure 1 and Table 5 suggest that the inclusion of proximate treatment effects may attenuate the estimates on *TAC* in prior tables. For example, when a proximate TAC closes and a nearby TAC opens, the zip code that benefits from the TAC opening was previously benefiting from positive spillovers from the proximate TAC that closed.

To explore the possibility that proximate treatment events attenuate prior estimates on *TAC*, we re-estimate Eq. (1) after excluding the twenty zip codes (ten pairs) that experience proximate treatment events (again defined as those occurring in two zip codes within ten miles of each other). Table 8 reports the results of estimating the modified Eq. (1). Consistent with the inclusion of proximate treatment events attenuating estimates on *TAC*, the coefficients on *TAC* in Table 8 are slightly larger than their counterparts in Table 3 (estimates of 0.203 and 0.114 compared to 0.159 and 0.086 in Table 3). In total, we conclude that the inclusion of proximate treatment events does not drive inferences.

3.9 Tax complexity and business income

A potential concern with the prior inferences is that TACs may only encourage business registration, rather than real business activity. TAC workers may advise individuals asking about taxation on business income to form corporations, partnerships, or limited liability companies to enjoy the associated (non-tax) legal benefits. In this case, TACs would mechanically increase *Startups* without affecting overall business activity. Although TAC personnel are not supposed to provide non-tax advice, we nonetheless explore the possibility they do by re-estimating Eq. (1) with ihs(*Business income*) as the dependent variable and report results in Table 9. We find that

TAC increases *Business income* by approximately 7% (*t*-statistics of 2.57 and 2.55). The significant effect of TACs on business income suggests that TACs affect real business activity, rather than only business registration. That TACs do not merely encourage business registration is perhaps unsurprising given that TAC workers are not tasked with providing general business advice, nor trained in general business law.

4. Conclusion

We examine how tax complexity affects entrepreneurship. Pundits and politicians frequently debate the effect of tax complexity on entrepreneurship. We inform this debate by documenting how the ability to use a TAC to navigate the tax system affects local entrepreneurship. Consistent with assistance navigating tax complexity affecting entrepreneurship, we find TACs significantly increase local entrepreneur entry. We believe that further exploring the causes and consequences of tax complexity is a fruitful avenue for academic research and that policymakers should consider the burdens of tax complexity when designing tax systems.

We end on a final caveat and policy note. The tests do not directly examine variation in tax rules, only the assistance navigating the tax rules available to a subset of potential entrepreneurs. While this design choice allows causal inferences, it means that those same inferences may not generalize to all settings and entrepreneurs. For example, the inferences probably do not generalize to large business entrepreneurs because the estimated local average treatment effects apply to marginal entrepreneurs (e.g., tax complexity is unlikely to discourage entrepreneurs with billion-dollar ideas). Further, the results may not generalize to regulatory reductions in tax complexity unless potential entrepreneurs are aware of those reductions and believe that they are meaningful.

However, the results should be informative to the IRS in light of the agency's ongoing effort to develop tools to help taxpayers "navigate the complexity of our tax laws."[17]

[17] https://www.irs.gov/newsroom/written-testimony-of-daniel-werfel-commissioner-internal-revenue-service-before-the-hoac-subcommittees-on-government-operations-and-the-federal-workforce-and-health-care-and-financial-services-and-irs-operations. Accessed November 14th, 2023.

