The Labor Effects of R&D Tax Incentives: Evidence from VC-Backed Startups*

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Abstract

We examine whether VC-backed startups respond to R&D tax incentives by attempting to scale R&D activities through employment. We exploit a provision of the PATH Act of 2015, which allows qualified small businesses to offset payroll taxes with R&D tax credits, and show that marginally eligible startups increase their demand for R&D workers more than marginally ineligible startups after the PATH Act's enactment in 2015. Marginally eligible startups not only ramp up recruiting of workers of higher quality, but also subsequently file more patents with new inventors. Our findings reveal that tax incentives can stimulate startup R&D activities through skilled labor recruitment.

Keywords: Venture capital-backed startups, entrepreneurship, R&D tax incentives, payroll tax credit, skilled labor.

1. Introduction

Research and development (R&D) tax incentives, which have been widely adopted around the world, are an important policy tool for stimulating business R&D investments (Bloom, Griffith, and Van Reenen, 2002; Wilson, 2009; Bloom, Van Reenen, and Williams, 2019).[1] Out of approximately $280 billion in U.S. business R&D expenditures in 2014 (National Science Board, 2018), $12 billion are reimbursed by U.S. taxpayers through R&D tax credits.[2] Yet, large firms tend to claim the lion's share of these tax credits, suggesting this advantage has not been widely accessible to all firms.[3] In fact, while young, unprofitable venture-capital-backed startups play a critical role in driving innovation and economic growth in the U.S. (Kortum and Lerner, 2000; Decker et al., 2014; Gornall and Strebulaev, 2015), historically they have not been able to effectively take advantage of these federal tax credits since these startups do not have income tax liabilities to offset.[4] As a result, the channels through which R&D investments can manifest in startups from tax incentives remain underexplored. To address this gap in our understanding, this paper studies the extension of R&D tax credits to unprofitable startups from the enactment of the Protecting Americans from Tax Hikes (PATH) Act of 2015 and its ability to facilitate the *skilled labor* investments necessary for scaling up R&D activities within startups.

R&D tax incentives primarily serve to address market failures that can lead to underinvestment (e.g., knowledge spillovers, costly external financing, etc.). Deficiencies in

[1] As of 2020, 33 of the 37 OECD countries and 21 of the 27 EU countries offer tax relief for R&D expenditure. Specifically, in the OECD area, there has been an increase of more than 50% in the number of countries that provide R&D tax relief since 2000, and an increase ranging from 36% in 2006 to around 56% in 2018 in the share of tax relief in total government support (OECD, 2020).

[2] Latest Internal Revenue Service (IRS) statistics on aggregate R&D tax credit claims can be found here: https://www.irs.gov/statistics/soi-tax-stats-corporation-research-credit.

[3] For example, in 2014, 36% of total U.S. R&D spending was done by companies with over 25,000 employees (National Science Board, 2018).

[4] Using Pitchbook data, we find that fewer than 4% of VC-backed startups are profitable when they are 4 years old at their second round of VC financing.

skilled labor investments—the finding, hiring, and retaining of talented workers—can significantly curtail innovation particularly for startups (Chen, Hshieh, and Zhang, 2021; Coff and Kryscynski, 2011). Although several studies show that tax incentives increase firm R&D expenditure (e.g., Agrawal et al., 2020; Guceri and Liu, 2015; Rao, 2016; and Dechezlepretre et al., 2016), the scale of *real* R&D activities may remain unchanged. For example, the reported increase could be the result of firms "relabeling" ordinary spending as R&D expenditures (Chen et al., 2021). Additionally, R&D tax credits may merely be allocated to increasing wages of existing scientists and engineers (e.g., due to their inelastic supply) rather than funding employment of a larger number of researchers to scale up R&D activities (Goolsbee, 1998; Rogers, 2010; Brown and Howell, 2020). Finally, R&D projects pursued by VC-backed startups may have significant fixed costs which R&D tax credits may not sufficiently offset. Under such circumstances, R&D tax incentives may stimulate outsourcing rather than the scaling up of startups' own R&D workforces. To overcome these issues, our study directly tests whether access to R&D tax credits encourages startups to engage in labor market searches for talent, which we measure using a novel dataset of the near-universe of online job postings for full-time positions. Engagement in skilled labor searches would indicate a startup's desire to scale R&D through a larger and perhaps more skilled workforce.

To assess how unprofitable startups respond to R&D tax incentives, we estimate the impact of a provision in the PATH Act of 2015 which allows qualifying startups to apply R&D tax credits to the Social Security portion of the employer's payroll taxes starting in 2016. For a given tax year, startups that have 1) under $5 million in current revenue and 2) less than five years in revenue history can apply up to $250,000 in R&D tax credits to offset payroll taxes. To quantify the provision's impact on recruiting activities, we compare barely eligible (i.e., 2016 is the only eligible tax year) to nearly eligible startups. This comparison is based on the arbitrary qualifying criterion that startups have less than five years in revenue history at the time of the PATH Act's enactment, which we proxy with firm age. Specifically, our baseline results are derived from comparing 5-year-old (treated) to 6-year-old (control) startups in 2016 using a difference-in-differences (DD) framework. Anecdotal evidence suggests that the PATH Act was visible to many firms once it went into effect. For example, Holtzman (2017) reports that CEOs, CFOs, and tax directors at companies of various sizes and from different industries were fully aware of the 2015 PATH Act changes.[5]

Because revenue information of private firms cannot be observed without access to their tax filings, we can only exploit firm age as a forcing variable to assign payroll tax credit eligibility. Unlike firm age, which cannot be manipulated, current revenue could be a source of selection bias depending on whether it is close enough to the $5 million cutoff to matter in 2016. However, survey data show that startups between the age of 5 and 6 years rarely have revenue close to the $5 million threshold: sales information of new businesses in the high-tech sector surveyed in Robb et al. (2009) suggests that young startups (no older than 5 years) would always theoretically qualify for payroll tax credits, whereas startups that are at least 6 years old would only qualify 25% of the time. These survey findings thus indicate that a startup age of less than 6 years can be a reasonable proxy for payroll tax credit eligibility in 2016, and our estimates, therefore, would likely be conservative or downward biased (Angrist and Pischke, 2008).

To measure startup investments in the skilled labor search and recruitment of R&D workers, we use a combination of two datasets: the Burning Glass Technologies (BGT) job postings data

[5] Specific to VC-backed startups, the lobbying arm of the venture capital industry, the NVCA, has made significant efforts to ensure the PATH Act works for VC-backed startups and to make it visible to startups once it became effective (NVCA, 2020).

and inventor data extracted from patent filings. BGT provides details on all job postings by VC-backed startups. Over our sample period of 2010-2017, 8,397 VC-backed startups have posted close to 2 million jobs in more than 800 occupations. We use the detailed occupation information contained in each job posting to identify open R&D-related positions. To determine whether a skilled labor search translates to hiring, we construct measures of inventor recruitment from patent data. Specifically, we focus on the addition of new inventors that appear on patent filings.

Within the 4-year window around the passage of the PATH Act, we find that startups likely qualifying for payroll tax credits, on average, increase their demand for labor in terms of quantity and quality (e.g., skill and education) in the quarters following the enactment of the PATH Act. In terms of the overall labor market search, we estimate that treated startups are 4.2% more likely to submit job postings and they submit 21% more job postings compared to control startups. When we restrict to job postings requiring R&D skills as identified by the O*NET program, the economic magnitudes are even larger. Specifically, we find that treated startups submit 33% more job postings in R&D occupations and 35% more job postings in STEM occupations compared to control startups. Measuring the quality of labor demanded based on the required education level and length of work experience stated on job postings, we find that treated startups also demand more employees with higher education (i.e., at least a master's or bachelor's degree) and longer work experience after the enactment of the PATH Act.

To supplement our findings that VC-backed startups expand their search for R&D workers in response to the newly available R&D tax incentives, we examine the changes in the number and composition of inventors from patent filings. On average, we find that treated startups are 1.2% more likely to include new inventors in their patent filings and have 19% more new inventors in their patent filings after the PATH Act went into effect. These results suggest that startups' increasing demand for R&D workers in response to the passing of the PATH Act led to the recruitment of new R&D workers, particularly those capable of creating intellectual property.

Do higher quality and quantity skilled labor investments translate to higher quantity and quality innovation output? We measure the quantity and quality of a startup's innovation output from the quantity and quality of its filed patents. We find that, after the enactment of the PATH Act, treated startups file more patents overall, more patents that are eventually granted, and more patents that have a higher number of claims and citations. These results suggest that the R&D incentives indeed facilitate the scaling up of real R&D activity through skilled labor investments.

Our results are robust to the augmentation of our baseline DD model to a difference-in-difference-in-differences (DDD) model as well as to alternative ways of identifying job postings that target high-skilled workers. Our baseline DD model may not account for factors unrelated to payroll tax credit eligibility that differentially affect labor market search behavior by startup age or the stage of a startup's life cycle (Puri and Zarutskie, 2012). The DDD model addresses this issue by extending our baseline DD model with the addition of a second control group: startups at the same life cycle stage as the treated and control startups in our main setting but from a previous period of time. Specifically, we consider 2012 as an additional reference year so that we can include startups of age 5 and 6 in 2012 (i.e., founded in 2007 and 2008, respectively) into our main sample and analyze the evolution of skilled labor investments relative to reference years across our main sample and new control sample. By construction, these startups are not affected by payroll tax credits before and after 2012 and do not overlap with the startups in our main sample. Therefore, the DDD model allows us to additionally adjust for confounding trends in skilled labor investments that differ by age. Estimating the DDD model produces results similar to the estimated baseline DD model.

We also test whether our results are robust to using additional occupation classifications from the American Community Survey (ACS) Occupation Codes (OCC) to redefine our dependent variables that measure firms' skilled labor searches. We find that startups that are more likely to be eligible for payroll tax credits increase their number of job postings seeking engineers and job postings for positions in technical industry sectors (e.g., automation, software and electronics, finance, supply chain and logistics, etc.).

Finally, to understand the economic mechanism underlying our results, we conduct a set of cross-sectional tests to corroborate whether skilled labor investments are responding to R&D tax incentives due to financial constraints. Small, high growth firms such as VC-backed startups that depend on technological innovation tend to be extremely risky, as their R&D efforts may not lead to viable products. The valuation of this risk, which requires an accurate understanding of the startup's R&D, may vary between managers and investors due to their access to different information sets. Given this adverse selection cost, Myers (1977) and Meyers and Majluf (1984) predict that R&D subsidies, such as payroll tax credits, could increase levels of startup investments. We measure the severity of a startup's adverse selection cost by whether it operates in industries that raise more venture capital (i.e., more technologically driven) and whether it is located in states that pay higher R&D wages (i.e., more technically trained labor). We find that the effects of payroll tax credits are stronger in startups operating in industries that are more capital intensive and in startups located in areas with higher R&D labor costs. We therefore conclude that financial constraints are likely a key mechanism through which R&D tax incentives promote skilled labor investments.

In summary, we find that R&D tax incentives have a significant impact on VC-backed startups' investments in skilled labor searches, recruitment of R&D workers, and the quantity and quality of their innovation output. Our study provides direct evidence that R&D tax incentives are effective in scaling up *real* R&D activities within startups through building up their skilled workforce. Particularly, we document the increased quantity and quality of workers demanded in terms of education level, length of work experience, and whether the new positions advertised are classified as R&D-, STEM-, engineering-, or technical-sector-related after the enactment of the PATH Act. These recruiting efforts translate to the hiring of new inventors and the filing of new patents.

