R&D Expenditures, Productivity, and Wage Inequality: Evidence from R&D Tax Credits

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Abstract

This paper examines how R&D tax credits are passed onto wages and explores the underlying firm- and worker-level mechanism. Leveraging a regression kink design and matched employer-employee tax records, I find that R&D tax credits lead to a large and statistically significant increase in R&D expenditures. The results show that R&D-intensive firms respond to tax credits with substantial increases in R&D expenditures, leading to significant gains in profitability, productivity, and wages, while non-R&D-intensive firms show minimal changes. These firm-level gains are passed onto incumbent workers' earnings without impacting entrants. High-skill, long-tenured, and older incumbents experience the most significant earnings gains, with a 10 percent increase in the tax credits leading to a 1.2 to 1.9 percent rise in their annual earnings. In contrast, low-skill, low-tenured, and younger workers see no significant wage changes. These findings are consistent with a rent-sharing framework and highlight the role of R&D tax credits in contributing to within-firm wage inequality.

JEL Classification: O32, H25, J24, J31, D31

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1 Introduction

Innovative firms drive economic growth, create higher-paying jobs, and employ a larger share of high-skill workers (Romer, 1990; Van Reenen, 1996; Aghion et al., 2017). Government policies, such as Research and Development (R&D) tax credits, are designed to promote R&D activity and innovation. These policies aim to reduce input cost of R&D activity, in particular, R&D workers. However, little is known about the incidence of such R&D tax credits on workers. On one hand, tax credits may result in skill-biased technological change, which, in turn, change the relative skill demand and skill premium at the firm level (Lindner et al., 2022; Bøler, 2015). On the other hand, tax credits may increase the surplus at the firm level which, in turn, change the worker compensation (Kline et al., 2019; Carbonnier et al., 2022).

This paper studies how R&D tax credits are passed onto wages and investigate the underlying worker- and firm-level mechanisms. I use the unique design of a tax policy named Scientific Research and Experimental Develop (SRED), and an administrative employer-employee matched data from tax records in Canada to identify the causal impact of the R&D tax credits on firm-level and worker-level outcomes. Under SRED, small and medium-sized Canadian Controlled Private Corporations (CCPCs) are eligible for a 35 percent credit rate on R&D expenditure up a threshold called the Expenditure Limit (EL). The EL is a decreasing function of firms' lagged taxable income down to zero benefits. This creates a kink in the tax credits schedule which I exploit in a regression kink design to casually identify the impact of higher EL on firm-level and worker-level outcome.

The regression kink (RK) design exploits the presence of a kinked schedule in the relationship between the running variable (lagged taxable income) and the assignment variable (EL) to identify the impact of a higher EL. The identification comes from an induced kink in the mapping between the assignment variable and some outcome variable that coincide with the kink the policy schedule, and compare the relative magnitudes of the two kink. The identification in RK design relies on two assumptions: First, the density of the unobserved heterogeneity should evolve smoothly with the running variable at the kink (no-manipulation assumption). Second, the direct marginal effect of the running variable on the outcome should be smooth (smoothness assumption) (Card et al., 2015). I provide graphical and empirical evidence to show that the probability density function of firms around the kink point, indeed, evolve smoothly with the the running variable. I also show that the direct marginal effect of the running variable on observed predetermined covariates evolve smoothly with the running variable at the kink point.

I first examine the effects of the tax credits on firm-level R&D expenditures. A $100k increase in EL leads to an average $5,976 increase in annual R& D expenditure. In elasticity terms, a 10 percent increase in EL translates into a 2.3 percent increase in annual R&D expenditures. Although SRED aims to stimulate innovation in small and medium-sized firms, the response to eligibility for R&D tax credits may show significant heterogeneity due to lack of inventive capacity or burdensome administrative requirements (Agrawal et al., 2020; Dechezleprêtre et al., 2023; Cui et al., 2022). To build on this insight, I explore the heterogeneity of firms' responses to tax credit eligibility based on their R&D intensity. I define two measures of R&D intensity: R&D expenditure scaled by revenue and R&D wages and salaries scaled by total payroll. I find that R&D-intensive firms tend to respond more strongly to tax credit eligibility, while non-R&D-intensive firms show limited response. This distinction reflects the difference between the intensive margin – where firms already engaged in R&D increase their spending — and the extensive margin, where non-R&D-intensive firms might begin investing in R&D. The results are robust to the measure of R&D intensity. The results demonstrate that firms in the top quartiles of R&D intensity respond to tax credits with substantial increases in R&D expenditures, primarily driven by R&D wages and salaries rather than capital or material inputs.

Additionally, R&D-intensive firms experience significant increases in average wage, profitability, and total factor productivity (TFP) improvements, while non-R&D-intensive firms show minimal or no changes in these metrics. Kline et al. (2019) argue that the change in average wage, profitability, and TFP may be driven by a change in worker composition e.g. if R&D activities lead to a skill-biased technological change, treated firms increase their relative demand for skill which increase the skill premium and productivity at firm level. I show that these results are not attributable to changes in worker composition, as the gender and age composition, entrants' average wage before joining, movers' average wage before leaving, and the share of high-skill workers – proxied by worker fixed effects – remain stable across firms. Finally, I show that R&D-intensive firms experience a decline in their separation rate, while entry rate does not change. Relatedly, I find a large positive, although statistically insignificant, impact on employment. This evidence suggests that the rise in productivity induced by R&D tax credits is unlikely skill-biased.

Tax credit eligibility not only raises the average wages at R&D-intensive firms but also exacerbate within-firm inequality. Focusing on incumbent workers at R&D-intensive firms, I show that treated workers experience a 1.1 log points increase in annual earnings for $100k increase in the EL relative to the control workers. In elasticity terms, a 10 percent increase in EL leads to a 0.7 percent increase in annual earnings. The increase in earnings is concentrated among high-skill, high-tenure, and experienced workers. High-skill workers, measured through worker fixed effects or within-firm earnings distribution, benefit the most from increased R&D spending – with earning elasticity around 1.6 with respect to EL – while low-skill workers see no significant change in earnings. Additionally, high-tenure workers and older workers, those in their 40s and 50s, experience more significant gains in earnings, with earning elasticities ranging from 1.2 to 1.9 percent with respect to EL. Finally, consistent with the decline in separation rate at R&D-intensive firms, I find that retention rate, for the most part, is concentrated among high-skill and older workers.

Robustness checks confirm the stability of the results. First, I estimate the impact of tax credits on average R&D expenditure using a wider range of bandwidths around the kink point and find a comparable impacts in terms of magnitude and significance. Second, I address the issue of potential functional dependence between the running variable and the outcome (Landais, 2015; Ganong and Jäger, 2014). In practice, the relationship between these variables could either exhibit a kink or follow a quadratic pattern. To address this issue, I run a series of regressions for a wider selection placebo kink points and show that the relationship between R&D expenditure and the EL (hence, the running variable) quickly disappears as the placebo kink points get further from the true kink point. This suggest that the relationship between the running variable and the outcome is unlikely driven by their functional dependence.

The contributions of this paper are threefold. First, this paper builds on the existing literature that study the efficacy of innovation policies such as R&D tax credits (see Howell (2024), for a recent literature review). The availability of high-quality data on private firms' R&D expenditure, investment, and sales has made estimation of the impact on a wider set of firms with more credible designs possible (Lokshin and Mohnen, 2013; Rao, 2016; Melnik and Smyth, 2024) . My paper is closest to Agrawal et al. (2020) and Dechezleprêtre et al. (2023) who use firm-level data to estimate the impact of R&D tax credits. Agrawal et al. (2020), in a similar context as mine, study how the changes in the user-cost of R&D encourages firms to conduct more R&D. They find that small firms and those with lower fixed costs are more responsive to R&D tax credits. In the same light, using a regression discontinuity design based on changes in asset-based size threshold for tax credit eligibility in the UK, Dechezleprêtre et al. (2023) estimate the impact tax credits on small and medium-sized enterprises and find a large and significantly positive impact on patenting and R&D expenditure. The current paper differentiates from these papers in an important aspect; While they focus on R&D expenditure and patenting activities, I look at a wider set of outcomes, in particular, average wage and detailed worker-level outcome, to understand the implications of tax credits on wage policy of firms. I also find a large tax-adjusted price elasticity of 2.5 which is smaller but of the same order as 4.6 in Agrawal et al. (2020), and 4.1 in Dechezleprêtre et al. (2023). The potential reason for my smaller elasticity is that the baseline sample, here, is on average larger than the sample used by Agrawal et al. (2020), so the firms are less responsive to changes in tax-adjusted user cost. Relatedly, this paper also contributes to the literature on heterogeneous response to government policies (Zwick and Mahon, 2017; Criscuolo et al., 2019). Finish with my findings and contribution

Second, in this paper, I contribute to the literature on firm-level drivers of wage inequality. There is a growing body of evidence in labor economics that studies the role of firms in wage setting and wage inequality (Aghion et al., 2017; Faggio et al., 2010; Barth et al., 2016; Saez et al., 2019; Kline et al., 2019; Carbonnier et al., 2022; Howell and Brown, 2023). Barth et al. (2016), for instance, show that two-thirds of the increase in wage inequality – in the US between mid-1970s and 2000s – results from increased dispersion of wages between-establishment. Similarly, Faggio et al. (2010) document a simultaneous increase in wage inequality and productivity dispersion among firms in the UK between 1984 and 2001.

However, these aggregate relationships can be driven, in part, by changes in worker composition and sorting of different workers to different firms (Card et al., 2018). Song et al. (2019) discuss the increase in wage inequality may results from increase in firm pay premium, sorting, and segregation – which does not directly increase wage inequality but amplifies firm contribution to wage inequality.

Exploiting the employer-employee data, I address the sorting issue and show that the results are not driven by changes in worker composition, as the share of female employees, average age, entrants' wage, and movers' wage, and the share of high-skill workers remain stable across firms. I show that R&D tax credits exacerbate both between-firm and within-firm wage inequality.

Faggio et al. (2010) discuss the two main types of models that could rationalize the increased wage inequality and productivity dispersion: productivity/technology-base, and sorting-base. Caselli (1999) models how technological change such as introduction of Artificial Intelligence (AI) leads to wage dispersion. Firms adopt the new technology at different rate of technological adoption between firms – based on workers' skill – leads to wage dispersion, as well, as increase labor productivity and TFP. On the other hand, a sorting model predicts that high-skill workers are found in at high-paying firms which will leads to the dispersion of labor productivity. However, when we calculate TFP if we take these skill differences properly into account, we should not see any increase in TFP (Faggio et al., 2010).

Furthermore, I show that heterogeneous ability of firms to benefit from R&D tax credits drives the heterogeneous productivity growth, between-firm wage inequality, and rent sharing with high-skill, high-wage, and high-experience employees drives the within-firm wage inequality. Carbonnier et al. (2022) examine the impact of a policy aimed at firms with a higher proportion of low-wage workers and find a significant pass-through to high-skill incumbents, with no effect on the earnings of low-skill workers. Similarly, Kline et al. (2019) show that granting high-quality patents results in increased earnings for inventors and workers in the top 25 percentiles of a firm's wage distribution, arguing that less easily substitutable incumbents receive a higher wage premium. Conversely, Howell and Brown (2023), in their study of a one-time cash flow shocks at small innovative firms, find no variation in earnings based on skill proxies such as initial wage or education.

Finally, I also contribute to the endogenous growth literature that highlights the impact of R&D expenditure on productivity dispersion across firms (Romer, 1990; Hall and Mairesse, 1995). For instance, constructing an endogenous growth model, Doraszelski and Jaumandreu (2013) show how R&D affects the productivity dispersion across firms and over time. Exploiting the firm-level data and estimating total factor productivity a lá Ackerberg et al. (2015), I provide empirical evidence that R&D tax credits lead to an increase in total factor productivity. Also consistent with Doraszelski and Jaumandreu (2013), I find that interaction between current and past R&D expenditures contribute to productivity dispersion, in that, R&D expenditure is persistent, and R&D-intensive firm tend to respond more strongly to tax credit eligibility.