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Appendix A. Variable Definitions

Business income	The sum of business income (Schedule C income) reported on tax returns filed in the zip code. Obtained from IRS Statistics of Income.
Number of EITC	The number of tax returns filed that claim the Earned Income Tax Credit. Obtained from IRS Statistics of Income.
Number of exemptions	The number of exemptions on the tax returns filed in the zip code. Obtained from IRS Statistics of Income.
Number of returns	The number of tax returns filed in the zip code. Obtained from IRS Statistics of Income.
Number unemployed	The number of tax returns filed in the zip code that report unemployment compensation. Obtained from IRS Statistics of Income.
Population	The population of the zip code. Obtained from Census.
Population 65+	The number of people in the zip code who are 65 years of age or older. Obtained from Census.
Population Asian	The number of people in the zip code who are Asian. Obtained from Census.
Population Black	The number of people in the zip code who are Black. Obtained from Census.
Population Native	The number of people in the zip code who are Native American. Obtained from Census.
Population other	The number of people in the zip code who are a race other than White, Black, Native American, Asian, or Pacific Islander. Obtained from Census.
Population Pacific	The number of people in the zip code who are Pacific Islander. Obtained from Census.
Population White	The number of people in the zip code who are White. Obtained from Census.
Startups	The number of new business registrations. Obtained from the Startup Cartography Project.
TAC	An indicator variable for whether there is an operational Taxpayer Assistance Center in the zip code. Obtained via Freedom of Information Act request to the IRS.
TAC nearby	The number of Taxpayer Assistance Centers in zip codes that are within 10 miles of the focal zip code.
Taxable income	The total of taxable income (in thousands) reported across all tax returns filed in the zip code. Obtained from IRS Statistics of Income.

Figure 1: TAC location map

This figure maps TAC locations in the sample. Black dots denote TACs that operate continuously over the sample period, red boxes denote TACs that closed during the sample period, green pluses denote TACs that opened during the sample period, and blue diamonds denote TACs that both closed and opened during the sample period.