Our findings contribute to the literature on R&D tax incentives in two fundamental ways. First, unlike past studies that are primarily concerned with estimating the cost elasticity of R&D spending (e.g., Altshuler, 1988; Eisner et al., 1984; Mansfield, 1984, Hall and Van Reenen, 2000; Rao, 2016; and Dechezlepretre et al., 2016; Finley et al., 2015; and Agrawal, Rosell, and Simcoe, 2020), we focus on the sensitivity of skilled labor searches to gaining access to R&D tax credits for unprofitable VC-backed startups—those with perhaps the most to gain from payroll tax credits. This approach directly quantifies efforts in scaling up the R&D workforce in startups. Additionally, our novel use of job postings enables us to decompose overall labor demand into various categories based on skill, education, and work experience. Our study, therefore, is the first to provide insight into how the demand for labor quality changes in response to R&D tax incentives. Second, by identifying new inventors that appear in patent filings, our study also allows us to determine whether R&D tax incentives for startups go solely toward paying higher R&D wages (crowding out) or hiring additional employees (real effects).[6]

We also contribute to the VC literature by highlighting the importance of labor costs in inhibiting the speed at which startups can potentially grow. The traditional VC literature has shown

[6] To our knowledge, the only papers to examine innovation-related outcome variables other than R&D spending are Czarnitzki et al. (2011) and Dechezleprêtre et al. (2016).

that a few market frictions including information asymmetry and agency problems matter for startup financing and innovation; VCs are able to mitigate these frictions using a set of investment tools such as ex-ante screening and stage financing (e.g., Lerner, 1995; Gompers, 1995; Hellmann, 1998). However, Kortum and Lerner (2000) show that the additional investments from pension funds that were freed to invest in venture capital spurred more innovation, which suggests that despite being monitored and carefully vetted by VC, startups may still face an underinvestment problem. Our study complements this literature by estimating a positive relationship between skilled labor demand and federal tax subsidies and showing that this relationship is amplified when VC-backed startups are likely financially constrained. In other words, we provide suggestive evidence that the VC market may be underestimating the real cost of building up a startup's workforce.

Lastly, while other quasi-natural empirical studies examine non-U.S. settings, our findings have direct U.S. tax policy implications over the design of R&D tax credits. Specifically, we show that firms with likely zero-tax liability (such as VC-backed startups) do respond to R&D tax incentives through investments in skilled labor search, hiring of inventors, and filing of patents. Therefore, tax policy can be an effective means to support the growth and development of highly innovative small firms in the form of wage subsidies, allowing these firms to better compete for skilled workers against larger companies.[7]

2. Institutional Background and Data

[7] For example, Bernstein, Townsend and Xu (2021) show that during the economic downturn of Covid-19, high-quality job applicants shifted their searches toward more established firms and away for early-stage startups. In addition, the Wall Street Journal in 2011 documented how tech titans such as Google, Facebook, and Twitter draw from the engineering talent pool in the Bay Area and compete with startups trying to hire: https://www.wsj.com/articles/SB130650430883419575.

2.1. The Path Act of 2015

On December 18, 2015, the "Protecting Americans from Tax Hikes" (PATH) Act was signed into law by President Obama. The PATH Act made several changes to R&D tax credits.[8] One provision that is important for startups and relevant for our study is Section 121 (c) "Treatment of research credit for certain startup companies" (new Section 41 (h) of IRS code). For the first time, this provision allows startups—officially labeled as qualified small businesses (QSBs)—to use R&D credit to offset the employers' payroll taxes up to $250,000 in a given tax year up to the maximum of five tax years.[9] To qualify for using the R&D tax credit to offset payroll taxes (or simply "payroll tax credits"), a startup must have gross receipts for the tax year of less than $5 million and not have gross receipts for any tax year preceding the five-taxable-year period ending with the credit year. For example, a startup claiming the R&D tax credit for the 2016 tax year must have had less than $5 million in gross receipts in 2016 and cannot have had gross receipts in 2011 or prior.

The amount of R&D tax credits a startup can claim is calculated based on so-called qualified research expenditures (QRE) that include in-house research expenses, such as *wages* and the cost of supplies incurred in the conduct of qualified research, and contract research expenses.[10] There are generally two approaches in the current tax system to compute the specific amount of

[8] The PATH Act also made permanent the previously temporary R&D credits. In addition, the PATH Act allows small businesses with an average of $50M or less in revenue over the last four years to use their R&D credit to offset Alternative Minimum Tax (AMT). This AMT provision applies to both treated and control startups in our sample since young VC-backed startups typically generate revenue lower than $50M, which we confirm with the Kauffman survey data and Pitchbook data.

[9] Based on the Kauffman Firm Survey, our estimation in Figure A1 suggests that the $250,000 cap is far from binding. For example, a startup of 5 years old in the high-tech sectors on average only has about $6,000 R&D tax credits while the amount of payroll tax they can offset is around $15,000. To offset the maximum $250,000 in payroll taxes each year under the new law, a company would need to have more than $4 million in annual payroll (e.g., 50 employees with an average salary of $95,000) and $2.5 million in eligible R&D costs. See relevant estimations at: https://www.bdo.com/insights/tax/r-d-tax/r-d-tax-credit-faqs-for-large-and-small-businesses.

[10] Qualified research is defined as research undertaken for the purpose of discovering information that is technological in nature and that is intended to be useful in the development of a new or improved business component.

R&D credit: the regular approach that requires research expense and gross receipts information from the 1980s period, and the alternative simplified credit (ASC) approach. However, there are also special provisions for startups to calculate R&D credits. The computation of R&D credits for startups is relatively complex, and there is large heterogeneity in the amount of R&D credits a startup can claim depending on the patterns of QRE and sales growth. As estimated by Hall (2020), for a typical R&D-intensive startup with high QRE intensity in the first three years and steady sales growth, the average credit is about 12% of QRE in the first 6 years and then declines to 2% by year 11 since founding.

The PATH Act directly benefits VC-backed startups. Prior to the Act, startups could only use R&D tax credits to offset regular tax liability such as income or capital gains.[11] Because VC-backed startups are typically unprofitable and have no regular tax liability (see Footnote 4), they have been generally unable to realize the benefits of the R&D tax credits in the past. Despite this, many highly innovative VC-backed startups incur substantial R&D expenditures, with worker wages accounting for as much as 70% of total qualified R&D expenditures (Hall, 2020). Under the PATH Act, qualified VC-backed startups can offset their payroll taxes with their R&D tax credits. These immediate tax deductions of their R&D expenses improve their incentives to scale up their R&D.[12]

2.2 Data Sources

[11] The US R&D tax credit dates back to 1981, when it first became available on a temporary basis. Firms regardless of age can claim the credits based on their R&D spending to offset their regular tax liability, and unused R&D tax credits can be carried forward.

[12] Similar to other tax policy changes (Zwick and Mahon, 2017), the PATH Act essentially alters the timing of deductions for VC-backed startups but not their amount, and the R&D incentive works because future deductions are worth less than current deductions. This is particularly important for startups because the failure rate of startups is high, and startups face a higher level of financing constraints at an earlier age.

We retrieve a sample of VC-backed startups incorporated in the U.S. from the VentureXpert database in SDC Platinum. Our empirical analysis compares different cohorts of startups that each have a different propensity to satisfy the conditions of the PATH Act but are otherwise similar (see Panel A of Table 1). The main analysis focuses on the sample of startups that are founded in 2011 (control group) and 2012 (treatment group). The precise founding date of startups in the VentureXpert database are not accurately reported. Therefore, we are not able to define cohorts using a narrower window. Focusing on startups that are founded only one year apart provides a set of the most comparable startups in our setting. To ensure that startups have R&D expenditures when the treatment starts in 2016, our sample includes only startups that have raised their first round of VC financing within 4 years of founding. The main sample includes 882 startups founded in 2011 and 803 startups founded 2012. As a robustness check, we also expand our treatment and control groups to include startups founded in 2013 (younger startups with more eligible tax years) and in 2010 (older startups that are even less likely to be eligible for payroll tax credits), respectively.

We measure a VC-backed startup's desire to scale their R&D workforce through its job postings. We take advantage of a novel database by Burning Glass Technologies (BGT) which covers the near universe of job postings in the U.S. since 2010. Over the 2010-2017 period, 8,397 VC-backed startups have posted close to 2 million jobs in more than 800 occupations. Since job postings provide detailed occupation level information, we can identify a startup's demand for R&D related labor. Additionally, job postings provide a measure of demand for labor quality based on the required skills or education stated in each job posting.

We observe startups' new inventors and innovation output through USPTO patent data, which we retrieve from PatentsView, a database created through a program funded by the U.S.

Patent and Trademark Office (Marco et al., 2016). We focus on a set of innovation outcomes that include inventor contribution, patent quantity (i.e., frequency of filings), and patent quality (i.e., forward citation and claims count).

We match VC-backed startup companies in VentureXpert with companies in the two other databases using a fuzzy string-matching algorithm based on company name. We standardize company names, ensuring that legal entity type identifiers (e.g., “LLC”, “Inc”, etc.) are formatted consistently across databases. To further ensure the integrity of the name matches, we manually inspect the final set of matched company names.

We construct a company-quarter panel using the merged dataset. For our main sample, we keep company-quarters over the years between 2014 and 2017, a 4-year window around the passage of the PATH Act.

3. Estimation Strategies

3.1. Treatment assignment based on firm age

Our goal is to create a variable that approximates the relative exposure of a VC-backed startup to payroll tax credit eligibility from the enactment of the PATH Act in 2015. Specifically, we rely on the differences in firm age for a set of startups that are founded in a narrow window prior to 2016. In 2016, startups not older than 5 years will likely qualify for payroll tax credits since they are unlikely to have receipts greater than $5 million in 2016 and are guaranteed to not have gross receipts in any tax year preceding the five-taxable-year period ending in 2016. Conversely, startups at least 6 years old in 2016 are more likely to have receipts greater than $5 million in 2016, and to have 5 or more years of revenue history, precluding them from taking advantage of payroll tax credits from the PATH Act. This critical observation motivates the design of our treatment assignment. That is, falling on the younger side of the startup age cutoff yields a discontinuity in the propensity to qualify for payroll tax credits, and therefore, we assign the set of startups founded in 2012 (the young cohort) and 2011 (the old cohort) into the treatment and control group, respectively. We then compare changes in startups' skilled labor investments around the passage of the PATH Act. In Figure 1, we provide an illustration of the treatment assignment.

Our treatment assignment design is also supported by the small business survey conducted by the Kauffman Foundation. The Kauffman Firm Survey (KFS) is a panel study of around 5,000 businesses founded in 2004 which tracks their operations for 7 years. KFS offers a glimpse of what a startup's sales history could look like. If the PATH Act was hypothetically enacted in 2008, all 326 high-tech startups among the random sample of startups surveyed would qualify for payroll tax credits at 5 years old, while only about 25% of these startups would qualify once they turn 6 years old (Figure 2).[13]

Since these two cohorts of startups are founded only one year apart in our baseline sample, by design, the treated and control startups should be very similar in both observable and unobservable dimensions. To validate this similarity, we compare the characteristics of treated and control startups at the fourth quarter of 2015. The results in Table 1 Panel A show that the two sets of startups are comparable in all outcome variables including labor search and inventors as well as headquarter state and industry sector. As expected, the treated startups raised slightly fewer rounds of VC financing given their slightly younger age. On the other hand, the two sets of startups raise

[13] Biotech startups can generate zero revenue for long periods of time before their drug receives U.S. Food and Drug Administration approval. As a robustness check, we exclude biotech startups from our sample in Table A3 and find similar results.

almost the same amount of venture capital. On balance, treated and control startups in our main sample have largely comparable characteristics before the enactment of the PATH Act.