To the best of my knowledge, this is the first paper to provide empirical evidence on the relationship between wage inequality and productivity, focusing on an important determinant of productivity, R&D expenditure. My paper is close to Faggio et al. (2010). They show that an increase in TFP dispersion mainly drives wage inequality and labor productivity dispersion in the United Kingdom. This pattern may be driven by the sorting of workers and changes in worker composition at the firm level. Exploiting the employer-employee data, I show that the worker composition likely remains the same since the R&D tax credits increase the retention rate at the R&D-intensive firms that take up the tax credit eligibility. Moreover, they argue that the increased productivity dispersion is linked to new technologies. Consistent with their findings, I show that R&D expenditure, a key determinant of technological change, does lead to an increase in TFP.

The rest of the paper is organized as follows. Section (2) summarizes the institutional background of SRED tax credits. Section (3) presents the regression kink design framework and introduces the data. Section (4) presents the main results. Section (5) discusses the heterogeneity results and potential mechanism explaining the results. Section (6) computes the implied tax-adjusted user cost of R&D tax credits. Section (7) concludes.

2 Institutional Background

The Canadian government has a long history of supporting R&D activities through tax policies. As early as 1994, firms could deduct 100 percent of their scientific research expenditure from their taxable income. In 1986, the government expanded their definition of R&D expenditure by including experimental development and introduced the term Scientific Research and Experimental Development (SRED) which to encourage R&D activities.[1] The Scientific Research and Experimental Development (SRED) is the main federal tax incentive program to encourage all companies to conduct research and development in Canada. The program provides an investment tax credit for qualifying R&D expenditures, which fall under four main categories: (i) Basic Research (aimed at advancing the scientific knowledge without a practical application in view), (ii) Applied Research (aimed at advancing scientific knowledge with a practical application in view), (iii) Experimental Development (aimed at generating or discovering technological knowledge or know-how in order to develop or improve materials, devices, products, or processes, including incremental improvements), and (iv) Support work (tasks which directly support basic research, applied research, or experimental development work such as engineering, design, and data collection). Moreover, the following work is ineligible R&D expenditure under SRED: market research, quality control tests, prospecting, exploring or drilling for, or producing, minerals, petroleum or natural gas as well as purchasing proprietary knowledge such as patents.[2]

SRED is a two-tier tax credits which provides an investment tax credits at the general rate of 20 percent for all firms.[3] Small and medium-sized Canadian Controlled Private Corporations (CCPCs) are eligible for 35 percent credit rate on R&D expenditures up to a threshold called the Expenditure Limit (EL). The EL is a kinked function of prior-year

[1]See the link for details about the evolution of SRED program in Canada.

[2]In this paper, I cannot distinguish between different categories of qualifying R&D expenditure, however, in future research, one can explore the importance of SRED tax credits for basic research vs. other R&D activities as emphasized by Akcigit et al. (2021).

[3]As of January 1, 2014, the general credit rate is 15 percent.

taxable income and prior-year taxable capital employed in Canada.[4] The function, as shown in Figure (1), can be characterized by three parameters: Maximum expenditure limit, EL_t^{max}, start of phase-out threshold, z_t^{top*}, and end of phase-out threshold, $z_t^{bottom*}$. The EL function for firm j in year t can be written as:

$$EL_{jt} = \begin{cases} EL_t^{max} & \text{if } TY_{jt} \leq z_t^{top*} \\ EL_t^{max} - 10(z_t^{top*} - TY_{j(t-1)}) & \text{if } z_t^{top*} < TY_{j(t-1)} \leq z_t^{bottom*} \\ 0 & \text{if } TY_{jt} > z_t^{bottom*} \end{cases} \tag{1}$$

where EL_{jt} is firm j's EL at year t, $TI_{j(t-1)}$ is lagged taxable income. In my empirical design, I exploit the kinked relationship of EL and lagged taxable income, which provides a credible exogenous variation in tax credits generosity. While Agrawal et al. (2020); Dechezleprêtre et al. (2023) exploit a change in the eligibility threshold over time to identify the impact of R&D tax credits, here the identification comes from the kinked relationship between lagged taxable income and EL (i.e. cross-sectional variation in the data). I will discuss the identification in more details in Section (3).

Reforms. The SRED tax credits schedule is part of the Canadian Federal Budget and is annually revised and announced by Ministry of Finance. Firms are unlikely to be aware of the exact changes of the tax credits schedule during each tax year.[5] During 2001-2019 period, the tax credits schedule experienced four major reforms in 2004, 2006, 2008, and 2009. Figure (**??**) shows these reforms. In 2004, the start of the phase-out threshold, \$200k, and the end of phase-out threshold, \$400k, shifted to \$300k and \$500k, respectively. In 2006, the phase-out region shifted to new thresholds, \$400k to \$600k. In 2008, there were two major changes in the tax credit schedule: an increase in the maximum expenditure limit and an increase in end of phase-out threshold. The maximum expenditure limit shifted to \$3 million and the end of phase-out region threshold shifted to \$700k. Finally, in 2009, the phase-out region shifted to new thresholds, \$500k to \$800k. Despite the reforms, in all years, the kinked relationship between the lagged taxable income and EL, and more importantly, the slope of this relationship in the phase-out region remained unchanged.

Top Kink vs. Bottom Kink. Figure (1) shows the presence of two kink points in the relationship between lagged taxable income and the EL: Top kink at z_t^{top*} and the bottom

[4]Since taxable capital is only relevant for a small share of firms in the analysis sample, I abstract it from my formulation.

[5]During the analysis period, three different federal governments were in power in Canada: Liberal government led by Jean Chrétien (until 2003) and Paul Martin (2003–2006), Conservative government led by Stephen Harper (2006-2015), and Liberal government led by Justin Trudeau (2015-present). The alternating governments made predicting the generosity of SRED tax credits difficult.

kink $z_t^{bottom*}$. For the rest of the paper I focus only on the bottom kink for two reasons. First, the top kink coincides with another policy aimed at small CCPCs. Small Business Deduction is an important policy that provides a reduced corporate tax rate their business income for small CCPCs. In particular, Table A1 shows that Small Business Deduction threshold coincides with top kink, z_t^{top*}. Since the policy creates a cross-sectional variation among firm below and above the threhold, it can bias the estimate of the R&D tax credits. Second, the policy implications of firms around the top kink and the bottom kink is quite different. The estimand in bottom kink identifies the response of firms that just become eligible for R&D tax credits. The estimand in the top kink identifies the response of firms that have close to maximum expenditure limit, EL_t^{max}. Since a small share of firms reach or cross the maximum expenditure limit, the policy implications of the estimands are different and potentially less interesting.

3 Empirical Strategy

This section describes the empirical design to estimate the causal effect of generosity of SRED tax credits on firm-level and worker-level outcomes. As discussed in Section (2), I exploit the kink in the relationship between firms' lagged taxable income and their expenditure limit to identify the impact of the tax credits. Next I describe my data and outcomes variables of interest and close with some descriptive statistics on firms and workers.

3.1 Estimating the Impact on Firms using a Regression Kink Design

Suppose firm j is eligible for the more generous tax credits up to the expenditure limit, EL_j. Suppressing time-related considerations, I write the outcome y_j (e.g. R&D expenditure, employment) as

$$y_j = \kappa + EL_j\theta + u_j \tag{2}$$

where θ is the marginal impact of an increase in tax credits generosity and u_j represents all other determinants of the outcome. But R&D expenditure may be correlated with other firm characteristics. For instance, larger firms may access to more capital - physical or human - to invest in R&D activities. This will yield a biased estimate of θ.

To causally estimate θ, I exploit the presence of a kinked schedule in the relationship between lagged taxable income and EL. Following Landais (2015); Card et al. (2017); Bell et al. (2024), I model firm j's outcome, y_j, as a polynomial function of its lagged taxable income (the running variable) z_j, allowing the slope of the relationship to differ on either side of the cutoff $z_j = 0$. [6]

$$y_j = \alpha + \sum_{p=1}^{P} \left[\beta_p (z_j)^p + \gamma_p (z_j)^p \cdot \mathbb{1}\{z_j \geq 0\} \right] + X_j + \epsilon_j \tag{3}$$

where X_j is a set control variables such as lagged dependent variable, firm age, industry fixed effects, and province fixed effects.[7] Standard errors are clustered at the firm level. Here γ_1 is the change in the slope of the relationship between the outcome and the running variable at the kink point. To interpret this parameter as the causal effect of an increase in EL, I scale it based on the relationship between the running variable and the EL. As mentioned in Section 2, I focus on the bottom kink where the expenditure limit can be written as

$$EL_j(z_j) = -10 z_j \times \mathbb{1}\{z_j < 0\} + 0 \times \mathbb{1}\{z_j \geq 0\} \tag{4}$$

where z_j is the normalized lagged taxable income (the running variable). If firm j's lagged taxable income is below the kink, EL is a linear function of z_j. If firm j's lagged taxable income is above the kink, EL is equal to zero. Since EL schedule is a deterministic function of lagged taxable income, the parameter of interest θ in Equation (2) is $\frac{\gamma_1}{10}$. Note that since I observe all firms with positive or zero R&D expenditure, the estimates should be interpreted as Intention-To-Treat (ITT) effect. Moreover, this allows me to study the extensive margin as well as the intensive margin.

Identification Assumptions and Testing Their Validity. The identification in RK design relies on two assumptions: First, the density of the unobserved heterogeneity should evolve smoothly with the running variable at the kink (no-manipulation assumption). Second, the direct marginal effect of the running variable on the outcome should be smooth (smoothness assumption).

[6] The kink cutoff is normalized to zero throughout the paper.

[7] As discussed by Lee and Lemieux (2010), inclusion of controls is unnecessary for identification in RD [and similarly RK] designs. But to exploit the panel structure of the data and to increase precision, I include the lagged dependent variable as a baseline covariate. Lee and Lemieux (2010) say "In case where Y_{it} is highly persistent over time, Y_{it-1} may well be a very good predictor and has a very good chance of reducing the sampling error."

The SRED tax credits schedule is part of the Canadian Federal Budget and is annually revised and announced by Ministry of Finance. Firms are unlikely to be aware of the exact changes of the tax credits schedule during each tax year.[8] Although the firms could somewhat manipulate their taxable income, I do not find any evidence of such manipulation around the kink. To present the graphical evidence in support of no-manipulation assumption, I pool data from all the kinks in 2002-2019 period. I plot the pooled probability density function of the running variable in order to detect potential manipulation at kink point.

Figure (2) shows the number of firms observed in each bin of lagged taxable income around the kink. The graph shows no sign of discontinuity in the relationship between the number of firms and the running variable at the kink point. The corresponding McCrary (2008) test yields a discontinuity estimate of -0.9802 (p-value = 0.3270), which is not statistically different from zero. I also extend the McCrary test to validate the continuity assumption of the first derivative of the p.d.f. around the kink. Following Card et al. (2015); Landais (2015), I fit a series of polynomial models that allows the first- and higher-order derivatives of the number of firms at the kink. I find that the change in the first-order derivative is not statistically different from zero.

Another testable implication of RK design assumption is that the direct marginal effect of the running variable on observed covariates evolve smoothly with the running variable at kink. To test the smoothness assumption, I run a regression analogous to equation (3) where the outcome variables are covariates such R&D expenditure, employment, investment at the year before the treatment ($\tau = -1$). Controls includes firm age and lagged dependent variable (i.e. covariates at $t = -2$). Table (1) reports the estimates which show that, before the treatment, there is no statistically significant difference between firms below and firms above the threshold across a range of covariates. In particular, estimates for R&D expenditure have a negative sign (column (1)) which suggests that RK design captures the lower bound of eligibility on firm outcomes. In Appendix A I develop a Difference-in-Kink Regression design to address potential existence of a kink in covariates before the treatment.