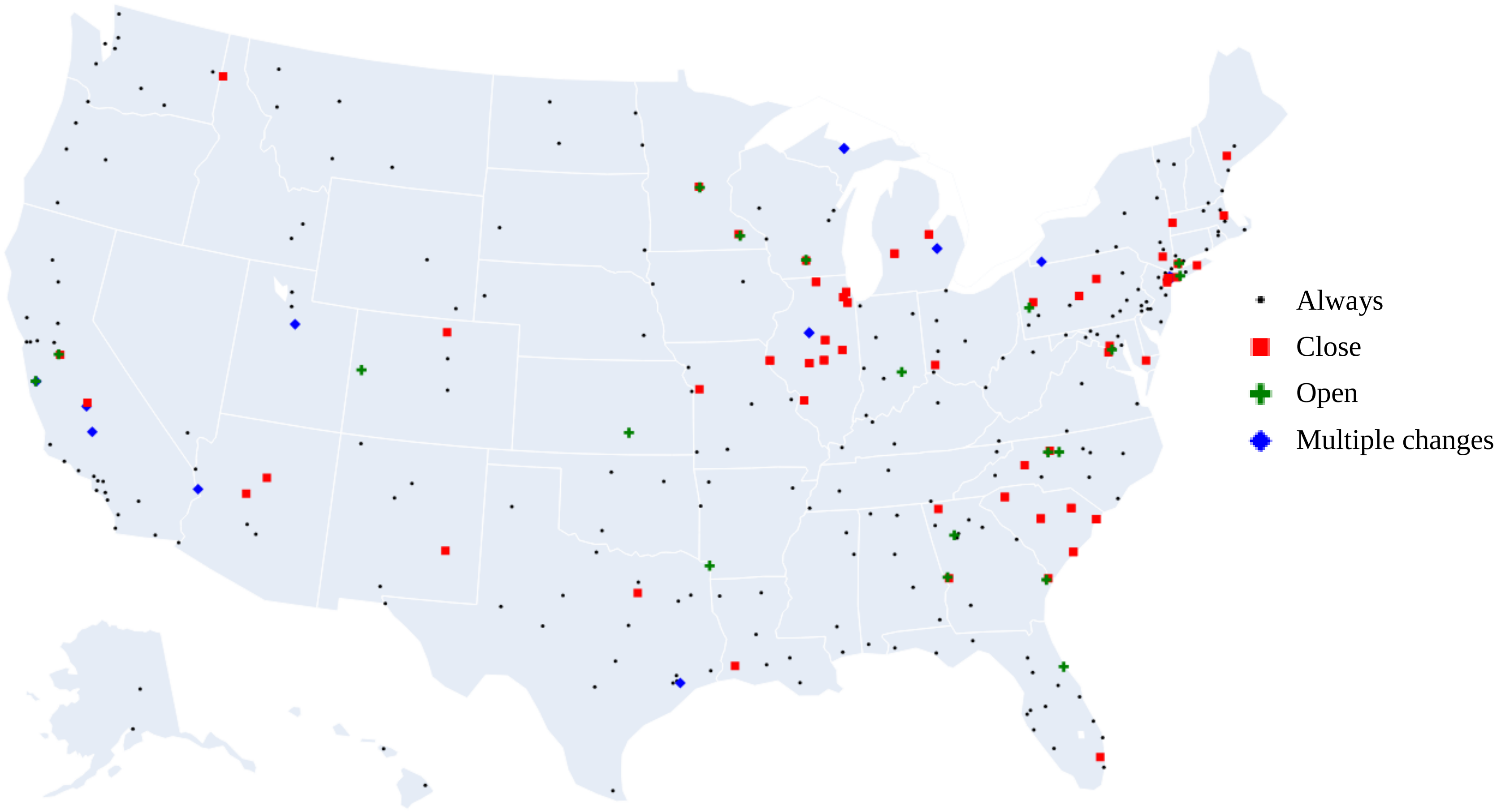
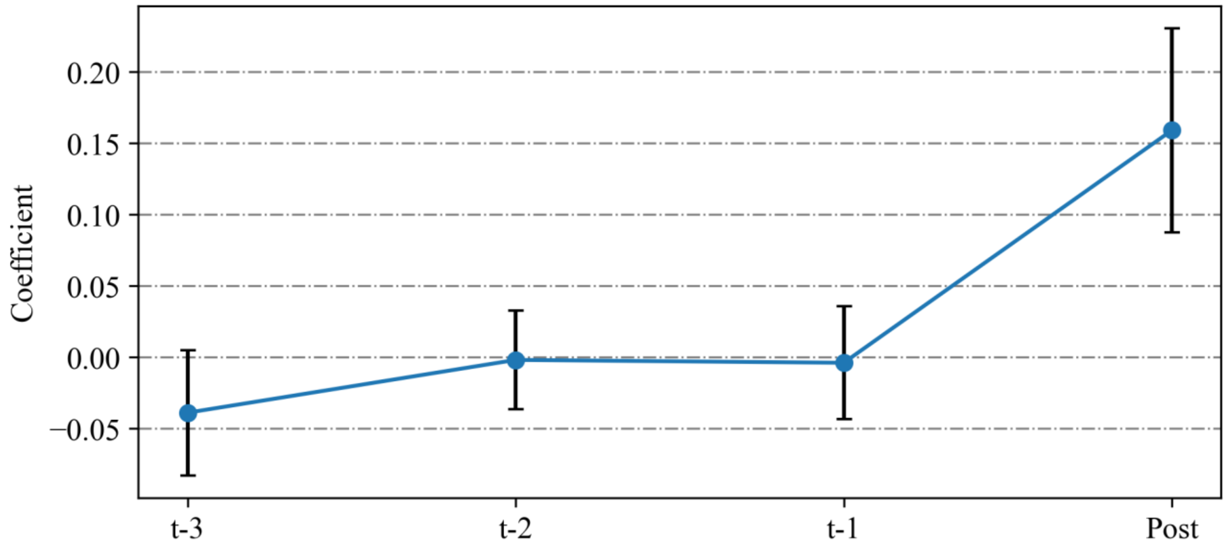


Figure 2: Tax complexity and entrepreneurship, parallel trends

These graphs present the coefficient and 90% confidence intervals for *TAC* from the parallel trends test tabulated in Table 4. Panel A reports coefficients from the MSA-year fixed effects specification, and Panel B reports coefficients from the county-year fixed effects specification. The x-axis refers to the year *t* in which startup activity is measured relative to TAC activity in year *t*=0.