3.2. Empirical design

We exploit the heterogeneity in exposure to the PATH Act to identify the impact of the newly available R&D tax incentives on VC-backed startups' labor investments. Our estimation strategy is a standard difference-in-differences (DD) regression at the startup-quarter level using the following model:[14]

$$y_{it} = \beta(Treated_i \times Post_t) + \gamma X_{it} + Industry_j \times \tau_t + \alpha_i + \varepsilon_{it}. \quad (1)$$

The left-hand-side is the startup outcome variable of interest. $Treated_i$ is a dummy variable equal to one if the startup is in the young cohort (founded in 2012 in the baseline sample), and zero otherwise. $Post_t$ is a dummy variable equal to one if quarter t is greater than or equal to the first quarter of 2016, and zero otherwise. We control for time-varying startup characteristics, X_{it}, which include the cumulative venture capital raised, cumulative patents granted, industry-quarter interacted fixed effects, and startup fixed effects. These controls help ensure that our estimates are based on a comparison of similar treated and control startups. Following Petersen (2009), we cluster standard errors by company.

As with any DD estimation strategy, our key identifying assumption is parallel trends—startups that are less likely to benefit from the PATH Act provide an appropriate counterfactual for what would have happened to startups that are more likely to benefit from the Act. While the parallel trends assumption cannot be tested, we show that it is not empirically violated in several ways. First, in Figure 3, we show that the number of overall job postings by startups in the young

[14] We focus on the quarter level analysis as firms can claim the payroll tax credits by quarter.

cohort evolves quite similarly to those in the older cohort over a long period of time prior to the passage of the PATH Act (2012-2015). Only after passage does the trend start to diverge between the two groups of startups. Second, in our main analysis, we also show in dynamic specification that there is no evidence of pre-trends; the timing of the increase in job postings and appearance of new inventors via patent filings is consistent with the passage of the PATH Act, providing further support for the parallel trends assumption.

Our identification is also predicated on a second key assumption that no other systematic change in 2016 impacts skilled labor investments across startups in precisely the same way as we have identified through startup age—i.e., in a manner consistent with our findings but through some other channel. We attempt to control for such confounding factors through industry-quarter interacted fixed effects.

Caution should be exercised when interpreting our coefficient estimates, however. While firm age is plausibly exogenous in 2016 as startups cannot adjust their founding year to gain payroll tax credits eligibility, it is ultimately only an imprecise measure of whether a startup meets the condition of the PATH Act (i.e., a QSB). As noted in Angrist and Pischke (2008), in the case of a binary independent variable with measurement error, coefficient estimates will be biased towards zero. Therefore, our estimates likely only provide a lower bound for the true treatment effect.

4. Results on the Quantity of Labor Investments

We first document that the passage of the PATH Act increases VC-backed startups' investments in skilled labor searches, suggesting that VC-backed startups are responsive to new R&D tax incentive in attempting to scale up their real R&D activity. We show these results with labor outcome variables measured by both job posting and new inventor frequencies.

4.1. Impact on labor demand

First, we visually examine the changes in overall labor demand. We provide descriptive evidence of the impact of the PATH Act on startups' overall labor demand by tracking the changes in their quarterly number of job postings relative to that of the fourth quarter of 2015, the last quarter before the PATH Act went into effect. In Figure 3, we observe a much larger jump in the number of job postings for treated startups compared to control startups only after the policy change; prior to the policy change, job postings by treated and control startups evolve similarly. This finding suggests treated startups are responding more than control startups to access to new R&D tax credits.

We quantify this effect by estimating Eq. (1) using company-quarter observations over the 2014-2017 period.[15] Table 2 reports the estimation results in which the dependent variables are a dummy variable indicating whether a startup has positive labor demand in a given quarter in column (1) and the natural logarithm of one plus the number of a startup's job postings in a given quarter in columns (2) through (5). The results in the first two columns of Table 2 suggest that there is a significant increase in overall job postings by the treated startups after the passage of the PATH Act in comparison to the control startups. The effects are economically substantial. Compared to control startups, treated startups are 4.2 percentage points more likely to post a job advertisement, and they submit 21% more job postings after 2016.[16] In column (3), we additionally control for certain time-varying characteristics of startups, including their cumulative rounds of

[15] Compared to control startups, treated startups mechanically have a higher likelihood of qualifying for payroll tax credits in 2017 as well (see Figure 2). Therefore, we include observations two years after the enactment of the PATH Act to capture effects from this additional differential in R&D tax incentives. There may also be a delay in treatment effects as startups adjust to the new tax policy.

[16] Consider this regression: $(1+Y)=a+bX+u$. For each unit of change in X, the change in Y, ΔY, is approximately $(1+Y+\Delta Y)/(1+Y)=\exp(b)$. Solving the equation yields $\Delta Y/Y=[\exp(b)-1](1+1/Y)$. For each unit change in X, Y changes by $100*[\exp(b)-1](1+1/Y)$ percent. In our case, $21\% = 1*100*[\exp(0.085)-1](1+1/0.714))$, where 0.085 is the estimated coefficient in column (2), and 0.714 is the average number of job postings in the sample (Table 1 Panel B).

financing raised and their cumulative number of patents granted. The result remains similar. In column (4), we examine a narrower event window that ranges from 2015 to 2016 and again find similar results. The result in this column also suggests that the timing of the changes in startups' labor demand is consistent with the passage of the PATH Act. In column (5), we conduct our analysis on a larger sample of startups that are founded between 2010 and 2013 (four cohorts of startups instead of two in our main sample), and also find similar results. Taken together, the results in Table 2 suggest that startups with access to new R&D tax credits attempt to expand their overall labor force following the enactment of the PATH Act.

To understand the kind of workforce startups are building up, we further classify job postings using detailed occupation-level information. In particular, based on the job classifications developed by the Occupational Information Network (O*NET) program in combination with the existing literature (Liu, 2019),[17] we use four categories to capture the jobs that are closely related to startups' R&D process: (1) occupations that require education in disciplines of "Research, Development, Design, and Practitioners" ("R&D" hereafter);[18] (2) occupations that require education in science, technology, engineering, and mathematics disciplines ("STEM" hereafter); (3) occupations that require considerable or extensive preparation (Job Zone four and five under O*NET classification);[19] and (4) occupations that require either at least a bachelor's degree or a minimum of five years of work experience. For each of these four categories, we examine how the passage of the PATH Act impacts the number of job postings in the targeted category in comparison to the remaining job postings.

[17] The O*NET program provides a crosswalk between the O*NET code and each job category, and we use this crosswalk to link the job posting data to each category. See more details at: https://www.onetonline.org/find/.
[18] Note that this is defined at the occupation level based on O*NET code. It is different from the definition of R&D used in IRS' R&D tax credit, which is based on the type of work conducted.
[19] According to O*NET, there are five job zones, which are defined based on the levels of education, experience, and training necessary to perform the occupation.

Table 3 reports the estimation results. Column (1) shows that treated startups demand more R&D related labor than control startups after the enactment of the PATH Act. Column (2) shows that treated startups also demand more non-R&D-related labor, suggesting possible spillover effects on demand for non-R&D-related jobs that may complement R&D-related occupations. Although the coefficients in columns (1) and (2) are both statistically significant, the economic magnitude is much larger for R&D related labor demand: compared to control startups, treated startups post 33% more R&D-related job ads versus 22% more non-R&D-related job ads. Using additional job classifications, we find similar results in the remaining columns of Table 3. Specifically, in columns (3) and (4), we find that access to payroll tax credits leads to more labor demand in STEM fields in comparison to other types of labor demand (35% vs. 21%). The results in columns (5) and (6) suggest that access to payroll tax credits leads to more demand for jobs requiring high preparation in comparison to demand for jobs requiring low preparation (26% vs. 21%). Lastly, the results in columns (7) and (8) suggest that access to payroll tax credits leads to more demand for jobs requiring high skill in comparison to other types of labor demand (23% vs. 18%). Overall, the findings in Table 3 show that the policy change for R&D tax incentives had a direct impact on VC-backed startups and induced them to increase their demand for R&D related talent.

In sum, by measuring skilled labor investments with job postings for R&D related positions, we find that access to payroll tax credits has a large and direct impact on VC-backed startups' efforts to scale their R&D workforce.

4.2. Impact on inventors

Posting job advertisements may not necessarily translate to actual recruitment of skilled workers. For example, an inelastic supply of skilled labor overall would make recruiting prohibitively expensive, and it is unclear if the payroll tax credits, as a wage subsidy, are sufficient to attract talent from non-startups. To test whether actual hiring occurred, we examine changes in startups' inventors that appear on their patent applications. Since training newly hired workers to produce patents may take time, we estimate Eq. (1) with all patent-related dependent variables shifted forward by one quarter.[20]

Table 4 reports the estimation results. We first investigate the changes in the number of unique inventors for startups and use the natural logarithm of one plus the number of unique inventors over all the patents filed by a startup in a quarter as the dependent variable in column (1). Column (1) shows that treated startups increase the number of unique inventors by 12% more than control startups after the enactment of the PATH Act. Columns (2) and (3) examine the addition of new inventors from patent filings. The dependent variables in columns (2) and (3) are a dummy variable for whether a startup has a new inventor appearing in the new patent applications in a quarter and the natural logarithm of one plus the number of unique new inventors over all patent applications filed by a startup in a quarter, respectively. We find that the treated startups have a 1.2 percentage points higher likelihood of including a new inventor and 19% more new inventors in their patent applications than control startups after the passage of the PATH Act. In combination with our earlier findings on R&D related labor demand, these results in columns (2) and (3) provide direct evidence that treated startups expanded their skilled labor investments following the enactment of the PATH Act and hired more R&D workers. Finally, as a robustness check, we examine R&D intensity in columns (4) and (5); the dependent variables are the average number of inventors per patent and the average number of new inventors per patent, respectively. We find that there are not only more inventors but also more new inventors per patent for the

[20] While it is not obvious how many quarters forward we should shift our patent-related outcome variables, we conduct robustness checks by shifting up to 4 quarters and find similar results.

treated startups over the post PATH Act period, indicating a larger set of active R&D workers in treated startups than in control startups.

Based on startups' patent filings, the results in this subsection show that startups' actual R&D-related labor investments increase following the passage of the PATH Act. Taken together with our earlier results based on job postings, we have shown that VC-backed startups respond to the new R&D tax incentives by scaling up their real R&D investments through the recruitment of R&D workers.

4.3. The parallel trend assumption

As discussed earlier, the DD framework requires the parallel trends assumption to make causal inferences. Because the assumption is not directly testable, researchers usually inspect the pre-treatment outcome variable trends of the treated and control groups to determine whether this assumption is empirically violated. We examine pre-treatment trends of the outcome variables using the dynamic version of Eq. (1). Specifically, we replace the single interaction variable with a set of interaction variables between the treated dummy and quarter dummies. To avoid multicollinearity, we omit from the regression the interaction term for the fourth quarter of 2015 (the last quarter before the passage of the PATH Act). If the outcome variable trends diverge prior to the passage of the PATH Act, the coefficients on the interaction variables of quarters in 2014 or 2015 would be statistically significant. Table 5 shows that the coefficients are insignificant for all quarters concerning skilled labor search as measured by job posting frequency and intensity.[21] Overall, the results in Table 5 corroborate the validity of our DD specification.

4.4. Falsification tests

[21] In Table A1, we find similar results for patent inventors.