Sample Restriction. For the analysis sample, I impose the following restrictions. First, I focus on all R&D firms i.e. firms with positive R&D expenditure in at least one year before the treatment, that operated as CCPC throughout the sample period. Second, I exclude

[8] During the analysis period, three different federal governments were in power in Canada: Liberal government led by Jean Chrétien (until 2003) and Paul Martin (2003–2006), Conservative government led by Stephen Harper (2006-2015), and Liberal government led by Justin Trudeau (2015-present). The alternating governments made predicting the generosity of SRED tax credits difficult.

firms with fewer than five workers in the year before the treatment, thereby dropping very small businesse with less economic impact. Third, I focus on firms operating in only one province in the year before the treatment to avoid complication arising firms re-allocating their R&D activities in response to differences in provincial supports. Finally, to account for survival bias, firms exited after the treatment are kept in the sample and are given zero values for R&D expenditures, patents, and employment.

3.2 Estimating the Impact on Workers using a Regression Kink Design

I estimate a similar RK model to Equation (3) to evaluate the impact of tax credits on worker-level outcomes:

$$y_i = \alpha + \sum_{p=1}^{P} \left[\beta_p (z_{j(i)})^p + \gamma_p (z_{j(i)})^p \cdot \mathbb{1}\{z_{j(i)} \geq 0\}\right] + X_i + \epsilon_i \tag{5}$$

where y_j is the outcome of worker i, $z_{j(i)}$ is the lagged taxable income of firm j where worker i was employed at treatment, X_i is a set control variables such as lagged dependent variable, worker age, industry fixed effects, and province fixed effects. Here γ_1 is the change in the slope of the relationship between the outcome and the running variable at the kink point. To interpret this parameter as the causal effect of an increase in EL, I scale it based on the relationship between the running variable and the EL. Since EL schedule is a deterministic function of lagged taxable income, the parameter of interest θ, as in Equation (2), is $\frac{\gamma_1}{10}$. Standard errors are clustered at the worker level.

Sample Restriction. For the analysis sample, I impose the following restrictions. First, I drop workers with multiple jobs in the year before the treatment. Second, I limit the sample to workers who were continuously employed in a treated or control firm at least for one years before the treatment, following Arnold et al. (2023); Duan and Moon (2024). This tenure restriction ensure that the analysis is on a sample of workers with attachment to the treated or control firms.

3.3 Data

This section describes the main datasets used for my analysis. The firm-level and worker-level information comes from the Canadian Employer-Employee Dynamics Database.

Canadian Employer Employee Dynamics Database (CEEDD). The CEEDD is a matched employer-employee dataset that covers the universe of workers and firms in Canada over 2001-2019 period. The CEEDD draws information from both individual (T1) and corporate (T2) tax return records. It also includes job-level information from employee tax records (T4) and Record of Employment (ROE) data, and firm-level information from the National Accounts Longitudinal Micro-data File (NALMF). A major advantage of this data set, that allows using a RK design, is that taxable income, hence, firms' eligibility is directly reported in the tax return records. This is useful to estimate the extensive margin since I observe firms' eligibility even when they have zero R&D expenditures. The main outcome variable used in the firm-level analysis is R&D expenditure. R&D expenditure consists of multiple components separately reported in the data. Firms report their in-house R&D expenditure, arm-length and nonarm-length contacts. The in-house R&D expenditure consists of wages and salaries to R&D workers, R&D capital expenditure, other R&D costs such as material. Other outcome variables used in the firm-level analysis are employment, average payrolls, investment, and profit margins. Employment is defined as the number of employees reported from the T4s.

At the worker-level, the key outcome is annual earnings which are aggregated across all employers in given year. While I include earnings across all employers, I associate workers with the "dominant" employer (i.e. the employer from which the employee receives the highest pay in the year). I also use information on workers' age and gender derived from the T1 income tax form.

Finally, following Abowd et al. (1999) (AKM), I estimate the firm-specific and worker-specific components of workers' annual earnings following a two-way fixed effect model. I borrow the notation used in Arnold et al. (2023); Duan and Moon (2024). Let y_{it} denote the log earnings of worker i in year t and $j(i,t)$ index the worker's employer. We regress y_{it} against the worker fixed effects ω_i, the employer fixed effects $\psi_{j(i,t)}$, and year fixed effects τ_t:

$$y_{it} = \omega_i + \psi_{j(i,t)} + \tau_t + u_{it}. \tag{6}$$

I use the estimated worker fixed effects $\hat{\omega}_i$ to categorize workers into high skills versus low skills. In particular, I label workers in the top 25 percentiles of worker fixed effects distribution across the entire workers sample as *high skill*, and workers in the bottom 75 percentiles of worker fixed effects distribution as *low skill*. The results are robust to various measures of skill (not reported).

3.4 Descriptive Statistics

The baseline sample contains 5,210 firms within a $67,600 bandwidth of lagged taxable income around the normalized kink threshold, with 2,960 treated firms and 2,250 control firms. The choice of baseline bandwidth is based on Calonico et al. (2014) optimal bandwidth approach using R&D expenditure as the main outcome variable. The results are robust to alternative bandwidths (Figure 4). All outcomes are winsorized at 1 percent to mitigate the impact of outliers. R&D expenditures and patents are winsorized at 1 percent of non-zero values.

Table (2) shows the average value of key variables measured in the year before treatment ($\tau = -1$), separately for treated firms and control firms. Column (1) and (2) show the averages for all the firms in the baseline sample. Column (3) and (4) show the averages for R&D intensive firms - measured by R&D expenditure scaled by revenue. Reassuringly, treated firms and control firms, in both samples, are similar in terms of SRED Expenditure, revenue, investment, employment, average payroll, and average number of patents owned. R&D intensive treated firms and their control firms have higher R&D expenditure in levels, higher ratio of R&D wages to total payroll, higher average wage, but have lower levels of employment and investment in physical capital relative to firms in the baseline sample.

Table (3) shows the average value of key variables in the worker sample in the year before treatment ($\tau = -1$), separately for treated workers and control workers. Column (1) and (2) show the averages for workers at firms in the baseline sample. Column (3) and (4) show the averages for workers at R&D intensive firms. Reassuringly, treated workers and control workers, in both sample, are similar in terms of earnings. Moreover, the worker composition at treated firms and control firms in terms of age, gender and tenure are quite similar. Workers at R&D intensive firms, on average, earn more but are similar to the workers in the baseline sample.

The majority of R&D firms in the baseline sample are in manufacturing and services sector. In the subsample of R&D-intensive firms, the share of firms in services sector substantially increases. The largest industries in this subsample are 5415 (Computer systems design and related services), 5416 (Management, scientific and technical consulting services), 5417 (Scientific research and development services).

4 Results

This section presents the main results, demonstrating that treated firms, on average, increase their R&D expenditure relative to control firms. I then explore whether the results are driven by the intensive or extensive margin and the implications for the pass-through of tax credits to workers. Next, I examine worker-level results, focusing on the impact on incumbent workers' earnings and retention rates. Finally, I show that my results are robust to alternative specification tests.

In all tables, I report the estimates of the average treatment effect, $\hat{\theta} = \frac{\hat{\gamma_1}}{10}$, where $\hat{\gamma_1}$ is the estimated change in slope in the relationship between the outcome variables and the running variable at the kink point from Equation (3) and (5). The denominator represents the deterministic change in slope of the EL schedule at the kink point from Equation (4). Each estimate should be interpreted as the effect of a \$100k increase in EL on the mean outcome over a post-treatment window. I also report the elasticity with respect to the EL, $\epsilon = \theta\frac{EL^{max}}{\bar{y_j}}$, where $\bar{y_j}$ is the mean outcome variable before the treatment, and EL^{max} is the maximum EL in the sample, e.g., \$676,000 in the baseline sample. Note that in the baseline sample, the average change in EL is \$26k with a standard deviation, which suggests 20 percent as the mean percentage change in EL. To side on caution, I report the results with respect to a 10 percent change in EL.

4.1 The Impact of Tax Credits on Firm-level Outcomes

SRED Expenditure. Table (4) presents the RK estimate results corresponding to Equation (3). Columns (1) to (3) report the estimates of the impact of tax credits on R&D expenditure across various post-treatment windows, controlling for lagged dependent variables and firm age. Column (4) includes additional controls for industry fixed effects, while Column (5) adds province fixed effects. The preferred specification is in Column (3), where I estimate a large and statistically significant impact on R&D expenditure. A \$100k increase in EL translates into an average \$5,976 increase (35 percent) in annual R&D expenditure. In elasticity terms, a 10 percent increase in EL leads to a 2.3 percent increase in annual R&D expenditure. Point estimates are stable across specifications. Table (4) also shows that the impact of eligibility on R&D expenditure increases over time. In Section 6, I discuss the price elasticity of R&D expenditure.

Extensive Margin vs. Intensive Margin. To differentiate between the impacts on the extensive margin and the intensive margin, I estimate the effects of R&D tax credits separately for R&D-intensive firms and non-R&D-intensive firms. To do so, I divide all the (treated and control) firms in the baseline sample based on their R&D intensity prior to the treatment. I label firms in the top 25 percentiles of R&D intensity distribution as *R&D-intensive*, and firms in the bottom 75 percentiles of R&D intensity distribution as *non-R&D-intensive*. I use two measures to define R&D intensity. The first measure, R&D expenditure scaled by revenue, is commonly used in the literature (Bøler, 2015; Griliches, 2007). For the second measure, I leverage detailed firm-level data, specifically the total wages and salaries paid to R&D workers. Using this variable, I define a novel measure of R&D intensity as R&D wages and salaries scaled by total payroll. Since I cannot distinguish R&D workers from non-R&D workers in my data, the share of wages and salaries that goes to R&D workers is a crude proxy of number of R&D workers at the firm.

If the extensive margin is significant, one would expect to see a substantial positive effect among non-R&D-intensive firms. The difference between the intensive margin and extensive margin also has important implications for between-firm wage inequality. R&D activity contributes to total factor productivity at the firm level. A small extensive margin means that new firms are unable or unwilling to increase their R&D expenditure even with access to tax credits, leading to a widening gap in between-firm productivity and wage inequality (Bøler, 2015; Song et al., 2019).

A key distinction between R&D tax credits and other government supports, such as loans and grants, is the take-up rate. Not all eligible firms take advantage of the policy, and this is important for several reasons. First, some firms may lack the inventive capacity—such as laboratory equipment, administrative expertise, or the knowledge base—to invest in R&D activities. For instance, Agrawal et al. (2020) find that firms with initial investments in R&D capital respond more strongly to R&D tax credits. Similarly, Dechezleprêtre et al. (2023) show that the impact of R&D tax credits is concentrated in firms with prior R&D expenditures, previous patents, or those in high-patenting industries. This suggests that firms with lower R&D fixed costs or R&D-intensive production functions are more likely to respond to tax credit eligibility. Second, unlike direct subsidies such as grants, tax credits do not create an immediate cash windfall. Eligible firms must first invest in R&D activities and then receive the refund or credit later. Additionally, and particularly relevant for SRED tax credits, firms must submit substantial evidence to support their R&D claims.[9] Indeed, I find significant heterogeneity in firms' responses to

[9] In an interview, Tobi Lütke, CEO of Shopify, remarked that firms must submit "an ungodly burden of documentation," which discourages R&D claims. Anecdotal evidence also suggests that smaller firms often outsource tax credit claims to consulting companies, which must be paid upfront, further reducing the potential tax credits accrued to firms.

eligibility for tax credits.

Table (**??**) presents the RK estimate results separately for R&D-intensive firms and non-R&D-intensive firms, based on two measures of R&D intensity prior to the treatment. Columns (1) and (5) show that R&D-intensive firms—those in the top 25 percentiles of R&D intensity—respond to R&D tax credits by increasing their R&D expenditures, while firms in the bottom 75th percentile do not. Columns (2) and (6) show that most of the impact stems from increases in R&D wages and salaries rather than changes in R&D capital, materials, or outsourcing contracts. Columns (3) and (7) show that the average wages at R&D-intensive firms increases significantly, whereas the change in average wages at other treated firms is small and statistically insignificant. In elasticity terms, a 10 percent increase in EL translate into 17 percent increase in annual average wage at firm level. Columns (4) and (8) reports the similar results where the outcome variable is log of average wages.

The concurrent increase in R&D expenditure and average wages aligns with the literature on the role of firms in wage inequality. Similarly, Aghion et al. (2017) find that R&D-intensive firms pay higher wages on average. Additionally, Van Reenen (1996) shows that innovative firms pay higher wages, driven by sharing in the rents generated by innovation.