Panel A: MSA-year fixed effects specification



Panel B: County-year fixed effects specification

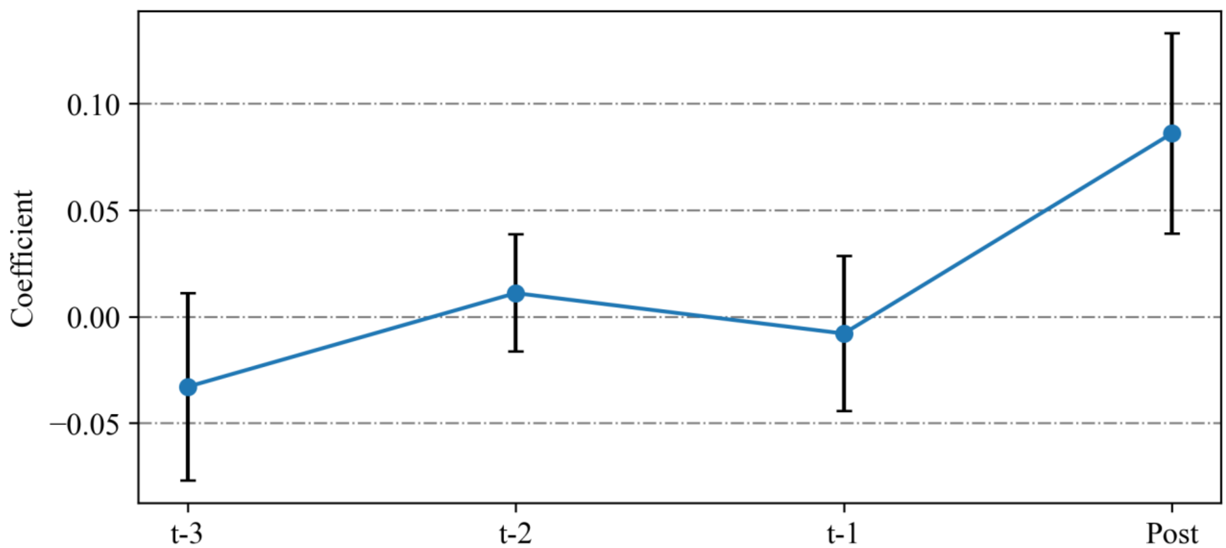


Table 1: Descriptive statistics

Panel A: Untransformed variables

This table presents descriptive statistics for the sample. The main sample begins in 2010 and ends in 2015. Panel A reports statistics for variables prior to transformation and Panel B reports statistics for variables after transformation.

	N	Mean	Std.	P25	P50	P75
Startups	51,636	168	172	55	114	220
Business income	51,636	28,185	24,890	11,193	20,138	36,411
TAC	51,636	0.032	.	.	.	.
TAC nearby	51,636	0.425	0.721	0	0	1
Number of EITC	51,636	2,448	1,995	1,060	1,861	3,180
Number of exemptions	51,636	25,311	13,587	14,680	22,331	32,362
Number of returns	51,636	12,807	6,615	7,540	11,480	16,450
Number of unemployed	51,636	899	677	414	700	1,174
Population	51,636	27,760	14,305	16,415	24,697	35,485
Population 65+	51,636	3,528	1,924	2,081	3,128	4,547
Population Asian	51,636	1,568	2,667	202	596	1,618
Population Black	51,636	3,778	5,866	449	1,435	4,306
Population Native	51,636	161	261	27	76	181
Population Other	51,636	1,569	2,948	152	469	1,488
Population Pacific	51,636	40	106	0	3	26
Population White	51,636	19,519	10,380	11,811	17,514	25,409
Taxable income	51,636	566,973	485,737	239,996	424,816	725,755