As a robustness check, we conduct a falsification test by estimating a placebo DD model that is similar to the one specified in Eq. (1) for a pseudo-treatment year 2012. The model differs from Eq. (1) in two ways. First, the post-treatment indicator takes the value of one if it is after the pseudo-treatment year 2012 rather than after 2016. Second, we classify placebo-treated startups based on the pseudo-treatment year 2012 as opposed to 2016 in our baseline analysis. Specifically, we assign startups that are 5 years old in 2012 (founded in 2008) to the pseudo-treatment group, and startups that are 6 years old in 2012 (founded in 2007) to the pseudo-control group. If our DD model is specified appropriately, the average treatment effect estimated from the placebo DD model should be insignificant.

Table 6 presents the results of the falsification test. We observe insignificant coefficients on the interaction variable for skilled labor investments as measured by both job postings (Panel A) and inventors from patent filings (Panel B). The falsification test results indicate that our DD model is well specified and does not produce false positive treatment effects.

Using the same set of startups as those in Table 6, we provide another falsification test by estimating a model analogous to Eq. (1) over the quarters of 2014-2017 (i.e., the same period as our baseline model) for 9- (founded in 2008) and 10-year-old startups (founded in 2009) in 2016. The results, reported in Table A2, show that these older cohorts of startups (between 9 and 10 years old in 2016), which are very unlikely to benefit from the new R&D tax incentive in 2016, do not respond to the policy change. These results provide further support that our baseline DD model is well specified and that our main results are unlikely driven by confounding factors around the tax policy change other than the actual R&D tax incentive from the PATH Act.

5. Results on the Demand in Labor Quality and Innovation Output

The previous sections show that VC-backed startups increase their demand and recruitment of R&D workers after the enactment of the PATH Act. However, it is not clear if startups on average are onboarding workers for entry-level positions or searching for top talent who can spearhead new breakthrough innovations. The former could be a symptom of agency conflicts in startups such as empire-building motives of founders, which may represent wasteful spending of newly available payroll tax credits.[22] For example, startups may hire more R&D workers of low quality to offset a larger amount of payroll tax with R&D credits.

Because the quality of labor is critical for the success of innovation, we next investigate the changes in demand for labor quality. Occupation-level job postings data allow us to examine the position requirements listed in each job posting in terms of the level of education and length of work experience. To investigate if labor quality demand translates to superior innovation output, we study the evolution of the quality and quantity of patents filed before and after the enactment of the PATH Act. Patent data allow us to measure the overall innovation output and the quality of the innovation output based on both overall patent application filings and patent filings that are eventually granted. We proceed to test these predictions in the framework of Eq. (1).

5.1. The demand in labor quality

To examine changes in labor quality demand, we first focus on the required education level stated in each job posting and classify postings into two categories: (1) postings that require a master's or Ph.D. degree and (2) postings that require at least a bachelor's degree. Then, for each of the categories defined above, we examine how the enactment of the PATH Act impacts the

[22] For example, the free cash flow hypothesis suggests that founders may have empire-building motives, and an exogenous expansion in financing would just lead them to pursue unprofitable investments (Hart and Moore, 1995; Jensen 1986; Stulz, 1990). The prediction of the free cash flow hypothesis is that the quality of marginal investment will decline.

number of job postings in each category in comparison to the remaining job postings. Panel A of Table 7 reports the estimation results. Columns (1) and (2) show that access to payroll tax credits leads to a 40% increase in the number of job postings that require at least a master's degree and only a 17% increase in the number of job postings that have no such requirement, respectively. Similarly, in columns (3) and (4), we find that access to payroll tax credits leads to more job postings that require at least a bachelor's degree in comparison to job postings without such conditions (19% vs. 15%). These findings suggest that there is an increase in the demand for labor quality.

We next focus on the required work experience stated in each job posting and again classify postings into two categories: (1) postings that require at least one-year of work experience and (2) postings that require at least two years of work experience. Similar to Panel A of Table 7, for each of the categories defined above, we examine how access to payroll tax credits impacts the number of job postings in each category in comparison to the remaining job postings. Panel B of Table 7 reports the estimation results. In columns (1) and (2), we show that access to payroll tax credits leads to more job postings requiring at least one year of work experience, in comparison to job postings having no such requirement (24% vs. 20%). In columns (3) and (4), we find that access to payroll tax credits leads to more job postings requiring at least two years of work experience in comparison to job postings without such a condition (25% vs. 22%). Consistent with the results in Panel A, the findings in Panel B suggest that the demand in labor quality increases following the enactment of the PATH Act.

Taken together, by measuring the labor quality demand by the required level of education and length of work experience stated in job postings, we find that the enactment of the PATH Act increases the quality of skilled labor investments by startups.

5.2. The quality of innovation output

We next examine the quality and quantity of innovation output. Patent filings, including those that do not receive grants, provide direct evidence of startups elevating R&D activities. Therefore, we first measure the quality of innovation output using all patent filings, including those that do not result in grants. Panel A of Table 8 reports the estimation results, where the dependent variables in columns (1) and (2) are a dummy variable indicating whether a startup has a new patent filing and the natural logarithm of one plus the number of patent filings of a startup in a quarter, respectively. The estimation results suggest that there is a significant increase in the number of patent filings for the treated startups after the passage of the PATH Act in comparison to the control startups. The effects are economically substantial. The estimates suggest that the treated startups (those likely qualifying for new R&D tax credits) have a 1.7 percentage points higher likelihood in filing new patents and that these startups submit 10% more patent filings after 2016 compared to control startups. Based on patent filings, the results suggest that the treated startups have higher overall innovation output post PATH Act enactment.

Panel A of Table 8 shows that the overall attempt at innovation output increases for the treated startups following the passage of the PATH Act. However, this finding does not rule out the possibility that startups may be producing lower quality patents. Lower quality patent filings may be less likely to be approved and have weaker technology protection conditional on being granted. Therefore, we focus on the patent filings that are eventually granted in Panel B of Table 8. The dependent variables in columns (1) and (2) are a dummy variable for whether a startup has a new patent filing that is eventually granted and the natural logarithm of one plus the number of granted patent filings for a startup in a quarter, respectively. The estimates in columns (1) and (2) suggest that there is a significant increase in the number of eventually granted patent filings for the treated startups after the passage of the PATH Act in comparison to the control startups. In columns (3) and (4), we measure the average patent quality using the number of patent claims associated to each patent and the number of citations they received in the three years after filing (Bernstein, 2015), respectively. Although the coefficient in the fourth column is not statistically significant, it is positive and consistent with the results derived from other patent quality measures. The results in columns (3) and (4) suggest that the average patent quality also increases for the treated startups following the enactment of the PATH Act.

In sum, based on the labor quality demanded and patents developed, the results in this section suggest that the PATH Act has a direct and large impact on the quality of startups' skilled labor investments and R&D output. In other words, VC-backed startups not only attempt to hire more skilled workers, but also hire those that are more educated and experienced in response to R&D tax incentives.

6. Robustness Checks and Cross-sectional Analysis

In this section, we provide robustness checks for our main specification and conduct some cross-sectional analyses. First, to filter out the potential impact of firm age on our results, we estimate a Difference-in-Difference-in-Differences (DDD) model. Next, we use more job classifications to examine the changes in startups' labor demand following the enactment of the PATH Act. Lastly, we investigate how our results depend on the industry in which startups are operating and the conditions of the local labor market for skilled workers.

6.1. Difference-in-Difference-in-Differences

In our baseline DD regressions, we compare changes in labor outcomes between a young cohort (treated) and an old cohort of startups (control) and show that the young cohort scales up their skilled labor investments in response to access to new payroll tax credits. We compare cohorts of startups that are founded in a narrow window around an age cutoff—and are therefore similar in observable characteristics (see Panel A of Table 1)—and control for startup and quarter fixed effects in all our regression models. However, startups' skilled labor investments may still evolve differently for different cohorts based on age, biasing our estimations (Wooldridge, 2010). To better control for the potential impact of firm age on our results, we combine our main sample with the placebo sample in Table 6 (Section 4.4) and estimate a DDD model.

The results are reported in Panel A of Table 9. The coefficients on the triple interaction term in all columns are statistically significant. The results show that even controlling for the investment trend that may be correlated with the stage of a startup's life cycle, treated startups still increase their labor demand more than the control startups after the enactment of the PATH Act. These results further suggest that our baseline findings are driven by the treatment of qualifying for payroll tax credits under the PATH Act rather than differences in investment trends due to firm age.

6.2. Labor demand for engineers and workers in technical occupations

To provide additional evidence that startups scale their R&D workforce after the PATH Act, we examine the job postings for engineering occupations and technical occupations as a robustness check. These classifications are narrower and therefore are potentially more associated with startups' R&D operations. We rely on the American Community Survey (ACS) Occupation Codes (OCC) and classify job postings into two categories: (1) postings that demand engineers and (2) postings for positions classified as technical occupations.[23] For each of the categories

[23] Based on OCC code, we refer to the "Professional, Scientific, and Technical Services" sector as the technical sector. See more details in: https://usa.ipums.org/usa/volii/occ_acs.shtml.

defined above, we examine how the passage of the PATH Act impacts the number of job postings in each category in comparison to the remaining job postings (similar to Section 5.1). Panel B of Table 9 reports the estimation results. In columns (1) and (2), we show that the passage of the PATH Act leads to more job postings that demand engineers in comparison to other job postings (48% vs. 18%). In columns (3) and (4), we find that the passage of the PATH Act leads to more open positions in technical occupations in comparison to other positions (40% vs. 18%). These findings in Panel B of Table 9 affirm that startups indeed attempt to scale up their R&D workforce in response to the PATH Act.

6.3. Cross-sectional analysis: heterogeneous treatment effects

Finally, we conduct a set of heterogeneity tests designed to shed light on the mechanisms underlying startups' response to the R&D tax incentives. In particular, we consider how our results depend on the capital intensity of the industry sector in which a startup operates and the salary level of skilled labor in the state in which the startup is headquartered.

To test how our results depend on the capital intensity of the sectors, we construct a *Capital Intensity* dummy to indicate whether the startup is in an industry sector that has capital intensity, as measured by average venture capital raised by startups, above the sample median among all VC invested sectors; we then interact the dummy with *Treated x Post* in Eq. (1). The coefficient on this triple interaction variable will be positive if our results are more pronounced for startups that are in capital-intensive sectors. We estimate the augmented versions of Eq. (1) and report the results in Panel A of Table 10. To preserve space, we present only the coefficient on the triple interaction variable of interest and *Treated x Post.* We observe that the coefficient on the triple interaction variable is always positive and statistically significant in all columns. These results suggest that the R&D tax incentives produce larger effects for startups operating in capital intensive sectors.

To test how our results depend on the conditions of the local skilled labor market, we construct a *High Salary* dummy to indicate whether the startup is located in a state that has skilled labor salary, as measured by the median annual wage of STEM workers,[24] above the sample median among all VC invested states and interact the dummy with *Treated x Post* in Eq. (1). The coefficient on this triple interaction variable will be positive if the results are more pronounced for startups located in states that have higher skilled labor costs. We estimate the augmented versions of Eq. (1) and report the results in Panel B of Table 10. To preserve space, we again present only the coefficient on the triple interaction variable of interest and *Treated x Post.* We observe that the coefficient on the triple interaction variable is always positive and statistically significant in four out of the five columns. These results suggest that the R&D tax incentive produces larger effects for startups located in states that have higher skilled labor costs.