Profitability and Growth. Table (6) presents the RK estimate results separately for R&D-intensive firms and non-R&D-intensive firms. Columns (1) and (4) show that R&D-intensive firms experience a large and statistically significant increase in profitability. While non-R&D-intensive firms also see a statistically significant increase in profitability (Column(1) only), the magnitude is much smaller than R&D-intensive firms. Columns (2) and (5) reveal that R&D-intensive firms also experience a large and statistically significant increase in their total factor productivity – which I describe its estimation in Appendix A.1. The results for non-R&D-intensive firms are much smaller than those of R&D-intensive firms but less precisely estimated. Finally, R&D-intensive firms experience a substantial increase in their size based on employment (Columns (3) and (7)) and revenue (Columns (4) and (8)) relative to non-R&D-intensive firms. Using the standard errors of estimates in Columns (3) and (4), the 95 percent confidence interval centered on zero excludes elasticities above 0.079 percent for employment, and 0.018 for revenue for non-R&D-intensive firms.

The evidence suggest that the increase in R&D expenditures leads to an increase in firm-level productivity and profitability which leads to increase in the average wage. This is consistent with the literature on productivity dispersion and wage inequality (Faggio et al., 2010), where the widening gap in between-firm productivity explains a substantial part of the wage inequality. But this finding is potentially driven by the change in worker composition, in particular, changes in the degree to which different groups of workers are assigned to different firms (Card et al., 2018). Next, I explore whether the increase in average wages is driven by changes in worker composition or changes in worker compensation.

Worker Composition. Table (7) presents the RK estimates for changes in worker composition separately for R&D-intensive firms and non-R&D-intensive firms. The results suggest that neither the share of female employees nor the share of high-skill workers, as defined in Section (3.3), shows a meaningful change. The findings on average age are less conclusive. While the signs of the estimates in Columns (2) and (7) are opposite, in both cases the impact is economically and statistically insignificant. Taken together, these results do not provide evidence of a change in worker composition.

Furthermore, I investigate whether the composition of entrant workers and movers changes after the treatment. Column (3) and (9) show that the entrant workers' average wage, a year prior to entry, at R&D-intensive firms is not statistically different than that of entrant workers at non-R&D intensive firms. Columns (4) and (9) show that the movers' average wage, a year prior to separation from R&D-intensive firms, is also not statistically different than that of movers from non-R&D-intensive firms. Despite the insignificance of estimates, the results on changes in worker composition, specially for entrants, is less than convincing since the coefficient estimates are quite large and comparable with estimated impact on average wages in Table (6).

Entry Rate and Separation Rate. The size and imprecision of the estimates may be due to (i) mean reversion, or (ii) the small number of entrants at the firms after the treatment. Mean reversion may be likely since the average earnings of entrants a year prior to the entry is significantly lower than average wage at the firm (16k vs. 46.9k). So, the large estimate might just capture the reversion of entrants wage to its mean. To address the lack of precision, following Carbonnier et al. (2022), I use the share of entrant and the share of movers as dependent variables in Table (8). Column (1) and (3) show that the share of entrants does not change for neither R&D-intensive nor non-R&D-intensive firms. On the other hand, the share workers separating from the firms decrease by 1.2 - 1.8 percent (5 - 8 percent). While the share of workers separating from non-R&D-intensive firms does not changes relative to the control group.

Motivated by the increase in R&D expenditure, total factor productivity, profitability, and average wages, and the decrease in turnover rate at the firm-level, the rest of the paper focuses on R&D-intensive firms to investigate how changes in R&D expenditures affect within-firm wage inequality.

4.2 Worker-Level Earnings and Job Transition

To control for potential changes in worker composition, I focus on incumbent workers with at least one year of tenure at their (R&D-intensive) firms.[10] Table (9) presents the RK estimate results corresponding to Equation (5)). Columns (1) to (3) report the estimates for the impact of tax credits on the log of average earnings of all incumbent workers across various post-treatment windows, with controls for the lagged dependent variable. Column (4) reports the estimates for the log of average earnings of incumbent workers during their time at the firm. On average, treated incumbent workers experience a 1.1 log point increase in earnings relative to control workers. In elasticity terms, a 10 percent increase in EL leads to a 0.7 percent increase in annual earnings. Point estimates are similar for stayers and across post-treatment windows. Column (5) reports the estimates for the log of average earnings of workers who move from the firms. These movers do not experience any change in their annual earnings relative to control workers. The results are consistent with the rent-sharing framework, where incumbent workers benefit from increased R&D expenditure at the firm level. In Section (5), I explore potential drivers behind the changes in incumbent workers' earnings.

4.3 Robustness and Internal Validity

I conduct several robustness checks to strengthen the internal validity of the results. First, I estimate the impact of tax credits on average R&D expenditure over a 5-year window after the treatment, using a wider range of bandwidths around the kink point. Figure (4) displays the coefficients and their 95 percent confidence intervals estimated from Equation (3). All coefficients are comparable in magnitude and significance to those in the baseline sample in Table (4). Second, in the baseline analysis, I use a level-level specification following Dechezleprêtre et al. (2023). Log transformation of R&D expenditure can attenuate the results towards zero for two reason: (i) the identification comes from the kinked relationship of lagged taxable income and the EL. The log transformation may artificially over-smooth the distribution of the outcome around the kink, hence, attenuate the results towards zero, and (ii) R&D expenditure has a right-skewed distribution –

[10] I report the results based on 'R&D expenditure scaled by revenue' as the measure of R&D intensity. The results are qualitatively and quantitatively similar with the second measure of intensity.

where for many observations R&D expenditure is zero. A log-linear specification may produce biased estimates (Agrawal et al., 2020). Table (**??**) reports the estimates for two alternative specification. Columns (1) to (3) uses a log transformation, log(R&D Exp +1), and Columns (4) to (6) uses inverse hyperbolic sine transformation, $asinh$(R&D Exp). In Columns (1) and (4), I control for lagged dependent variable and firm age. In Columns (2) and (5), I control for lagged dependent variable, firm age, and industry fixed effects. And in Columns (3) and (6), I control for lagged dependent variable, firm age, industry fixed effects, and province fixed effects. Reassuringly, the results in all specifications are still economically and statistically significant, although as expected, smaller than my baseline estimates in Table (4).

Third, I address the issue of potential functional dependence between the running variable and the outcome. In practice, the relationship between these variables could either exhibit a kink or follow a quadratic pattern. As a result, RKD estimates may capture this functional dependence between z_j and y_j rather than the actual effect of EL_j on y_j. To address this issue, I run a regression similar to Equation (3) for a wider selection placebo kink points. The placebo kink point selection ranges from -\$100k to \$100k with \$10k steps. Figure (5) shows the estimates for these regressions. The figures show that the relationship between the R&D expenditure and the EL quickly disappears as the placebo kink points get further from the true kink point. This suggest that the relationship between the running variable and the outcome is unlikely driven by their functional dependence.

5 Within-Firm Wage Inequality

Results so far show, on average, incumbent workers benefited from increased R&D expenditures induced by the tax credits. This section explores how the increase in R&D expenditures affects within-firm wage inequality. I investigate how the impact on workers varies across skills, tenure, within-firm wage distribution, and age.

5.1 Skill

A growing body of evidence shows significant heterogeneity in the pass-through of rents to workers (Kline et al., 2019; Saez et al., 2019; Carbonnier et al., 2022). Heterogeneous demand for skill can help us understand the resulting within-firm wage dynamics. For instance, Carbonnier et al. (2022) examine the impact of a policy aimed at firms with a higher proportion of low-wage workers and find a significant pass-through to high-skill incumbents, with no effect on the earnings of low-skill workers. Similarly, Kline et al. (2019) show that the grant of high-quality patents results in increased earnings for inventors and workers in the top 25 percentiles of a firm's wage distribution, arguing that less easily substitutable incumbents receive a higher wage premium. Additionally, Lindner et al. (2022) demonstrate that technological changes at the firm level lead to shifts in relative demand for skills and an associated skill premium. Conversely, Howell and Brown (2023), in their study of one-time cash flow shocks at small innovative firms, find no variation in earnings based on skill proxies such as initial wage or education.

A key limitation of this study, in contrast to works like Kline et al. (2019); Carbonnier et al. (2022), is the need for more data on workers' specific occupations, making it impossible to differentiate between R&D and non-R&D workers. To address this, I rely on proxies for worker skills and job complexity to analyze how increases in R&D expenditures affect earnings heterogeneity.

Workers Fixed Effects. How does an increase in firms' R&D expenditure impact workers' earnings based on their skill levels? I use worker fixed effects, as estimated in Section (3.3), to proxy for skill. Table (10) presents estimates for incumbent workers and stayers, distinguishing between high-skill and low-skill workers. The results show that low-skill workers experience no significant changes in either their annual earnings or retention rates. However, high-skill workers at treated firms see a 1.6 log points increase in annual earnings and a 0.7 percentage point rise in retention rate compared to control workers with similar skill levels. In terms of elasticity, a 10 percent increase in EL leads to a 1 percent rise in annual earnings and a 0.4 percent increase in the retention rate. These findings suggest that high-skill workers benefit most from increased firm rents, supporting the rent-sharing framework.

Within-Firm Earnings Distribution. Another way to approximate workers' skill is by using the within-firm earnings distribution, which serves as a rough indicator of job complexity and the worker's value to the firm. Table (11) provides estimates for incumbent workers and stayers, broken down by quartiles of the within-firm earnings distribution. The results show that workers in the bottom half of the distribution experience no significant changes in their annual earnings or retention rates. However, workers in the top half of the distribution at treated firms see a 1.6 to 1.7 log point increase in their annual earnings. In terms of elasticity, a 10 percent increase in EL results in a 1.1 percent increase in annual earnings.

5.2 General Experience and Firm-Specific Experience

Tenure. Returns to tenure arise for several reasons, including firm-specific human capital (Topel, 1991), hiring costs (Oi, 1962), implicit employee financing (Guiso et al., 2013; Howell and Brown, 2023), and rent-sharing (Card et al., 2014). Table (12) presents estimates for incumbent workers and stayers, separating high-tenure workers (those with more than 4 years at the firm) from low-tenure workers (those with 3 years or less). The results show no significant changes in the annual earnings of low-tenure workers, while high-tenure workers at treated firms experience a 1.8 to 2 log point increase in their annual earnings compared to control workers with similar tenure. In terms of elasticity, a 10 percent increase in EL leads to a 1.2 to 1.3 percent rise in annual earnings. Although low-tenure workers have a slightly higher retention rate than high-tenure workers, the difference is small and statistically insignificant.

Age. Prior studies have found that firm-level shocks can have varying effects on workers' earnings depending on their age (Saez et al., 2019). Table (13) reports the estimates for incumbent workers and stayers, broken down by different age groups. In contrast to Saez et al. (2019), I find that the largest impact is on workers in their 40s and 50s, with little to no effect on those under 40. In terms of elasticity, a 10 percent increase in EL leads to a 1.2 to 1.9 percent rise in annual earnings. These results align with the rent-sharing framework, suggesting that older workers (with more general knowledge) and high-tenure workers (with greater firm-specific knowledge) gain the most from an increase in firm rents—in this case, induced by R&D tax credits.

Overall, the results indicate that the rents generated by R&D tax credits at R&D-intensive firms disproportionately benefit high-skill workers—measured by worker fixed effects or within-firm earnings distribution—along with older workers and those with longer tenure at their firms. My results are complement to Bøler (2015); Lindner et al. (2022), in that, they show that innovation increases firms' relative demand for skill. However, I do not find evidence of change in worker composition at firm-level. This is consistent with theoretical framework of Caselli (1999) that show the adoption rate of new technologies depends on workers'skill (in my context R&D intensity). The difference in adoption rate predicts the increased wage dispersion between (and within) firms, as well as, increased productivity, but no change in sorting of workers among firms.