Panel B: Transformed variables

	N	Mean	Std.	P25	P50	P75
ihs(*Startups*)	51,636	5.231	1.377	4.701	5.429	6.087
ihs(*Business income*)	51,636	10.602	0.838	10.016	10.603	11.196
ihs(*Number of EITC*)	51,636	8.196	0.796	7.659	8.222	8.758
ihs(*Number of exemptions*)	51,636	10.698	0.519	10.287	10.707	11.078
ihs(*Number of returns*)	51,636	10.023	0.510	9.621	10.042	10.401
ihs(*Number of unemployed*)	51,636	7.231	0.744	6.719	7.244	7.761
ihs(*Population*)	51,636	10.801	0.497	10.399	10.808	11.170
ihs(*Population 65+*)	51,636	8.716	0.550	8.334	8.741	9.115
ihs(*Population Asian*)	51,636	6.969	1.686	6.001	7.083	8.082
ihs(*Population Black*)	51,636	7.872	1.622	6.800	7.962	9.061
ihs(*Population Native*)	51,636	4.713	1.833	3.989	5.024	5.892
ihs(*Population Other*)	51,636	6.771	1.838	5.717	6.844	7.998
ihs(*Population Pacific*)	51,636	2.099	2.251	0.000	1.818	3.952
ihs(*Population White*)	51,636	10.412	0.614	10.070	10.464	10.836
ihs(*Taxable income*)	51,636	13.634	0.795	13.082	13.653	14.188

Table 2: Determinants of TAC operation

This table presents OLS regressions of TAC operation as a function of zip code characteristics. All variables are defined in Appendix A. *t*-statistics appear in parentheses and are based on standard errors clustered by zip code. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two–tail). Sample descriptive statistics are reported in Table 1.

Variable:	*TAC*			
	(1)	(2)	(3)	(4)
ihs(*Number of EITC*)	0.039***	0.016	0.015	0.017
	(5.06)	(1.34)	(1.20)	(1.34)
ihs(*Number of exemptions*)	-0.192***	-0.007	-0.034	-0.032
	(-7.46)	(-0.17)	(-0.85)	(-0.80)
ihs(*Number of returns*)	0.083***	-0.007	0.005	-0.001
	(3.13)	(-0.27)	(0.22)	(-0.04)
ihs(*Number of unemployed*)	-0.008*	0.001	0.007*	0.009*
	(-1.76)	(0.38)	(1.67)	(1.65)
ihs(*Population*)	0.059***	0.002	-0.007	-0.005
	(2.73)	(0.15)	(-0.49)	(-0.38)
ihs(*Population 65+*)	-0.001	0.003	0.002	0.002
	(-0.17)	(0.55)	(0.43)	(0.44)
ihs(*Population Asian*)	0.002	-0.001**	-0.001**	-0.001*
	(1.17)	(-2.06)	(-1.98)	(-1.87)
ihs(*Population Black*)	-0.001	0.000	0.001	0.000
	(-0.85)	(0.41)	(0.76)	(0.31)
ihs(*Population Native*)	0.004***	-0.000	-0.000	-0.000
	(4.08)	(-0.44)	(-0.59)	(-1.00)
ihs(*Population Other*)	-0.002	-0.000	-0.000	-0.000
	(-1.55)	(-0.42)	(-0.38)	(-0.89)
ihs(*Population Pacific*)	0.001*	-0.000	-0.000*	-0.000
	(1.65)	(-1.46)	(-1.69)	(-1.60)
ihs(*Population White*)	0.014***	0.005	0.003	0.003
	(3.18)	(1.14)	(0.80)	(0.77)
ihs(*Taxable income*)	0.023***	0.001	0.001	-0.000
	(2.94)	(0.14)	(0.17)	(-0.06)
Year FE	Yes	Yes	No	No
Zip code FE	No	Yes	Yes	Yes
MSA-year FE	No	No	Yes	No
County-year FE	No	No	No	Yes
Observations	51,636	51,636	51,636	51,636
Adj. R-squared	0.0211	0.922	0.925	0.922