Taken together, the results in Table 10 suggest the effects of payroll tax credit eligibility are more pronounced for startups operating in capital intensive sectors and located in states with higher costs in skilled labor. Therefore, R&D tax incentives would be more effective for startups that likely face higher financial constraints. Our findings indicate that the cost of skilled labor is an important hurdle for startups to scale up their R&D activities.

7. Conclusion

[24] We use the 2015 wage data of STEM employment provided by U.S. bureau of labor statistics, see more details at: https://www.bls.gov/oes/additional.htm.

This study documents the effects of a provision of the PATH Act of 2015 that allowed for first time VC-backed startups to use R&D tax credits to offset their payroll tax liabilities. This unique policy change offers us an ideal empirical setting to understand the labor effects of R&D tax incentives. By comparing startups that nearly qualify to those that barely qualify for R&D tax credits, we find that eligible VC-backed startups ramp up their search for R&D workers who are more educated and who have more years of work experience after the PATH Act. We provide evidence that increased skilled labor demand does translate to the hiring of more R&D workers by documenting the elevated appearance of new inventors in patent filings. Last, we examine the changes in the labor quality demand in response to the passage of the PATH Act and find a similar increase. Overall, our results suggest that R&D tax incentives have direct and large labor effects on VC-backed startups, which is critical in achieving the policy goals of both increasing employment and promoting innovation.

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Figure 1: Treatment Definition

In our baseline specification, startups are assigned into the treatment group if they marginally satisfy the less than 5-year revenue history criterion (depicted as the "founding year threshold" in the figure below) to qualify for payroll tax credits under the PATH Act of 2015 on January 1, 2016. Specifically, treated startups are those that were founded 5 years prior to the end of 2016 and therefore have the earliest 5-year revenue history window coinciding with the post-PATH Act period (i.e., 2016 is the first and only eligible tax year). Startups founded 6 years prior to the end of 2016 and therefore have the last taxable 5-year revenue history window prior to the PATH Act are assigned into the control group.

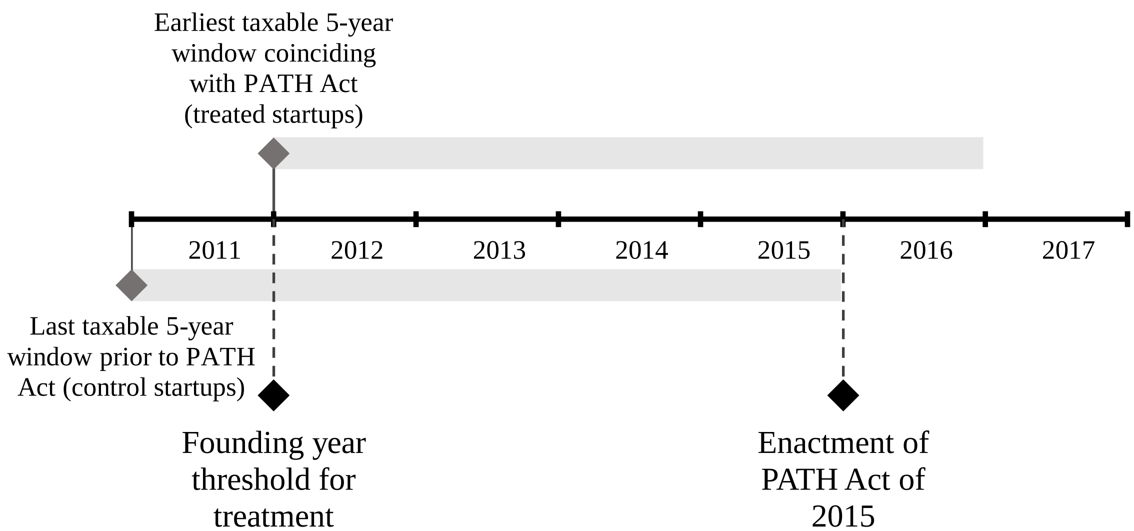

Figure 2: Estimated Percentage of Startups Eligible for Payroll Tax Credits by Age

In the absence of data on revenue history for VC-backed startups, we use available revenue data from a random sample of startups founded in 2004 provided by the Kauffman Foundation to gauge reliability in using firm age to infer eligibility of payroll tax credits from the PATH Act. This figure plots the percentage of surveyed startups that would be eligible for payroll tax credits by age had the PATH Act already been enacted. Revenue information is from the Kauffman Firm Survey (KFS). We exclude firm-years in which firms ceased operations. The red solid line and the blue dashed line represent the percentage of hypothetically eligible high-tech startups and all surveyed startups from KFS, respectively.

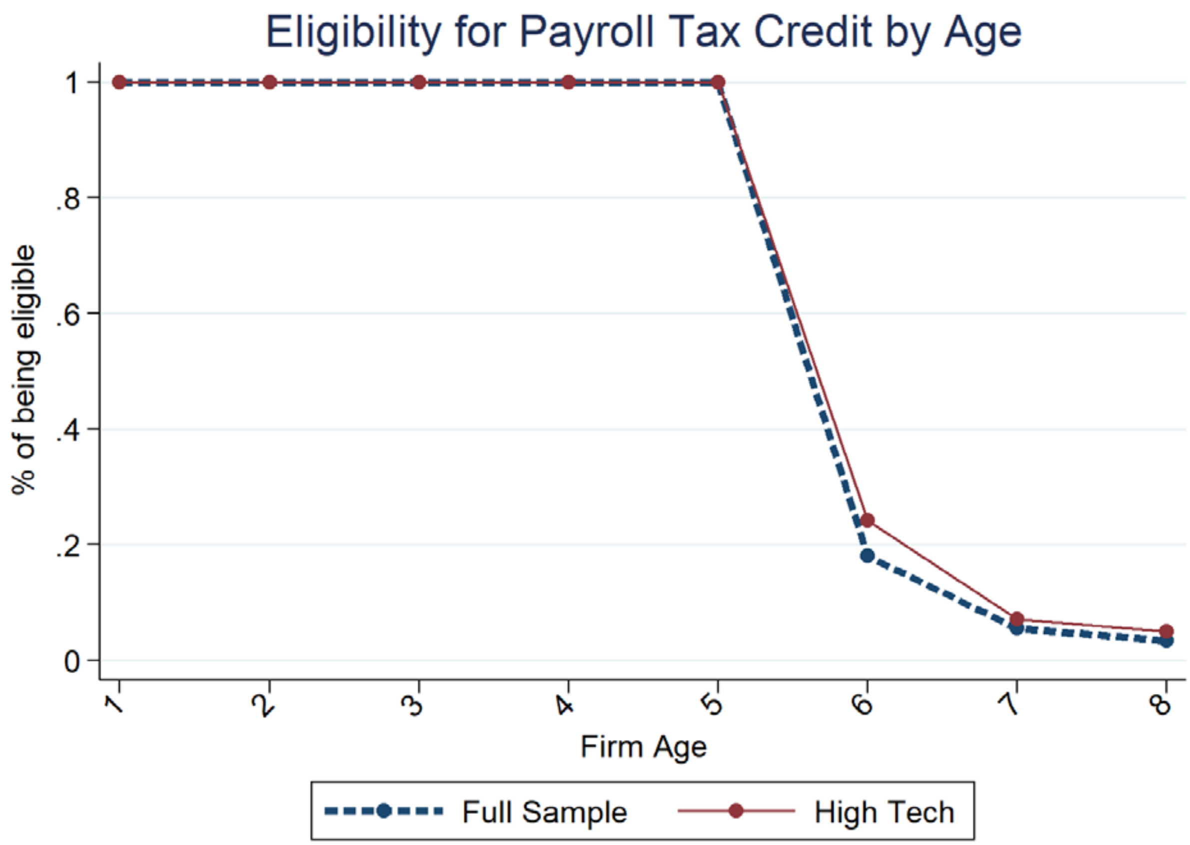

Figure 3: Trends of Job Postings Relative to the Fourth Quarter of 2015

This figure plots the average quarterly changes in the number of job postings relative to the fourth quarter of 2015 over the period 2012-2017. The solid and dashed lines are the average for VC-backed startups founded in 2012 (the treated group) and 2011 (the control group), respectively. The PATH Act went into effect in the first quarter of 2016.

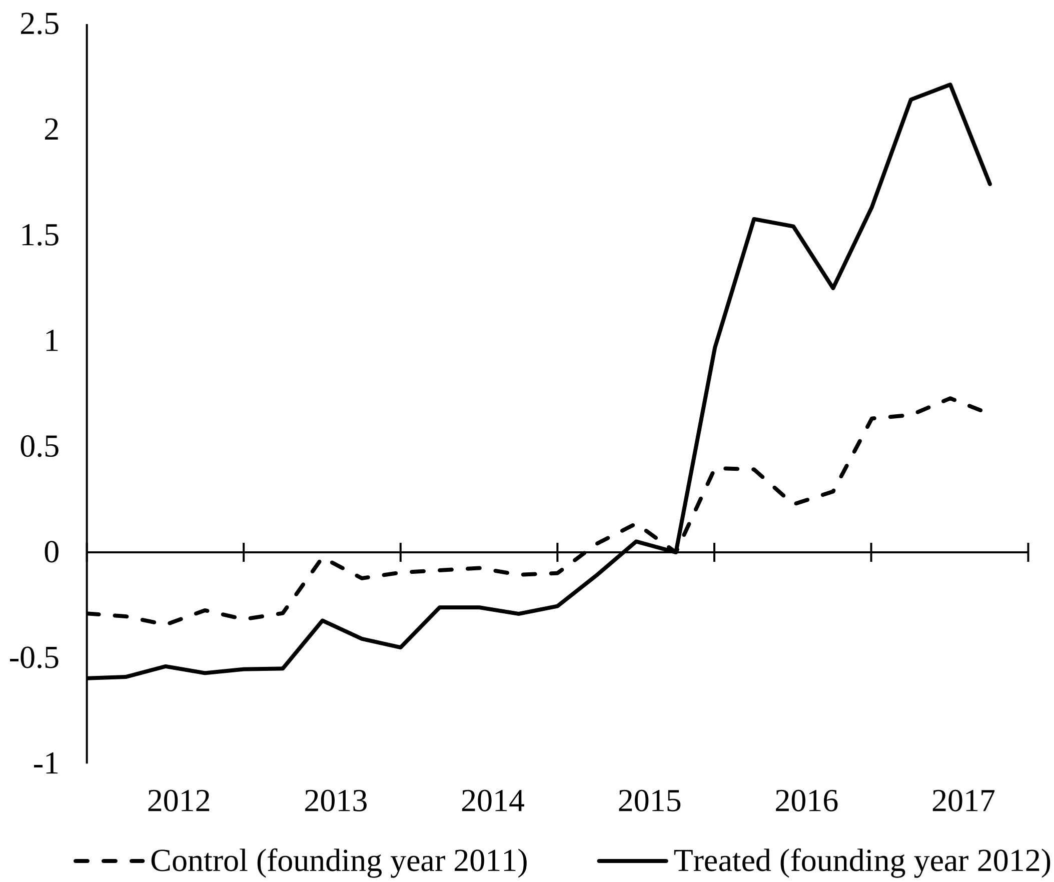

Table 1: Summary Statistics

This table presents summary statistics for the main variables in our study. Panel A compares the characteristics of treated and control startups in 2015Q4. Panels B and C provide summary statistics for the variables measuring startups' labor demand based on job posting information and startups' R&D recruitment based on patent filings, respectively.