6 Tax-Adjusted Price Elasticity

To evaluate the tax credit, I calculate the implied R&D elasticity with respect to tax-adjusted user cost of R&D (Hall and Jorgenson, 1967; Dechezleprêtre et al., 2023; Agrawal et al., 2020). The elasticity is calculated by the following formula:

$$\eta_{R\&D,uc} = \frac{\Delta RD}{\Delta uc} \cdot \frac{\bar{uc}}{\bar{RD}}$$

By rearranging the right hand side, I have

$$\eta_{RD,uc} = \frac{\frac{\Delta RD}{\Delta EL}}{\frac{\Delta uc}{\Delta EL}} \cdot \frac{\bar{uc}}{\bar{RD}}$$

where $\frac{\Delta RD}{\Delta EL}$ is the change in R&D expenditure with respect to the EL, as estimated in Equation (3), $\frac{\Delta uc}{\Delta EL}$ is the change in tax-adjusted user cost of R&D with respect to the EL, $\bar{RD}$ is the average R&D expenditure, and $\bar{uc}$ is the average tax-adjusted user cost of R&D.

Change in tax-adjusted user cost with respect to the EL, $\frac{\Delta uc}{\Delta EL}$. I use Hall and Jorgenson (1967) formula for the steady-state tax-adjusted user cost of R&D:

$$uc = \frac{(1 - A^d - A^c)}{1 - \tau}(r + \delta)$$

where r is the real interest rate, δ is the depreciation rate, τ is corporate tax rate, and A^d is the present value of deductions and depreciation allowances, and A^c is the value of tax credits. In Canada, $A^d = \tau$, the corporate tax rate, because R&D expenditures (including the capital) are fully deductible. Moreover, $A^c = \rho(1 - \tau)$ because R&D tax credits are taxable income (Agrawal et al., 2020). ρ is the marginal credit rate. Therefore,

$$uc = (r + \delta)(1 - \rho)$$

The marginal credit rate varies across firms base on their tax liability, and R&D expenditure relative to EL. There are four possible scenarios:

1. $RD_t <= EL_t$: The marginal credit rate is 0.35 and the credit is refundable.
2. $RD_t > EL_t$ and $Tax_t > 0$ and $t \leq 2013$: The marginal credit rate is 0.20 and the credit offsets the taxes.

3. $RD_t > EL_t$ and $Tax_t > 0$ and $t \geq 2014$: The marginal credit rate is 0.15 and the credit offsets the taxes.

4. $RD_t > EL_t$ and $Tax_t <= 0$: The marginal credit rate is 0.08 and the credit is refundable.[11]

For each scenario I calculate the tax-adjusted user cost of R&D and its change relative to EL, $\frac{\Delta uc}{\Delta EL}$, then calculate the average value for tax-adjusted user cost of R&D, $\bar{uc}$, for the analysis sample based on their tax liability, R&D expenditure relative to the EL. 0.15*0.25+0.2*0.35

$RD_t <= EL_t$:

$$uc = (r + \delta)(1 - 0.35) = 0.65(r + \delta)$$

In this case a change in EL (i.e. an increase in the EL) does not change the marginal credit rate. $\frac{\Delta uc}{\Delta EL} = 0$.

$RD_t > EL_t$ **and** $Tax_t > 0$ **and** $t \leq 2013$:

$$uc = (r + \delta)(1 - 0.20) = 0.80(r + \delta)$$

In this case a change in EL (i.e. an increase in the EL), $\frac{\Delta uc}{\Delta EL}$, is equal to $-0.15(r + \delta)$.

$RD_t > EL_t$ **and** $Tax_t > 0$ **and** $t \geq 2014$:

$$uc = (r + \delta)(1 - 0.20) = 0.85(r + \delta)$$

In this case a change in EL (i.e. an increase in the EL), $\frac{\Delta uc}{\Delta EL}$, is equal to $-0.20(r + \delta)$.

The average tax-adjusted user cost of R&D ,$\bar{uc}$ is then as follows:

$$uc = \{\text{PR}(RD_t <= EL_t)\times 0.65 + \text{PR}(RD_t > EL_t, t \geq 2014)\times 0.8 + \text{PR}(RD_t > EL_t, t < 2013)\times 0.85\}(r+\delta)$$

In the baseline sample, I have $\text{PR}(RD_t <= EL_t) = 0.40$, $\text{PR}(RD_t > EL_t, t \geq 2014) = 0.35$, and $\text{PR}(RD_t > EL_t, t < 2013) = 0.25$. So, the average tax-adjusted user cost of R&D is

$$\bar{uc} = (0.65 \times 0.4 + 0.8 \times 0.35 + 0.25 \times 0.85)(r + \delta) = 0.7525(r + \delta)$$

[11]This case is unlikely in my sample analysis since all firms have positive taxable income, so I exclude this scenario for the rest of the calculations. As discussed by Agrawal et al. (2020), in this case the credit can be carried forward to future years and are "somewhat more valuable". They also discuss the 8 percent marginal credit rate in more detail.

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Now, the elasticity of R&D expenditure with respect to tax-adjusted user of R&D equals:

$$\eta_{R\&D,uc} = \frac{\frac{\Delta RD}{\Delta EL}}{\frac{\Delta uc}{\Delta EL}} . \frac{\bar{RD}}{\bar{uc}} = \frac{\hat{\theta} \times 0.7525(r+\delta)}{-0.1075(r+\delta) \times \bar{RD}}$$

Using the baseline estimates and average R&D expenditure from Table (4), I compute $\eta_{R\&D,uc} = 2.50$. This elasticity suggests a significant crowd-in effect of R&D tax credits. Since the extensive margin is small in the baseline sample, if I focus on R&D-intensive firms, assuming similar distribution around the EL, the implied elasticity is 0.36 which suggests the tax credit might be subsidizing firms that would have invested in R&D even in the absence of the tax credits.

7 Conclusion

This paper contributes to the understanding of how R&D tax credits influence wage inequality among innovative firms. The findings demonstrate that while R&D tax credits increase R&D expenditures, productivity, and wages, they also exacerbate wage inequality both between and within firms. Between-firm wage inequality is driven by the stronger response of R&D-intensive firms to the tax credits, allowing these firms to widen the productivity and wage premium gap over less R&D-intensive firms. Within-firm wage inequality is amplified by rent-sharing mechanisms, where high-skill, long-tenured, and older workers capture most of the wage gains, while low-skill workers experience little to no benefit.

Future research can build on these results by using the kinked relationship between lagged taxable income and the EL as an instrumental variable to directly evaluate the impact of changes in R&D expenditure on within- and between-firm wage inequality (Bøler, 2015). This approach could provide more causal insights into the link between innovation policies and wage dynamics.

Moreover, the role of R&D in developing firms' absorptive capacity—where firms increase productivity without necessarily increasing innovative output—has received limited attention in the literature. This paper provides suggestive evidence that R&D expenditure enhances absorptive capacity, enabling firms to boost productivity by improving their ability to leverage external knowledge. Further research leveraging firm-level data could explore within-country knowledge flows and productivity patterns, similar to cross-country analyses by Griffith et al. (2004).

Similar to findings by Faggio et al. (2010), the tax credits in this study lead to an increase in total factor productivity (TFP) dispersion, suggesting that technological differences across firms may be driving the observed wage and productivity disparities. Faggio et al. (2010) also highlights that the majority of the growth in wage and productivity dispersion occurs within industries, implying that industry-level data alone may not capture the underlying causes of these changes. This underscores the importance of firm-level analyses in understanding the impact of new technologies and R&D activities on wage inequality.

The study emphasizes the need for policymakers to consider the heterogeneous effects of innovation policies like R&D tax credits. While these policies successfully stimulate innovation and economic growth, they also have unintended consequences on wage inequality, disproportionately benefiting workers at the top of the wage distribution. Addressing these disparities may require complementary policies that specifically target low-skill workers or less R&D-intensive firms, ensuring that the benefits of innovation are more equitably distributed.

Future work could also examine additional mechanisms, such as worker mobility or the role of complementarities between firm-level and worker-level characteristics, to deepen our understanding of how innovation policies shape labor market outcomes. Expanding the analysis to other countries or tax regimes would provide valuable insights into the generalizability of these findings across different economic contexts.

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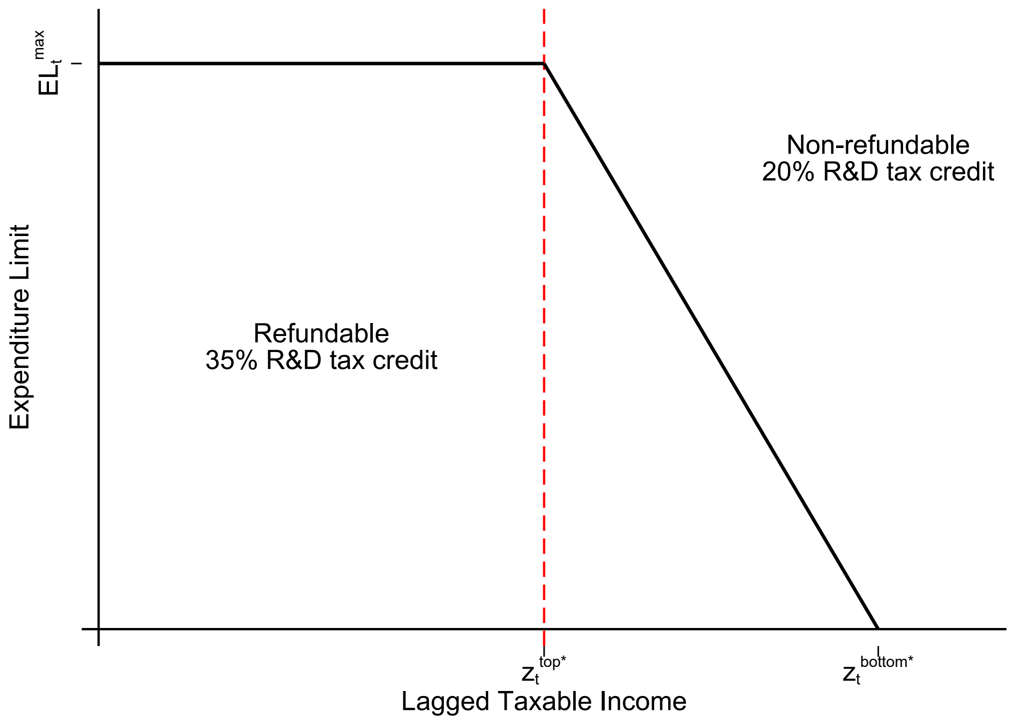
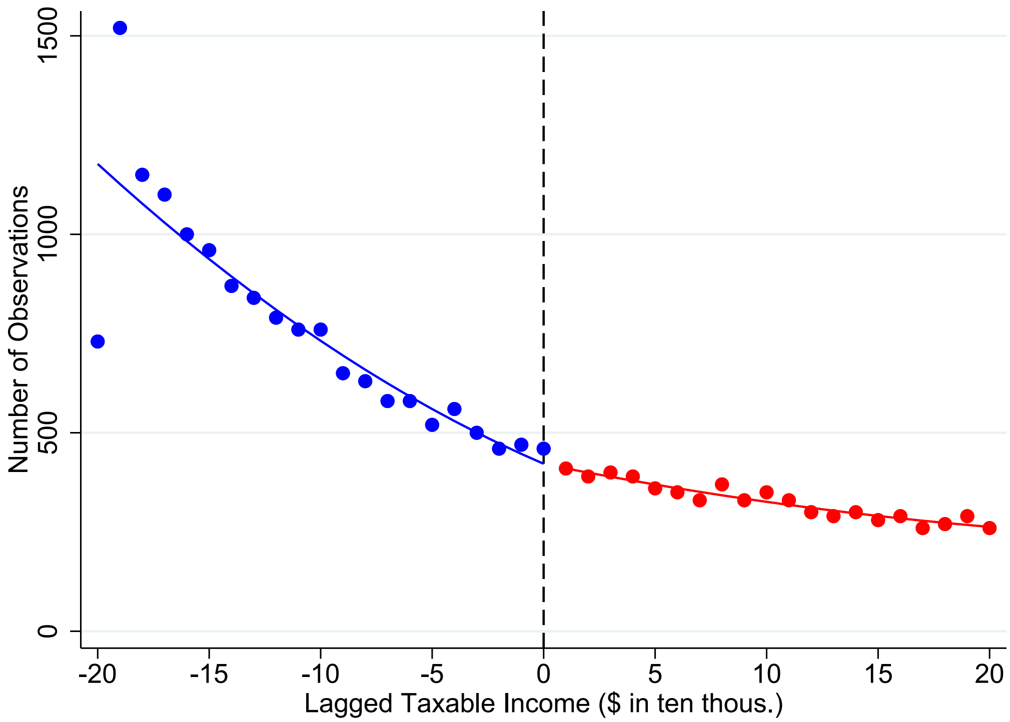
Figure 1: Expenditure Limit Schedule