Table 3: Tax complexity and entrepreneurship

This table presents OLS regressions of entrepreneurship as a function of TAC operation. All variables are defined in Appendix A. *t*-statistics appear in parentheses and are based on standard errors clustered by zip code. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two–tail). Sample descriptive statistics are reported in Table 1.

Variable:	ihs(*Startups*)			
	(1)	(2)	(3)	(4)
TAC	0.160***	0.089***	0.159***	0.086***
	(3.73)	(3.14)	(3.69)	(3.02)
ihs(*Number of EITC*)			0.154***	0.183***
			(3.39)	(5.18)
ihs(*Number of exemptions*)			-0.189	-0.220**
			(-1.61)	(-2.34)
ihs(*Number of returns*)			0.346***	0.293***
			(3.35)	(3.33)
ihs(*Number of unemployed*)			-0.079***	0.037*
			(-2.83)	(1.87)
ihs(*Population*)			-0.032	-0.078
			(-0.47)	(-1.57)
ihs(*Population 65+*)			-0.098***	-0.067***
			(-3.65)	(-3.60)
ihs(*Population Asian*)			-0.007*	-0.003
			(-1.77)	(-1.25)
ihs(*Population Black*)			-0.005	0.002
			(-0.81)	(0.54)
ihs(*Population Native*)			0.000	-0.001
			(0.28)	(-0.74)
ihs(*Population Other*)			0.009***	0.005**
			(3.38)	(2.33)
ihs(*Population Pacific*)			-0.001	-0.001*
			(-0.91)	(-1.67)
ihs(*Population White*)			0.078**	0.094***
			(2.45)	(3.81)
ihs(*Taxable income*)			-0.100***	-0.051**
			(-3.58)	(-2.36)
Zip code FE	Yes	Yes	Yes	Yes
MSA-year FE	Yes	No	Yes	No
County-year FE	No	Yes	No	Yes
Observations	51,636	51,636	51,636	51,636
Adj. R-squared	0.958	0.979	0.959	0.979

Table 4: Tax complexity and entrepreneurship, parallel trends

This table presents OLS regressions of entrepreneurship as a function of TAC operation over time. All variables are defined in Appendix A. *t*-statistics appear in parentheses and are based on standard errors clustered by zip code. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two–tail). Sample descriptive statistics are reported in Table 1. We do not report coefficients on control variables for parsimony. Panel A reports results including MSA-year fixed effects and Panel B reports results including county-year fixed effects.

Panel A: MSA-year fixed effects specification

Variable:	ihs($Startups_{t-3}$)	ihs($Startups_{t-2}$)	ihs($Startups_{t-1}$)	ihs(*Startups*)
	(1)	(2)	(3)	(4)
TAC	-0.039	-0.002	-0.004	0.159***
	(-1.46)	(-0.09)	(-0.18)	(3.69)
Controls	Yes	Yes	Yes	Yes
Zip code FE	Yes	Yes	Yes	Yes
MSA-year FE	Yes	Yes	Yes	Yes
Observations	25,818	34,424	43,030	51,636
Adj. R-squared	0.977	0.978	0.978	0.959

Panel B: county-year fixed effects specification

Variable:	ihs($Startups_{t-3}$)	ihs($Startups_{t-2}$)	ihs($Startups_{t-1}$)	ihs(*Startups*)
	(1)	(2)	(3)	(4)
TAC	-0.033	0.011	-0.008	0.086***
	(-1.22)	(0.65)	(-0.34)	(3.02)
Controls	Yes	Yes	Yes	Yes
Zip code FE	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
Observations	25,818	34,424	43,030	51,636
Adj. R-squared	0.977	0.978	0.978	0.979

Table 5: Tax complexity and entrepreneurship, spillover analysis

This table presents OLS regressions of entrepreneurship as a function of TAC operation in the same zip code, and TAC operation in zip codes within 10 miles. All variables are defined in Appendix A. *t*-statistics appear in parentheses and are based on standard errors clustered by zip code. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two–tail). Sample descriptive statistics are reported in Table 1. We do not report coefficients on control variables for parsimony.