Panel A: Comparison of the characteristics of treated and control startups in 2015Q4

	Treated startups		Control startups			
	Mean	Std. dev.	Mean	Std. dev.	Diff	p-value
No. of Postings	0.38	1.68	0.51	2.07	0.12	0.174
No. of Postings in R&D	0.02	0.14	0.02	0.15	0.00	0.586
No. of Postings Not in R&D	0.35	1.56	0.46	1.90	0.11	0.185
No. of Postings in STEM	0.03	0.18	0.04	0.19	0.00	0.660
No. of Postings Not in STEM	0.32	1.45	0.41	1.70	0.08	0.285
No. of Postings Requiring High Prep	0.15	0.71	0.21	0.89	0.06	0.119
No. of Postings Requiring Low Prep	0.03	0.16	0.03	0.17	0.00	0.694
No. of Postings Requiring High Skill	0.21	1.01	0.29	1.27	0.08	0.159
No. of Postings Requiring Low Skill	0.13	0.60	0.16	0.69	0.03	0.359
No. of Patent Applications	0.10	0.39	0.11	0.39	0.01	0.597
No. of Unique Inventors	0.26	1.02	0.31	1.10	0.05	0.343
No. of Unique New Inventors	0.05	0.21	0.04	0.20	-0.00	0.681
Avg. No. of Inventors	0.19	0.70	0.22	0.74	0.03	0.400
Avg. No. of New Inventors	0.04	0.20	0.04	0.18	-0.01	0.414
Headquartered in CA	0.45	0.50	0.46	0.50	0.01	0.651
Information Technology	0.78	0.41	0.78	0.42	-0.01	0.779
Biotech	0.13	0.33	0.14	0.35	0.02	0.274
Cum Rounds of Financing	2.18	1.32	2.65	1.66	0.47***	0.000
Cum Amount of Capital Raised (M)	15.12	35.51	18.89	69.46	3.77	0.156
Cum No. of Inventors	3.13	26.97	3.20	18.90	0.07	0.949

Panel B: Job postings

	N	Mean	Std. Dev.	5-%ile	25-%ile	50-%ile	75-%ile	95-%ile
Treated	26960	0.477	0.499	0.000	0.000	0.000	1.000	1.000
Post	26960	0.500	0.500	0.000	0.000	0.500	1.000	1.000
No. of Postings	26960	0.714	2.492	0.000	0.000	0.000	0.000	5.000
No. of Postings in R&D	26960	0.028	0.164	0.000	0.000	0.000	0.000	0.000
No. of Postings Not in R&D	26960	0.662	2.315	0.000	0.000	0.000	0.000	5.000
No. of Postings in STEM	26960	0.045	0.207	0.000	0.000	0.000	0.000	0.000
No. of Postings Not in STEM	26960	0.612	2.139	0.000	0.000	0.000	0.000	5.000
No. of Postings Requiring High Prep	26960	0.255	0.968	0.000	0.000	0.000	0.000	2.000
No. of Postings Requiring Low Prep	26960	0.044	0.206	0.000	0.000	0.000	0.000	0.000
No. of Postings Requiring High Skill	26960	0.389	1.481	0.000	0.000	0.000	0.000	3.000
No. of Postings Requiring Low Skill	26960	0.255	0.968	0.000	0.000	0.000	0.000	2.000

Panel C: Inventors

	N	Mean	Std. Dev.	5-%ile	25-%ile	50-%ile	75-%ile	95-%ile
No. of Patent Applications	26960	0.109	0.397	0.000	0.000	0.000	0.000	1.000
No. of Unique Inventors	26960	0.276	1.027	0.000	0.000	0.000	0.000	3.000
No. of Unique New Inventors	26960	0.043	0.203	0.000	0.000	0.000	0.000	0.000
Avg. No. of Inventors	26960	0.197	0.701	0.000	0.000	0.000	0.000	2.500
Avg. No. of New Inventors	26960	0.040	0.191	0.000	0.000	0.000	0.000	0.000

Table 2: Impact on Overall Job Postings

This table presents the OLS regression results of Eq. (1) at the startup-quarter level. The dependent variables are a dummy variable for whether a startup has posted any job in a quarter in column (1) and the natural logarithm of one plus the number of overall job postings in a quarter in columns (2) through (5). The sample period is over the quarters of 2014-2017 in all columns except column (4), which is over 2015-2016. The sample includes startups in the VentureXpert database that are between 5 and 6 years old in 2016 in columns (1) through (4) and between 4 and 7 years old in column (5). *Treated* is a dummy variable equal to 1 if the startup is at most 5 years old in 2016 (the first year the PATH Act takes effect), and 0 otherwise. Control variables include startups' cumulative rounds of financing, cumulative number of patents that are granted, startup fixed effects, and industry-quarter interacted fixed effects. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are clustered at the startup level.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Has Posting	ln(No. of Postings)	ln(No. of Postings) *(with controls)*	ln(No. of Postings) *(over 2015-2016)*	ln(No. of Postings) *(cohorts 2010-2013)*
Treated x Post	0.042***	0.085***	0.069***	0.066***	0.090***
	(0.012)	(0.025)	(0.024)	(0.024)	(0.017)
Lagged Cum Rounds			0.068***		
			(0.009)		
Lagged Cum Patents			0.011***		
			(0.004)		
Observations	26960	26960	26960	13480	51344
Adj. R-Squared	0.383	0.477	0.486	0.514	0.502
Company FE	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes

Table 3: Impact on Job Postings Categorized by Skill Requirements

This table presents the OLS regression results of Eq. (1) using various categorizations of job postings based on skill requirements as the dependent variable at the startup-quarter level. Specifically, the dependent variables are the natural logarithm of one plus the number of job postings that fall into one of the following skill requirement categories: (non-) R&D-related in column (1) (column (2)), (non-) STEM-related in column (3) (column (4)), high (low) preparation in column (5) (column (6)), and high (low) skilled in column (7) (column (8)). The sample period is over the quarters of 2014-2017. The sample includes startups in the VentureXpert database that are between 5 and 6 years old in 2016. *Treated* is a dummy variable equal to 1 if the startup is at most 5 years old in 2016 (the first year the PATH Act takes effect), and 0 otherwise. Control variables include startup fixed effects and industry-quarter interacted fixed effects. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are clustered at the startup level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	ln(No. of Postings in R&D)	ln(No. of Postings Not in R&D)	ln(No. of Postings in STEM)	ln(No. of Postings Not in STEM)	ln(No. of Postings Requiring High Prep)	ln(No. of Postings Requiring Low Prep)	ln(No. of Postings Requiring High Skill)	ln(No. of Postings Requiring Low Skill)
Treated x Post	0.009**	0.083***	0.015***	0.078***	0.052***	0.009*	0.063***	0.035**
	(0.004)	(0.024)	(0.005)	(0.023)	(0.016)	(0.005)	(0.020)	(0.015)
Observations	26960	26960	26960	26960	26960	26960	26960	26960
Adj. R-Squared	0.299	0.473	0.317	0.467	0.442	0.305	0.455	0.404
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Impact on Inventors

This table presents the OLS regression results of Eq. (1) using the count of inventors that appear on patent filings as the dependent variable at the startup-quarter level. Specifically, the dependent variables are the natural logarithm of one plus the number of unique inventors over all patents filed by the startup in a quarter in column (1), a dummy variable for whether the startup has a new inventor appearing in its patent filings in a quarter in column (2), the natural logarithm of one plus the number of unique new inventors over all patents filed by the startup in a quarter in column (3), the natural logarithm of one plus the average number of inventors per patent in column (4), and the natural logarithm of one plus the average number of new inventors per patent in column (5). The sample period is over the quarters of 2014-2017. The sample includes startups in the VentureXpert database that are between 5 and 6 years old in 2016. *Treated* is a dummy variable equal to 1 if the startup is at most 5 years old in 2016 (the first year the PATH Act takes effect), and 0 otherwise. Control variables include startup fixed effects and industry-quarter interacted fixed effects. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are clustered at the startup level.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	ln(No. of Unique Inventors)	Has New Inventors	ln(No. of Unique New Inventors)	ln(Avg. No. of Inventors)	ln(Avg. No. of New Inventors)
Treated x Post	0.026***	0.012**	0.008**	0.022***	0.006*
	(0.010)	(0.005)	(0.003)	(0.008)	(0.003)
Observations	26960	26960	26960	26960	26960
Adj. R-Squared	0.360	0.198	0.198	0.338	0.172
Company FE	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes

Table 5: Treatment Dynamics for Job Postings

Using various categorizations of job postings based on skill requirements as the dependent variable, this table presents the results estimated from a dynamic version of Eq. (1) that replaces the single interaction variable in Table 3 with a set of interaction variables between *Treated* and quarter dummies. The interaction variable for the quarter of 2015Q4 is omitted to avoid multi-collinearity and to make 2015Q4 the benchmark quarter. The dependent variables are the natural logarithm of one plus the number of job postings that falls into one of the following skill requirement categories: any job posting in column (1), R&D-related in column (2), STEM-related in column (3), high preparation in column (4), and high skill in column (5). Control variables include startup fixed effects and industry-quarter interacted fixed effects. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are clustered at the startup level.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	ln(No. of Postings)	ln(No. of Postings in R&D)	ln(No. of Postings in STEM)	ln(No. of Postings Requiring High Prep)	ln(No. of Postings Requiring High Skill)
Treated x Y2014Q1	-0.035	-0.002	-0.004	-0.003	-0.010
	(0.025)	(0.005)	(0.007)	(0.016)	(0.019)
Treated x Y2014Q2	0.003	0.001	0.005	0.014	0.005
	(0.025)	(0.006)	(0.007)	(0.017)	(0.019)
Treated x Y2014Q3	-0.007	-0.001	-0.001	0.005	0.009
	(0.024)	(0.005)	(0.007)	(0.016)	(0.019)
Treated x Y2014Q4	-0.010	0.002	-0.001	-0.004	0.001
	(0.024)	(0.005)	(0.007)	(0.016)	(0.019)
Treated x Y2015Q1	-0.001	-0.006	-0.008	0.002	0.005
	(0.024)	(0.006)	(0.007)	(0.016)	(0.018)
Treated x Y2015Q2	-0.013	0.001	-0.002	-0.009	-0.011
	(0.022)	(0.006)	(0.007)	(0.014)	(0.017)
Treated x Y2015Q3	-0.018	-0.000	-0.010	-0.010	-0.026
	(0.020)	(0.005)	(0.006)	(0.013)	(0.016)
Treated x Y2016Q1	0.023	0.002	-0.001	0.019	0.020
	(0.028)	(0.007)	(0.008)	(0.020)	(0.023)
Treated x Y2016Q2	0.030	0.011*	0.009	0.029	0.025
	(0.029)	(0.006)	(0.008)	(0.020)	(0.023)
Treated x Y2016Q3	0.092***	0.006	0.009	0.071***	0.079***
	(0.031)	(0.007)	(0.009)	(0.021)	(0.025)
Treated x Y2016Q4	0.084***	0.010	0.012	0.055***	0.067***
	(0.031)	(0.006)	(0.008)	(0.021)	(0.025)
Treated x Y2017Q1	0.091***	0.009	0.017*	0.053**	0.061**
	(0.033)	(0.007)	(0.009)	(0.022)	(0.026)
Treated x Y2017Q2	0.091***	0.016**	0.023**	0.054**	0.061**
	(0.034)	(0.007)	(0.009)	(0.023)	(0.026)
Treated x Y2017Q3	0.086***	0.018**	0.019**	0.058***	0.071***
	(0.033)	(0.007)	(0.009)	(0.022)	(0.027)
Treated x Y2017Q4	0.105***	-0.002	0.014	0.064***	0.091***
	(0.033)	(0.007)	(0.009)	(0.023)	(0.027)
Observations	26960	26960	26960	26960	26960
Adj. R-Squared	0.476	0.298	0.316	0.441	0.454
Company FE	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes

Table 6: Falsification Tests of the Difference-in-Differences Model using Pseudo Enactment of the PATH Act

We assume the PATH Act went into effect in 2012. This table presents estimation results of the placebo difference-in-differences model, analogous to Eq. (1), using various categorizations of job postings and the count of inventors that appear on patent filings as the dependent variables in Panels A and B, respectively, between 2010 and 2013. *Placebo Treated* is a dummy variable equal to 1 if the startup was 5 years old in 2012, and 0 if the startup was 6 years old in 2012. *Post 2011* is equal to 1 for quarters after 2011Q4, and 0 otherwise. The dependent variables in Panel A are the natural logarithm of one plus the number of job postings that falls into one of the following skill requirement categories: any job posting in column (1), R&D-related in column (2), STEM-related in column (3), high preparation in column (4), and high skill in column (5). The dependent variables in Panel B are the natural logarithm of one plus the number of unique inventors over all patents filed by the startup in a quarter in column (1), the natural logarithm of one plus the number of unique new inventors over all patents filed by the startup in a quarter in column (2), the natural logarithm of one plus the average number of inventors per patent in column (3), and the natural logarithm of one plus the average number of new inventors per patent in column (4).***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are clustered at the startup level.