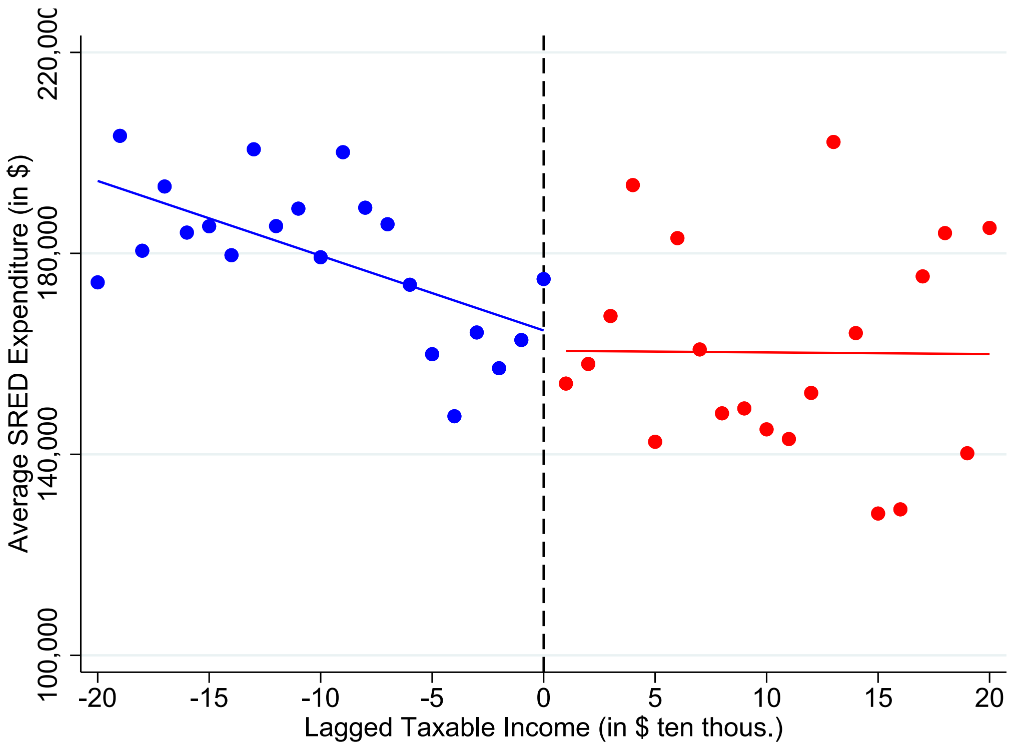
Notes: This graph shows the general SRED tax credit schedule. All CCPC firms are eligible for 35 percent refundable tax credits up to a threshold called Expenditure Limit – the black solid line – which is a function of lagged taxable income. If a firm's R&D expenditure exceed the Expenditure Limit, its marginal tax credit rate drops to 20 percent and the tax credits will be nonrefundable. EL_t^{max} is maximum expenditure limit, z_t^{top*} is start of phase-out threshold, and $z_t^{bottom*}$. is end of phase-out threshold.

Figure 2: McCrary Test For Manipulation at the Kink



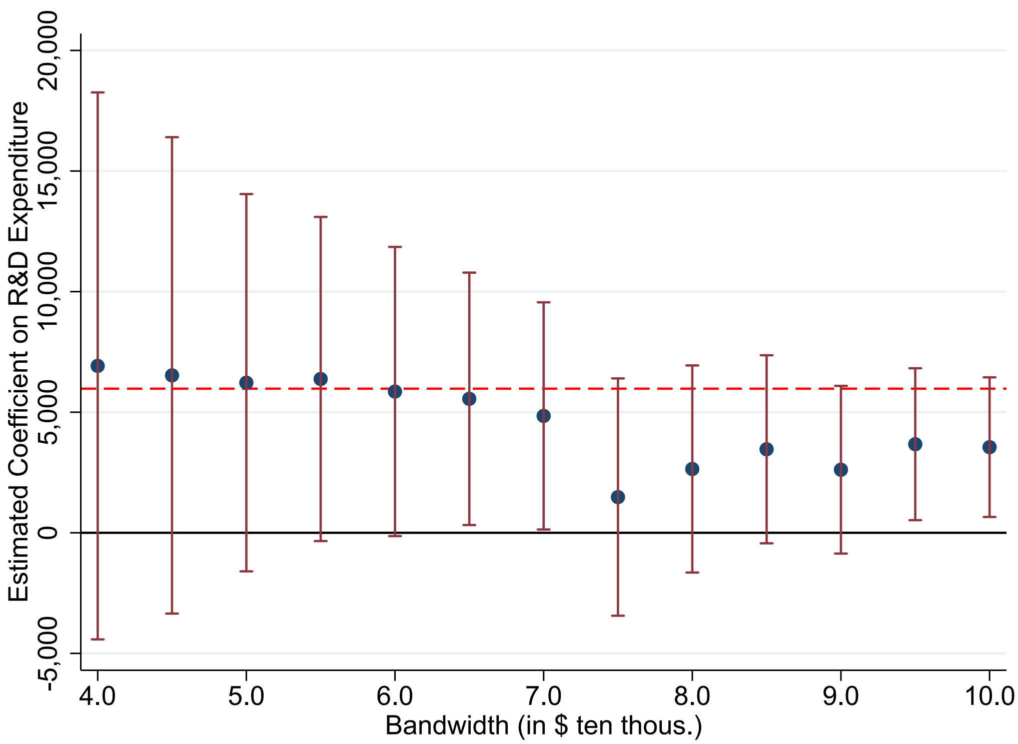
Notes: This figure reports the McCrary test for discontinuity in distribution of lagged taxable income at the normalized kink point. Estimation sample includes CCPC firms with lagged taxable income within $200k of the kink point. Section 3 describe the sample selection criteria.

Figure 3: Kink in Average SRED Expenditure



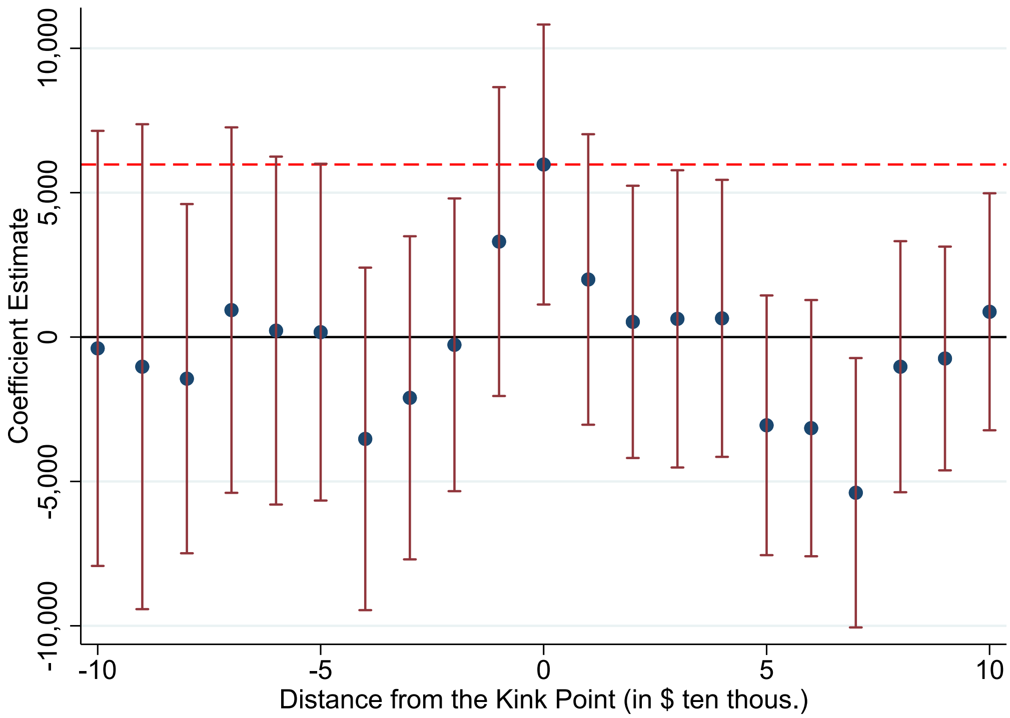
Notes: This figure reports the average R&D expenditure for firms within each $10k bins around the kink point. I pooled the data from all kink across 2002-2019 period. Section 3 describe the sample selection criteria.

Figure 4: Tax Credits Impact by Bandwidth



Notes: This figures plots the regression kink estimates corresponding to Equation (3) using a wider selection of bandwidth around the kink point. The outcome variable is R&D expenditure. The bandwidth selection is ranging from $40k to $100k with $5k steps. The red dash line shows the baseline estimate based on $67,600 bandwidth, which suggested by Calonico et al. (2014)' method.

Figure 5: Placebo Kink Point



Notes: This figures plots the regression kink estimates corresponding to Equation (3) for a wide selection of placebo kink points. The placebo kink point selection is ranging from -$100k to $100k with $10k steps. The true kink point is at 0 after normalization. The red dash line shows the baseline estimate for this kink point. The figure show that the relationship between R&D expenditure and the EL (and lagged taxable income) quickly disappears as the placebo kink point gets further from 0.

Table 1: Smoothness Assumption Test

	(1)	(2)	(3)	(4)
Dependent Variable	R&D Exp.	R&D Wages	Employment	Wage
Eligible $\times$ Z	-1108.618	179.385	0.115	-228.105
	(2030.544)	(1264.877)	(0.191)	(212.674)
Adj. R squared	0.812	0.818	0.976	0.655
Observations	4,880	4,880	4,870	4,870

Notes: This table reports the regression kink estimates corresponding to Equation (3) .The running variable is lagged taxable income a year before the treatment. Baseline sample controls include firm age and lagged dependent variable (i.e. covariates at $t = -2$). Columns (1) to (4) report the pre-treatment covariates test for R&D expenditure, and R&D wages, employment, and average wage, respectively. Standard errors are clustered at the firm-level.

Table 2: Descriptive Statistics on Firms

	All Firms		R&D-Intensive Firms	
	Treated	Control	Treated	Control
Firm Characteristics				
R&D Exp ('000)	167.4	164.8	453.5	493.4
R&D Wages/Total Payroll	0.07	0.06	0.20	0.19
Employment	52.2	56.0	39.2	41.7
Investment ('000)	149.9	162.9	116.9	127.8
Average Wage ('000)	47.6	47.3	53.5	51.4
Profit Margins	0.12	0.13	0.15	0.16
Leverage	0.54	0.52	0.54	0.48
Retained Earnings/Total Assets	0.42	0.44	0.41	0.47
Firm Age	15.5	16.1	12.9	13.5
Number of Firms	2,960	2,250	740	520
Sectors				
Utility/Mining	0.01	0.01	0.01	0.01
Construction	0.05	0.06	0.03	0.03
Manufacturing	0.53	0.52	0.47	0.49
Wholesale Trade	0.11	0.11	0.06	0.06
Transportation	0.01	0.01	0.01	0.00
Information	0.02	0.02	0.05	0.03
Services	0.12	0.12	0.27	0.28
Other	0.14	0.14	0.10	0.10

Notes:This table reports descriptive statistics on the firm sample, measured one year prior to the treatment. Panel A reports firm characteristics such as R&D expenditure, share of R&D wages out of total payroll, employment, investment, average wages, leverage ratio, retained earnings scaled by total assets, and firm age. Columns (1) and (3) report these statistics, respectively, for all treated firms and for treated R&D-intensive firms, based on R&D expenditure scaled by revenue. See section 4 for more details. Column (2) and (4) report these statistics for their respective control firms. Panel B reports the distribution of firms in the matched sample across 2-digit NAICS sectors. Other sectors include (1) Agriculture, forestry, and fishing, (2) Real estate and rental and leasing, (3) Arts, entertainment and recreation, (4) Accommodation and food services, (5) retail trades, (6) Other services, and (9) Public administration.