Variable:	ihs(*Startups*)
	(1)
TAC	0.178***
	(4.07)
TAC nearby	0.037***
	(4.39)
Controls	Yes
Zip code FE	Yes
MSA-year FE	Yes
Observations	51,636
Adj. R-squared	0.959

Table 6: Tax complexity and entrepreneurship, stacked differences-in-differences

This table presents stacked regressions of entrepreneurship as a function of TAC operation in the same zip code. All variables are defined in Appendix A. *t*-statistics appear in parentheses and are based on standard errors clustered by zip code. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two–tail). Sample descriptive statistics are reported in Table 1. We do not report coefficients on control variables for parsimony.

Variable:	ihs(*Startups*)	
	(1)	(2)
TAC	0.199***	0.101***
	(3.57)	(2.78)
Controls	Yes	Yes
Zip code-cohort FE	Yes	Yes
MSA-year-cohort FE	Yes	No
County-year-cohort FE	No	Yes
Observations	249,250	249,250
Adj. R-squared	0.958	0.979

Table 7: Tax complexity and entrepreneurship, shifted natural logarithm transformation

This table presents OLS regressions of entrepreneurship as a function of TAC operation using the shifted natural logarithm transformation of the dependent and control variables instead of the inverse hyperbolic sine transformation. All variables are defined in Appendix A. *t*-statistics appear in parentheses and are based on standard errors clustered by zip code. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two–tail). Sample descriptive statistics are reported in Table 1. We do not report coefficients on control variables for parsimony.

Variable:	ln(1 + *Startups*)	
	(1)	(2)
TAC	0.146***	0.080***
	(3.69)	(2.94)
Logged controls	Yes	Yes
Zip code FE	Yes	Yes
MSA-year FE	Yes	No
County-year FE	No	Yes
Observations	51,636	51,636
Adj. R-squared	0.962	0.980

Table 8: Tax complexity and entrepreneurship, excluding proximate treatments

This table presents OLS regressions of entrepreneurship as a function of TAC operation in the same zip code, after dropping zip codes in which a TAC opened or closed that are within 10 miles of another zip code in which a TAC opened or closed. All variables are defined in Appendix A. *t*-statistics appear in parentheses and are based on standard errors clustered by zip code. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two–tail). Sample descriptive statistics are reported in Table 1. We do not report coefficients on control variables for parsimony.

Variable:	ihs(*Startups*)	
	(1)	(2)
TAC	0.203***	0.114***
	(3.68)	(3.11)
Controls	Yes	Yes
Zip code FE	Yes	Yes
MSA-year FE	Yes	No
County-year FE	No	Yes
Observations	51,510	51,510
Adj. R-squared	0.959	0.979

Table 9: Tax complexity and business income

This table presents OLS regressions of business income as a function of TAC operation in the same zip code. All variables are defined in Appendix A. *t*-statistics appear in parentheses and are based on standard errors clustered by zip code. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two–tail). Sample descriptive statistics are reported in Table 1. We do not report coefficients on control variables for parsimony.

Variable:	ihs(*Business income*)	
	(1)	(2)
TAC	0.073**	0.073**
	(2.57)	(2.55)
Controls	Yes	Yes
Zip code FE	Yes	Yes
MSA-year FE	Yes	No
County-year FE	No	Yes
Observations	51,510	51,510
Adj. R-squared	0.987	0.987