Panel A: Job postings

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	ln(No. of Postings)	ln(No. of Postings in R&D)	ln(No. of Postings in STEM)	ln(No. of Postings Requiring High Prep)	ln(No. of Postings Requiring High Skill)
Placebo Treated x Post 2011	0.015 (0.019)	0.000 (0.004)	0.001 (0.005)	0.008 (0.012)	0.010 (0.015)
Observations	24352	24352	24352	24352	24352
Adj. R-Squared	0.490	0.266	0.299	0.427	0.445
Company FE	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes

Panel B: Inventors

	(1)	(2)	(3)	(4)
Dependent Variable	ln(No. of Unique Inventors)	ln(No. of Unique New Inventors)	ln(Avg. No. of Inventors)	ln(Avg. No. of New Inventors)
Placebo Treated x Post 2011	0.010 (0.014)	0.008 (0.009)	0.012 (0.012)	0.008 (0.007)
Observations	24352	24352	24352	24352
Adj. R-Squared	0.478	0.317	0.360	0.137
Company FE	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes

Table 7: Quality of Labor Demanded

This table presents the OLS regression results of Eq. (1) using various categorizations of job postings based on education (Panel A) and length of work experience requirements (Panel B) as the dependent variables at the startup-quarter level. The dependent variables in Panel A are the natural logarithm of one plus the number of job postings having one of the following education requirements: at least a (no) master's degree in column (1) (column (2)) and at least a (no) bachelor's degree in column (3) (column (4)). The dependent variables in Panel B are the natural logarithm of one plus the number of job postings with one of the following work experience length requirements: at least (less than) 1 year in column (1) (column (2)) and at least 2 (between 0 and 1) years in column (3) (column (4)). In both panels, the sample period is over the quarters of 2014-2017. The sample includes startups in the VentureXpert database that are between 5 and 6 years old in 2016. *Treated* is a dummy variable equal to 1 if the startup is at most 5 years old in 2016 (the first year the PATH Act takes effect), and 0 otherwise. Control variables include startup fixed effects and industry-quarter interacted fixed effects. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are clustered at the startup level.

Panel A: Job postings by education degree required

	(1)	(2)	(3)	(4)
Dependent Variable	ln(No. of Postings Requiring Master)	ln(No. of Postings Not Requiring Master)	ln(No. of Postings Requiring Bachelor)	ln(No. of Postings Not Requiring Bachelor)
Treated x Post	0.015***	0.084***	0.064***	0.047**
	(0.005)	(0.028)	(0.021)	(0.021)
Observations	26960	26960	26960	26960
Adj. R-Squared	0.317	0.493	0.473	0.452
Company FE	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes

Panel B: Job postings by work experience required

	(1)	(2)	(3)	(4)
Dependent Variable	ln(No. of Postings Requiring 1-yr or more Experience)	ln(No. of Postings Requiring less than 1-yr Experience)	ln(No. of Postings Requiring 2-yrs or more Experience)	ln(No. of Postings Requiring less than 2-yrs Experience)
Treated x Post	0.066***	0.038***	0.062***	0.048***
	(0.020)	(0.014)	(0.019)	(0.016)
Observations	26960	26960	26960	26960
Adj. R-Squared	0.456	0.395	0.449	0.414
Company FE	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes

Table 8: Quality of Innovation

This table presents the OLS regression results of Eq. (1) using various measures of innovation output quality as the dependent variable at the startup-quarter level. The dependent variables in Panel A are a dummy variable for whether the startup files at least 1 patent application in column (1) and the natural logarithm of one plus the number of patent applications in column (2). Note that patent applications include even those that are not eventually granted. The dependent variables in Panel B are a dummy variable for whether the startup files at least 1 patent that is eventually granted in column (1), the natural logarithm of one plus the number of patent filings that are eventually granted in column (2), the natural logarithm of one plus the average number of claims per patent filed and eventually granted in column (3), and the natural logarithm of one plus the average number of citations per patent filed and eventually granted in column (4). The sample period in Panels A and B is over the quarters of 2014-2017. The sample includes startups in the VentureXpert database that are between 5 and 6 years old in 2016. *Treated* is a dummy variable equal to 1 if the startup is at most 5 years old in 2016 (the first year the PATH Act takes effect), and 0 otherwise. Control variables include startup fixed effects and industry-quarter interacted fixed effects. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are clustered at the startup level.

Panel A: Innovation output based on all patent applications (including those that are not granted)

	(1)	(2)
Dependent Variable	New Patent Application	ln(No. of Patent Applications)
Treated x Post	0.017***	0.015**
	(0.007)	(0.006)
Observations	26960	26960
Adj. R-Squared	0.338	0.374
Company FE	Yes	Yes
Industry x Quarter FE	Yes	Yes

Panel B: Innovation output and quality based on patent filings that are eventually granted

	(1)	(2)	(3)	(4)
Dependent Variable	New Patent Filing	ln(No. of Patent Filings)	ln(Avg. No. of Claims)	ln(Avg. No. of Citations)
Treated x Post	0.015***	0.010***	0.041***	0.003
	(0.005)	(0.004)	(0.014)	(0.002)
Observations	26960	26960	26960	26960
Adj. R-Squared	0.335	0.335	0.336	0.288
Company FE	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes

Table 9: Robustness Checks for the Impact on Job Postings

Panel A presents the OLS regression results of a difference-in-difference-in-differences (i.e., triple differences) model using various categorizations of job postings based on skill requirements as the dependent variables at the startup-quarter level. The dependent variables in Panel A are the natural logarithm of one plus the number of job postings that falls into one of the following skill requirement categories: any category in column (1), R&D-related in column (2), STEM-related in column (3), high preparation in column (4), and high skill in column (5). The sample in Panel A combines our main sample in Table 3 and the placebo test sample in Table 6. *Main* is a dummy variable equal to 1 if the observation is in our main sample, and 0 otherwise. *Treated* is a dummy variable equal to 1 if the startup is at most 5 years old in 2016 for the main sample or if the startup is at most 5 years old in 2012 for the placebo sample, and 0 otherwise. *Post* is a dummy variable equal to 1 if the quarter is after 2015Q4 for the main sample or if the quarter is after 2011Q4 for the placebo sample, and 0 otherwise. Panel B presents the OLS regression results of Eq. (1) using alternative categorizations of job postings based on the American Community Survey (ACS) Occupation Codes (OCC) at the startup-quarter level. The dependent variables in Panel B are the natural logarithm of one plus the number of job postings that falls into the following categories: (non-) engineering-related in column (1) (column (2)) and (non-) technical-related in column (3) (column (4)). ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are clustered at the startup level.

Panel A: Triple differences model based on the main and placebo samples

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	ln(No. of Postings)	ln(No. of Postings in R&D)	ln(No. of Postings in STEM)	ln(No. of Postings Requiring High Prep)	ln(No. of Postings Requiring High Skill)
Main x Treated x Post	0.070**	0.009*	0.015**	0.044**	0.053**
	(0.031)	(0.005)	(0.007)	(0.020)	(0.025)
Treated x Post	0.015	0.000	0.001	0.008	0.010
	(0.019)	(0.004)	(0.005)	(0.012)	(0.015)
Observations	51312	51312	51312	51312	51312
Adj. R-Squared	0.483	0.283	0.309	0.436	0.451
Company FE	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes

Panel B: Job postings for engineers and workers in technical occupations

	(1)	(2)	(3)	(4)
Dependent Variable	ln(No. of Postings for Engineers)	ln(No. of Postings Not for Engineers)	ln(No. of Postings in Technical Sector)	ln(No. of Postings Not in Technical Sector)
Treated x Post	0.009**	0.088***	0.021***	0.085***
	(0.004)	(0.028)	(0.006)	(0.027)
Observations	26960	26960	26960	26960
Adj. R-Squared	0.225	0.498	0.411	0.489
Company FE	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes

Table 10: Cross-sectional Analysis: Heterogeneous Treatment Effects

This table presents the OLS regression results of an augmented version of Eq. (1) that includes an additional interaction variable: *Capital Intensity* in Panel A and *High Salary* in Panel B. To conserve space, only coefficients on two interaction variables are shown. *Capital Intensity* is a dummy variable equal to 1 if the startup is in a sector that has capital intensity, as measured by average venture capital raised, above the sample median among all VC invested sectors. *High Salary* is a dummy variable equal to 1 if the startup is located in a state that has skilled labor salary, as measured by the median annual wage of STEM workers, above the sample median among all VC invested states. We also control for *Capital Intensity*, *Post* × *Capital Intensity,* and *Treated* × *Capital Intensity* in Panel A, and *High Salary*, *Post* × *High Salary*, and *Treated* × *High Salary* in Panel B. The dependent variables in Panels A and B are the natural logarithm of one plus the number of job postings that falls into one of the following skill requirement categories: any job posting in column (1), R&D-related in column (2), STEM-related in column (3), high preparation in column (4), and high skill in column (5). ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are clustered at the startup level.

Panel A: Interacting with capital intensity of industries

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	ln(No. of Postings)	ln(No. of Postings in R&D)	ln(No. of Postings in STEM)	ln(No. of Postings Requiring High Prep)	ln(No. of Postings Requiring High Skill)
Treated x Post x	0.114**	0.015**	0.024**	0.074**	0.064*
Capital Intensity	(0.047)	(0.007)	(0.010)	(0.031)	(0.038)
Treated x Post	-0.003	-0.003	-0.003	-0.005	0.013
	(0.035)	(0.005)	(0.007)	(0.023)	(0.029)
Observations	26960	26960	26960	26960	26960
Adj. R-Squared	0.478	0.300	0.317	0.443	0.456
Company FE	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes

Panel B: Interacting with salary of high-skilled labor

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	ln(No. of Postings)	ln(No. of Postings in R&D)	ln(No. of Postings in STEM)	ln(No. of Postings Requiring High Prep)	ln(No. of Postings Requiring High Skill)
Treated x Post x	0.106*	0.022**	0.027**	0.057	0.093**
High Salary	(0.059)	(0.010)	(0.014)	(0.041)	(0.047)
Treated x Post	-0.012	-0.011	-0.010	-0.000	-0.022
	(0.053)	(0.010)	(0.013)	(0.038)	(0.042)
Observations	26960	26960	26960	26960	26960
Adj. R-Squared	0.477	0.299	0.317	0.443	0.456
Company FE	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes

Internet Appendix to:

The Labor Effects of R&D Tax Incentives: Evidence from VC-Backed Startups

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Figure A1: Estimation of FICA Tax and R&D Credits for High-tech firms

This figure plots the estimated Federal Insurance Contributions Act (FICA) tax a startup pays and the amount of R&D tax credits a startup can claim by startup age based on a sample of high-tech startups randomly surveyed by the Kauffman Foundation (i.e., the Kauffman Firm Survey or KFS). To estimate the average amount of FICA tax a startup pays, we multiply its total payroll tax reported in the Survey by 6.2%, the current average FICA tax rate for employers. To estimate the average amount of R&D tax credits a startup can claim, we multiply its total R&D expenses reported in the KFS (available since 2007, i.e., when the tracked firms are 4 years old) by 10%, the approximate R&D tax credit rate. The blue dashed line and the red solid line represent the estimated FICA tax and R&D tax credits, respectively.