Table 3: Descriptive Statistics on Workers

	All Firms		R&D Intensive Firms	
	Treated	Control	Treated	Control
Worker Characteristics				
Earnings ('000)	43.5	45.1	46.9	48.6
Age	39.2	39.3	37.8	38.3
Female	0.29	0.29	0.30	0.29
Tenure	3.82	3.87	3.20	3.02
Number of Workers	92,750	80,110	17,410	11,830
Sectors				
Utility/Mining	0.01	0.01	0.01	0.01
Construction	0.05	0.06	0.03	0.03
Manufacturing	0.63	0.59	0.55	0.55
Wholesale Trade	0.08	0.07	0.04	0.03
Transportation	0.02	0.01	0.01	0.01
Information	0.02	0.01	0.04	0.02
Services	0.11	0.15	0.22	0.26
Other	0.08	0.10	0.08	0.09

Notes:This table reports descriptive statistics on the worker sample, measured one year prior to the treatment. Panel A reports worker characteristics such as worker earnings, age, gender, and tenure at the firm. Columns (1) and (3) report these statistics, respectively, for workers at all treated firms and for workers at treated R&D-intensive firms, based on R&D expenditure scaled by revenue. See section 4 for more details. Column (2) and (4) report these statistics for their respective control workers. Panel B reports the distribution of firms in the matched sample across 2-digit NAICS sectors. Other sectors include (1) Agriculture, forestry, and fishing, (2) Real estate and rental and leasing, (3) Arts, entertainment and recreation, (4) Accommodation and food services, (5) retail trades, (6) Other services, and (9) Public administration.

Table 4: Tax Credits Impact on R&D Expenditure

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	R&D Expenditure				
Window:	3 Years	4 Years	5 Years	5 Years	5 Years
Eligible × Z	5428.6**	5704.0**	5975.5**	6162.0**	6100.2**
	(2362.4)	(2413.5)	(2473.9)	(2533.8)	(2520.1)
Mean at t = -1	167436.5	167436.5	167436.5	167664.5	167664.5
Adj. R squared	0.670	0.642	0.620	0.632	0.632
Observations	5,200	5,200	5,200	5,160	5,160

Notes: This table reports the regression kink estimates of the average treatment effect $\hat{\theta} = \frac{\hat{\gamma_1}}{10}$ where $\hat{\gamma_1}$ is the estimated change in slope in the relationship between the outcome variables and the running variable at the kink point from Equation 3. Baseline sample includes R&D firms with lagged taxable income within $67,600 of the kink. The running variable is the lagged taxable income. In Columns (1) to (3) controls include (i) lagged dependent variable, and (ii) firm age. In Column (4), controls include (i) lagged dependent variable, (ii) firm age, and (iii) industry fixed effects. In Column (5), controls include (i) lagged dependent variable, (ii) firm age, (iii) industry fixed effects, and (iv) province fixed effects. Standard errors are clustered by firm.

Table 5: R&D Expenditures and Wages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Measure of Intensity:	R&D Exp. Scaled by Revenue				R&D Wages Scaled by Total Payroll			
Dependent Variable:	R&D Exp.	R&D Wages	Wages	log(Wages)	R&D Exp.	R&D Wages	Wages	log(Wages)
Eligible × Z (R&D-Int. = 1)	24424.3***	18489.9***	1367.4***	0.016***	20184.5**	16488.1***	1186.1***	0.016***
	(8860.0)	(5750.9)	(422.9)	(0.006)	(8266.6)	(5583.7)	(437.4)	(0.006)
Eligible × Z (R&D-Int. = 0)	629.5	916.3	-233.0	-0.004	1488.4	871.7	-263.0	-0.004
	(1705.6)	(1112.3)	(213.8)	(0.013)	(1807.2)	(1115.0)	(210.8)	(0.003)
Difference:	23943.0***	17663.6***	1692.7***	0.020***	19001.5**	15860.5***	1458.6***	0.020***
	(8959.5)	(5860.9)	(461.9)	(0.006)	(8482.8)	(5735.9)	(474.8)	(0.006)
Mean at t = -1 (R&D-Int. = 1)	474536.3	292138.8	54734.8	10.79	442493.7	291083.9	52893.3	10.76
Mean at t = -1 (R&D-Int. = 0)	71548.0	47611.5	46572.5	10.64	77410.6	44560.6	46302.1	10.63
Adj. R squared (R&D-Int. = 1)	0.504	0.507	0.687	0.807	0.536	0.507	0.678	0.791
Adj. R squared (R&D-Int. = 0)	0.438	0.397	0.690	0.826	0.457	0.445	0.704	0.838
Observations (R&D-Int. = 1)	1,260	1,260	1,240	1,240	1,300	1,300	1,290	1,290
Observations (R&D-Int. = 0)	3,770	3,770	3,740	3,740	3,900	3,900	3,870	3,870

Notes: This table reports the regression kink estimates of the average treatment effect $\hat{\theta} = \frac{\hat{\gamma_1}}{10}$ where $\hat{\gamma_1}$ is the estimated change in slope in the relationship between the outcome variables and the running variable at the kink point from Equation 3, separately by R&D intensity measure. R&D-intensive firms include R&D firms in the top 25 percentiles of distribution, and non-R&D-intensive firms include R&D firms in bottom 75th percentile. Baseline sample includes R&D firms with lagged taxable income within $67,600 of the kink. The running variable is the lagged taxable income. Controls include (i) lagged dependent variable, and (ii) firm age. Standard errors are clustered by firm.

Table 6: Growth and Profitability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Measure of Intensity:	R&D Exp. Scaled by Revenue				R&D Wages Scaled by Total Payroll			
	Profit Margins	TFP	log(Revenue)	log(Employment)	Profit Margins	TFP	log(Revenue)	log(Employment)
Eligible × Z (R&D-Int. = 1)	0.024*	0.084*	0.039	0.013	0.031**	0.080*	0.050**	0.011
	(0.013)	(0.049)	(0.026)	(0.012)	(0.014)	(0.044)	(0.025)	(0.011)
Eligible × Z (R&D-Int. = 0)	0.009*	0.021	0.005	0.001	0.006	0.020	0.002	0.002
	(0.005)	(0.024)	(0.011)	(0.006)	(0.005)	(0.025)	(0.011)	(0.006)
Difference:	0.015	0.067	0.036	0.012	0.025*	0.065	0.046	0.009
	(0.014)	(0.056)	(0.028)	(0.013)	(0.015)	(0.051)	(0.028)	(0.013)
Mean at t = -1 (R&D-Int. = 1)	0.16	2.92	15.27	3.33	0.15	2.75	1539	3.22
Mean at t = -1 (R&D-Int. = 0)	0.15	2.09	159.93	3.73	0.16	2.13	15.89	3.74
Adj. R squared (R&D-Int. = 1)	0.046	0.769	0.438	0.779	0.018	0.782	0.449	0.771
Adj. R squared (R&D-Int. = 0)	0.004	0.844	0.641	0.825	0.031	0.840	0.637	0.830
Observations (R&D-Int. = 1)	1,250	1,080	1,250	1,240	1,280	1,150	1,280	1,290
Observations (R&D-Int. = 0)	3,760	3,330	3,750	3,740	3,730	3,260	3,720	3,870

Notes: This table reports the regression kink estimates of the average treatment effect $\hat{\theta} = \frac{\hat{\gamma_1}}{10}$ where $\hat{\gamma_1}$ is the estimated change in slope in the relationship between the outcome variables and the running variable at the kink point from Equation 3, separately by R&D intensity measure. R&D-intensive firms include R&D firms in the top 25 percentiles of distribution, and non-R&D-intensive firms include R&D firms in bottom 75th percentile. Baseline sample includes R&D firms with lagged taxable income within $67,600 of the kink. The running variable is the lagged taxable income. Controls include (i) lagged dependent variable, and (ii) firm age. Standard errors are clustered by firm.

Table 7: Worker Composition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Measure of Intensity:	R&D Exp. Scaled by Revenue					R&D Wages Scaled by Total Payroll				
	Share Female	Average Age	log(Wage) Entrants before Joining	log(Wage) Movers before leaving	Share High-Skill	Share Female	Average Age	Share High-Skill	log(Wage) Entrants before Joining	log(Wages) Movers before leaving
Eligible × Z (R&D-Int. = 1)	0.004**	-0.012	0.014	0.009	0.001	0.003	0.044	0.013	0.010	0.001
	(0.002)	(0.070)	(0.016)	(0.014)	(0.003)	(0.002)	(0.070)	(0.015)	(0.013)	(0.003)
Eligible × Z (R&D-Int. = 0)	0.001	-0.002	-0.006	-0.004	-0.000	0.001	-0.016	-0.007	-0.005	-0.000
	(0.001)	(0.039)	(0.007)	(0.007)	(0.001)	(0.001)	(0.040)	(0.007)	(0.007)	(0.001)
Difference:	0.004*	-0.007	0.020	0.011	0.001	0.002	0.063	0.021	0.013	0.001
	(0.002)	(0.079)	(0.018)	(0.016)	(0.003)	(0.002)	(0.081)	(0.017)	(0.015)	(0.003)
Mean at t = -1 (R&D-Int. = 1)	0.28	37.94	10.03	10.19	0.38	0.29	38.06	10	10.15	0.37
Mean at t = -1 (R&D-Int. = 0)	0.28	39.27	9.93	10.1	0.32	0.28	39.15	9.93	10.1	0.32
Adj. R squared (R&D-Int. = 1)	0.87	0.755	0.148	0.299	0.729	0.858	0.756	0.147	0.297	0.723
Adj. R squared (R&D-Int. = 0)	0.907	0.784	0.286	0.0380	0.751	0.905	0.784	0.283	0.39	0.749
Observation (R&D-Int. = 1)	1,240	1,240	1,040	980	1,240	1,286	1,286	1,090	1,010	1,290
Observation (R&D-Int. = 0)	3,736	3,736	3,360	3,140	3,740	3,867	3,867	3,450	3,240	3,870

Notes: This table reports the regression kink estimates of the average treatment effect $\hat{\theta} = \frac{\hat{\gamma_1}}{10}$ where $\hat{\gamma}_1$ is the estimated change in slope in the relationship between the outcome variables and the running variable at the kink point from Equation 3, separately by R&D intensity measure. R&D-intensive firms include R&D firms in the top 25 percentiles of distribution, and non-R&D-intensive firms include R&D firms in bottom 75th percentile. Baseline sample includes R&D firms with lagged taxable income within $67,600 of the kink. The running variable is the lagged taxable income. Controls include (i) lagged dependent variable, and (ii) firm age. Standard errors are clustered by firm.

Table 8: Entry and Separation

	(1)	(2)	(3)	(4)
Measure of Intensity:	R&D Exp. Scaled by Revenue		R&D Wages Scaled by Total Payroll	
	Share of Entrants	Share of Movers	Share of Entrants	Share of Movers
Eligible × Z (R&D-Int. = 1)	0.000	-0.012*	-0.002	-0.018***
	(0.003)	(0.007)	(0.003)	(0.007)
Eligible × Z (R&D-Int. = 0)	0.002	-0.005	0.002	-0.003
	(0.002)	(0.004)	(0.002)	(0.004)
Difference:	-0.002	-0.008	-0.004	-0.016**
	(0.003)	(0.008)	(0.003)	(0.008)
Mean at t = -1 (R&D-Int. = 1)	0.25	0.22	0.26	0.22
Mean at t = -1 (R&D-Int. = 0)	0.25	0.25	0.25	0.25
Adj. R squared (R&D-Int. = 1)	0.148	0.052	0.219	0.052
Adj. R squared (R&D-Int. = 0)	0.238	0.117	0.219	0.123
Observations (R&D-Int. = 1)	1,240	1,240	1,290	1,290
Observations (R&D-Int. = 0)	3,740	3,740	3,870	3,870

Notes: This table reports the regression kink estimates of the average treatment effect $\hat{\theta} = \frac{\hat{\gamma_1}}{10}$ where $\hat{\gamma_1}$ is the estimated change in slope in the relationship between the outcome variables and the running variable at the kink point from Equation 3, separately by R&D intensity measure. R&D-intensive firms include R&D firms in the top 25 percentiles of distribution, and non-R&D-intensive firms include R&D firms in bottom 75th percentile. Baseline sample includes R&D firms with lagged taxable income within $67,600 of the kink. The running variable is the lagged taxable income. Controls include (i) lagged dependent variable, and (ii) firm age. Standard errors are clustered by firm.