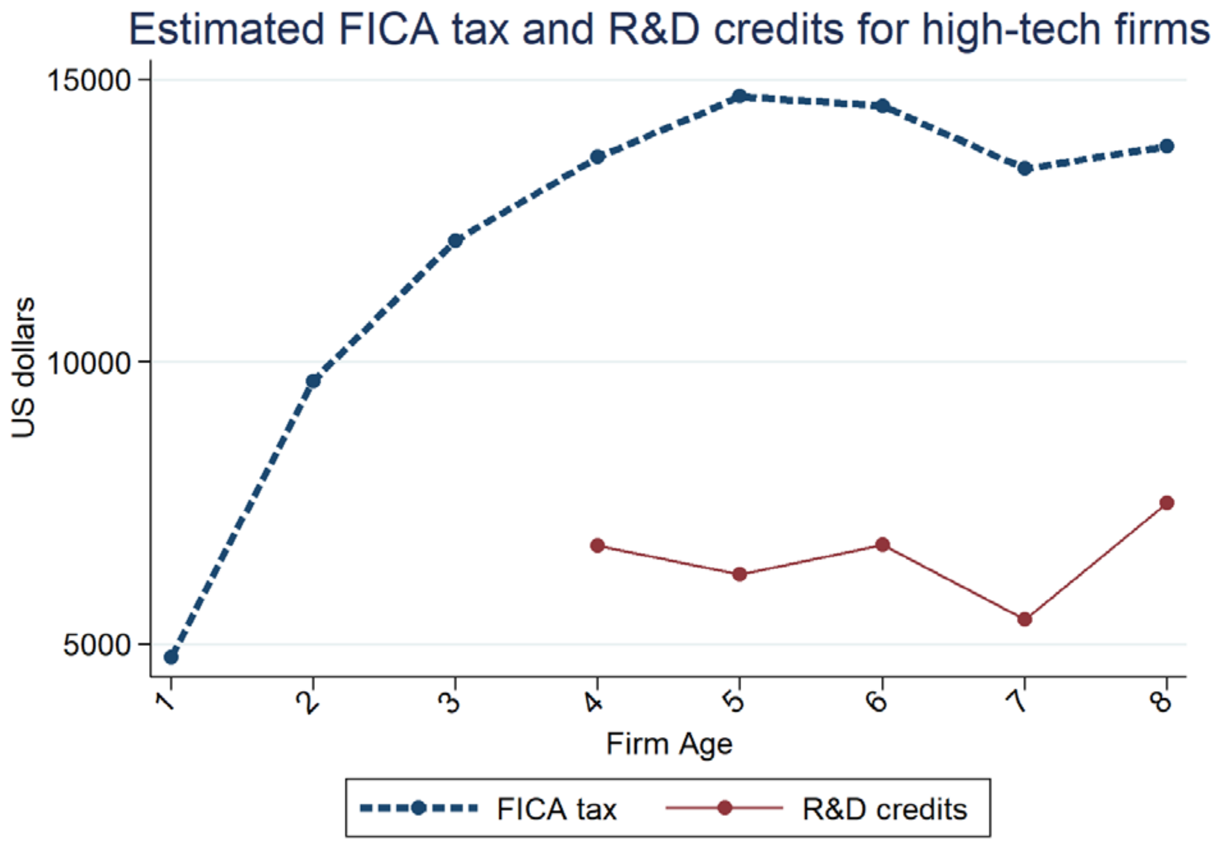

Table A1: Treatment Dynamics for Inventors

Using the count of inventors that appear on patent filings as the dependent variable at the startup-quarter level, this table presents the results estimated from a dynamic version of Eq. (1) that replaces the single interaction variable in Table 4 with a set of interaction variables between *Treated* and quarter dummies. The interaction variable for the quarter of 2015Q4 is omitted to avoid multi-collinearity and to make 2015Q4 the benchmark quarter. The dependent variables are the natural logarithm of one plus the number of unique inventors in column (1), the number of unique new inventors in column (2), the average number of inventors per patent in column (3), and the average number of new inventors per patent in column (4). Control variables include startup fixed effects and industry-quarter interacted fixed effects. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are clustered at the startup level.

	(1)	(2)	(3)	(4)
Dependent Variable	ln(No. of Unique Inventors)	ln(No. of Unique New Inventors)	ln(Avg. No. of Inventors)	ln(Avg. No. of New Inventors)
Treated x Y2014Q1	-0.005	0.006	-0.002	0.008
	(0.023)	(0.009)	(0.019)	(0.009)
Treated x Y2014Q2	0.010	0.007	0.008	0.008
	(0.022)	(0.008)	(0.019)	(0.008)
Treated x Y2014Q3	0.036*	0.012	0.033*	0.013
	(0.022)	(0.008)	(0.019)	(0.008)
Treated x Y2014Q4	0.018	0.011	0.016	0.014
	(0.023)	(0.009)	(0.019)	(0.009)
Treated x Y2015Q1	0.025	0.015*	0.021	0.015*
	(0.023)	(0.009)	(0.019)	(0.008)
Treated x Y2015Q2	0.025	0.012	0.019	0.012
	(0.023)	(0.009)	(0.020)	(0.009)
Treated x Y2015Q3	0.014	0.013	0.012	0.015*
	(0.023)	(0.008)	(0.019)	(0.008)
Treated x Y2016Q1	0.035	0.019**	0.030	0.018**
	(0.022)	(0.008)	(0.019)	(0.008)
Treated x Y2016Q2	0.022	0.021**	0.019	0.019**
	(0.022)	(0.009)	(0.019)	(0.008)
Treated x Y2016Q3	0.046**	0.015*	0.042**	0.015*
	(0.023)	(0.009)	(0.019)	(0.009)
Treated x Y2016Q4	0.058***	0.027***	0.047**	0.024***
	(0.021)	(0.008)	(0.019)	(0.008)
Treated x Y2017Q1	0.051**	0.020**	0.044**	0.018**
	(0.022)	(0.008)	(0.019)	(0.008)
Treated x Y2017Q2	0.041*	0.011	0.035*	0.011
	(0.022)	(0.008)	(0.019)	(0.008)
Treated x Y2017Q3	0.045**	0.016**	0.039**	0.015**
	(0.023)	(0.008)	(0.020)	(0.008)
Treated x Y2017Q4	0.036*	0.013	0.025	0.013*
	(0.021)	(0.008)	(0.017)	(0.007)
Observations	26960	26960	26960	26960
Adj. R-Squared	0.360	0.198	0.338	0.172
Company FE	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes

Table A2: Additional Falsification Tests

This table presents estimation results of a difference-in-differences model over the quarters of 2014-2017 analogous to Eq. (1); however, treated and control startups have founding years in 2008 and 2007, respectively, which are both far from the 2016 treatment assignment threshold. Note that this is the same set of startups as those in the placebo sample in Table 6, but the falsification test is conducted around the actual enactment of the PATH Act. The dependent variables in Panel A are the natural logarithm of one plus the number of job postings that falls into one of the following skill requirement categories: any job posting in column (1), R&D-related in column (2), STEM-related in column (3), high preparation in column (4), and high skill in column (5). The dependent variables in Panel B are the natural logarithm of one plus the number of unique investors over all patents filed by the startup in a quarter in column (1), the natural logarithm of one plus the number of unique new investors over all patents filed by the startup in a quarter in column (2), the natural logarithm of one plus the average number of inventors per patent in column (3), and the natural logarithm of one plus the average number of new inventors per patent in column (4). ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are clustered at the startup level.

Panel A: Job postings

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	ln(No. of Postings)	ln(No. of Postings in R&D)	ln(No. of Postings in STEM)	ln(No. of Postings Requiring High Prep)	ln(No. of Postings Requiring High Skill)
Placebo Treated x Post	-0.014	-0.004	-0.002	-0.002	-0.012
	(0.021)	(0.004)	(0.005)	(0.014)	(0.017)
Observations	24352	24352	24352	24352	24352
Adj. R-Squared	0.689	0.405	0.499	0.642	0.663
Company FE	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes

Panel B: Inventors

	(1)	(2)	(3)	(4)
Dependent Variable	ln(No. of Unique Inventors)	ln(No. of Unique New Inventors)	ln(Avg. No. of Inventors)	ln(Avg. No. of New Inventors)
Placebo Treated x Post	-0.003	-0.006	-0.005	-0.004
	(0.010)	(0.004)	(0.008)	(0.003)
Observations	24352	24352	24352	24352
Adj. R-Squared	0.508	0.307	0.479	0.254
Company FE	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes

Table A3: Excluding Biotech Companies

This table presents a robustness check for our main results by excluding Biotech companies from our main sample. The dependent variables in Panel A are the natural logarithm of one plus the number of job postings that fall into one of the following skill requirement categories: any job posting in column (1), R&D-related in column (2), STEM-related in column (3), high preparation in column (4), and high skill in column (5). The dependent variables in Panel B are the natural logarithm of one plus the number of unique inventors over all patents filed by the startup in a quarter in column (1), the natural logarithm of one plus the number of unique new inventors over all patents filed by the startup in a quarter in column (2), the natural logarithm of one plus the average number of inventors per patent in column (3), and the natural logarithm of one plus the average number of new inventors per patent in column (4). *Treated* is a dummy variable equal to 1 if the startup is at most 5 years old in 2016 (the first year the PATH Act takes effect), and 0 otherwise. Control variables include startup fixed effects and industry-quarter interacted fixed effects. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are clustered at the startup level.

Panel A: Job postings

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	ln(No. of Postings)	ln(No. of Postings in R&D)	ln(No. of Postings in STEM)	ln(No. of Postings Requiring High Prep)	ln(No. of Postings Requiring High Skill)
Treated x Post	0.086***	0.007*	0.015***	0.050***	0.064***
	(0.028)	(0.004)	(0.005)	(0.018)	(0.022)
Observations	23312	23312	23312	23312	23312
Adj. R-Squared	0.462	0.244	0.280	0.426	0.435
Company FE	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes

Panel B: Inventors

	(1)	(2)	(3)	(4)
Dependent Variable	ln(No. of Unique Inventors)	ln(No. of Unique New Inventors)	ln(Avg. No. of Inventors)	ln(Avg. No. of New Inventors)
Treated x Post	0.023**	0.009**	0.019**	0.007**
	(0.010)	(0.003)	(0.008)	(0.003)
Observations	23312	23312	23312	23312
Adj. R-Squared	0.345	0.213	0.321	0.184
Company FE	Yes	Yes	Yes	Yes
Industry x Quarter FE	Yes	Yes	Yes	Yes