Table 9: Tax Credits Impact on Earnings

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Log(Earnings)				
Sample:	All Workers			Stayers	Movers
Window:	3 Years	4 Years	5 Years		5 Years
Eligible × Z	0.011***	0.012***	0.011**	0.009**	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
Mean at t = -1	10.36	10.36	10.36	10.36	10.14
Adj. R squared	0.459	0.426	0.395	0.558	0.268
Observations	29,230	29,230	29,230	29,230	17,060

Notes: This table reports the regression kink estimates of the average treatment effect $\hat{\theta} = \frac{\hat{\gamma_1}}{10}$ where $\hat{\gamma_1}$ is the estimated change in slope in the relationship between the outcome variables and the running variable at the kink point from Equation 5, for worker at R&D-intensive firms. Baseline sample includes workers with at one year of tenure at the firm. I drop workers with multiple jobs. The running variable is the lagged taxable income. Controls include (i) lagged dependent variable. Standard errors are clustered by worker.

Table 10: Heterogeneity based on AKM Worker Fixed Effects

	(1)	(2)	(3)
Dependent Variable:	log(Earnings)		Retention
Sample:	All	Stayers	All
Eligible × Z (High Skill)	0.016***	0.011**	0.007***
	(0.005)	(0.004)	(0.002)
Eligible × Z (Low Skill)	0.000	0.002	-0.003
	(0.006)	(0.005)	(0.002)
Difference	0.017**	0.009	0.009***
	(0.008)	(0.007)	(0.002)
Mean at t = -1 (High Skill)	10.9	10.9	1
Mean at t = -1 (Low Skill)	10.03	10.03	1
Adj. R squared (High Skill)	0.388	0.543	0.003
Adj. R squared (Low Skill)	0.261	0.427	0.002
Observations (High Skill)	10,750	10,750	10,750
Observations (Low Skill)	16,820	16,820	16,820

Notes: This table reports the regression kink estimates of the average treatment effect $\hat{\theta} = \frac{\hat{\gamma_1}}{10}$ where $\hat{\gamma_1}$ is the estimated change in slope in the relationship between the outcome variables and the running variable at the kink point from Equation 5, for worker at R&D-intensive firms. Baseline sample includes workers with at one year of tenure at the firm. I drop workers with multiple jobs. The running variable is the lagged taxable income. Controls include (i) lagged dependent variable. Standard errors are clustered by worker.

Table 11: Heterogeneity based on Within-Firm Earnings Distribution

	(1)	(2)	(3)
Dependent Variable:	log(Earnings)		Retention
Sample:	All	Stayers	All
Eligible × Z (4th Quartile)	0.016**	0.012***	0.006***
	(0.006)	(0.004)	(0.002)
Eligible × Z (3rd Quartile)	0.017**	0.014***	0.000
	(0.007)	(0.005)	(0.002)
Eligible × Z (2nd Quartile)	0.009	0.007	0.002
	(0.009)	(0.007)	(0.003)
Eligible × Z (1st Quartile)	-0.007	-0.007	-0.001
	(0.013)	(0.012)	(0.003)
Mean at t = -1 (4th Quartile)	11.04	11.04	1
Mean at t = -1 (3rd Quartile)	10.45	10.45	1
Mean at t = -1 (2nd Quartile)	10.05	10.05	1
Mean at t = -1 (1st Quartile)	9.43	9.43	1
Observations (4th Quartile)	8,595	8,595	8,595
Observations (3rd Quartile)	8,535	8,535	8,535
Observations (2nd Quartile)	7,255	7,255	7,255
Observations (1st Quartile)	4,850	4,845	4,850

Notes: This table reports the regression kink estimates of the average treatment effect $\hat{\theta} = \frac{\hat{\gamma_1}}{10}$ where $\hat{\gamma_1}$ is the estimated change in slope in the relationship between the outcome variables and the running variable at the kink point from Equation 5, for worker at R&D-intensive firms. Baseline sample includes workers with at one year of tenure at the firm. I drop workers with multiple jobs. The running variable is the lagged taxable income. Controls include (i) lagged dependent variable. Standard errors are clustered by worker.

Table 12: Heterogeneity based on Tenure

	(1)	(2)	(3)
Dependent Variable:	log(Earnings)		Retention
Sample:	All	Stayers	All
Eligible × Z (High Tenure)	0.018**	0.020***	0.001
	(0.008)	(0.006)	(0.002)
Eligible × Z (Low Tenure)	0.007	0.005	0.003*
	(0.005)	(0.004)	(0.001)
Difference:	0.018*	0.019***	-0.002
	(0.010)	(0.007)	(0.002)
Mean at t = -1 (High Tenure)	10.84	10.84	1
Mean at t = -1 (Low Tenure)	10.22	10.22	1
Adj. R squared (High Tenure)	0.495	0.624	0.001
Adj. R squared (Low Tenure)	0.355	0.522	0.002
Observations (High Tenure)	6,240	6,240	6,240
Observations (Low Tenure)	22,990	22,990	22,990

Notes: This table reports the regression kink estimates of the average treatment effect $\hat{\theta} = \frac{\hat{\gamma_1}}{10}$ where $\hat{\gamma_1}$ is the estimated change in slope in the relationship between the outcome variables and the running variable at the kink point from Equation 5, for worker at R&D-intensive firms. Baseline sample includes workers with at one year of tenure at the firm. I drop workers with multiple jobs. The running variable is the lagged taxable income. Controls include (i) lagged dependent variable. Standard errors are clustered by worker.

Table 13: Heterogeneity based on Worker Age

	(1)	(2)	(3)
Dependent Variable:	log(Earnings)		Retention
Sample:	All	Stayers	All
Eligible × Z (50s)	0.024**	0.029***	0.005*
	(0.012)	(0.008)	(0.003)
Eligible × Z (40s)	0.019**	0.012*	0.002
	(0.008)	(0.006)	(0.002)
Eligible × Z (30s)	-0.002	0.001	0.006**
	(0.008)	(0.006)	(0.002)
Eligible × Z (20s)	0.007	0.012*	-0.000
	(0.008)	(0.007)	(0.003)
Mean at t = -1 (50s)	10.62	10.62	1
Mean at t = -1 (40s)	10.62	10.62	1
Mean at t = -1 (30s)	10.54	10.54	1
Mean at t = -1 (20s)	10.08	10.08	1
Observations (50s)	4,300	4,300	4,300
Observations (40s)	7,230	7,230	7,230
Observations (30s)	7,930	7,930	7,930
Observations (20s)	7,130	7,130	7,130

Notes: This table reports the regression kink estimates of the average treatment effect $\hat{\theta} = \frac{\hat{\gamma_1}}{10}$ where $\hat{\gamma_1}$ is the estimated change in slope in the relationship between the outcome variables and the running variable at the kink point from Equation 5, for worker at R&D-intensive firms. Baseline sample includes workers with at one year of tenure at the firm. I drop workers with multiple jobs. The running variable is the lagged taxable income. Controls include (i) lagged dependent variable. Standard errors are clustered by worker.

Table 14: Tax Credits Impact on R&D Expenditure

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	log(R&D Exp. + 1)			asinh(R&D Exp.)		
Eligible × Z	0.092*	0.109*	0.111**	0.097*	0.115	0.118**
	(0.055)	(0.056)	(0.056)	(0.058)	(0.059)	(0.059)
Mean at t = -1	8.00	8.01	8.01	8.47	8.49	8.49
Adj. R squared	0.506	0.535	0.537	0.503	0.533	0.534
Observations	5,200	5,160	5,160	5,200	5,160	5,160

Notes: This table reports the regression kink estimates of the average treatment effect $\hat{\theta} = \frac{\hat{\gamma_1}}{10}$ where $\hat{\gamma_1}$ is the estimated change in slope in the relationship between the outcome variables and the running variable at the kink point from Equation 3. Baseline sample includes R&D firms with lagged taxable income within $67,600 of the kink. The running variable is the lagged taxable income. In Columns (1) to (3) controls include (i) lagged dependent variable, and (ii) firm age. In Column (4), controls include (i) lagged dependent variable, (ii) firm age, and (iii) industry fixed effects. In Column (5), controls include (i) lagged dependent variable, (ii) firm age, (iii) industry fixed effects, and (iv) province fixed effects. Standard errors are clustered by firm.

Appendix A: Estimating Total Factor Productivity

In this appendix, we provide details on the productivity estimation. To begin, we assume that total revenue of a firm is given by the following production function:

$$y_{jt} = \beta_0 + \beta_k k_{jt} + \beta_l l_{jt} + \omega_{jt} + \eta_{jt} \tag{7}$$

where y_{jt} is log total revenue, k_{jt} is log total capital, which we capture through the variable fixed assets, and l_{jt} is log total employment. The goal of the production function estimation for our purposes is to retrieve an estimate of $\hat{\omega}_{jt} = y_{jt} - \hat{\beta}_k k_{jt} - \hat{\beta}_l l_{jt}$ which captures the productivity of firm j at time t. To allow for different production functions across countries and industries, the estimation procedure is implemented separately for each four-digit NAICS code and country.

Estimating Equation (1) by linear regression would face well-known endogeneity issues, as η_{jt} is generally unobserved.

To circumvent this issue, we follow Ackerberg et al. (2015) and use a control function that allows us to control for unobserved productivity. To derive the control function, we assume the demand for materials is a function of both capital and labor. Modeling materials as a function of capital and labor and including labor as a state variable of the firm are the key distinctions between Ackerberg et al. (2015) and earlier approaches developed by Olley and Pakes (1992) and Levinsohn and Petrin (2003), which model labor as a completely variable input that does not appear as a state variable:

$$m_{jt} = m_t(k_{jt}, l_{jt}, \omega_{jt})$$

Under an invertibility condition, this allows us to invert the demand function to get productivity as a function of labor, capital, and materials:

$$\omega_{jt} = m_t^{-1}(k_{jt}, l_{jt}, m_{jt}) = h_t(k_{jt}, l_{jt}, m_{jt})$$

The estimation procedure proceeds in two stages. In stage one, we model revenue of a firm as:

$$y_{jt} = \beta_0 + \beta_k k_{jt} + \beta_l l_{jt} + h_t(k_{jt}, l_{jt}, m_{jt}) \tag{8}$$

Note that k_{jt} and l_{jt} appear both directly, as well as indirectly through h_t. Therefore, in the first stage, neither β_k nor β_l are identified. However, the function Φ_t can be estimated by approximating the nonparametric function with a polynomial in labor, capital, and materials.

$$\Phi_t(k_{jt}, l_{jt}, m_{jt}) = \beta_0 + \beta_k k_{jt} + \beta_l l_{jt} + \omega_{jt}$$

Additionally, we assume productivity follows an exogenous first-order Markov process:

$$\omega_{jt} = E(\omega_{jt}|\omega_{j,t-1}) + \xi_{jt} = g(\omega_{j,t-1}) + \xi_{jt} = g(\Phi_{t-1} - \beta_0 - \beta_l l_{j,t-1} - \beta_k k_{j,t-1})$$

Using the first-stage estimates, we can now rewrite revenue in time t as:

$$y_{jt} = \beta_0 + \beta_l l_{jt} + \beta_k k_{jt} + g_t(\hat{\Phi}_{t-1} - \beta_0 - \beta_l l_{j,t-1} - \beta_k k_{j,t-1}) + \xi_{jt} + \eta_{jt} \tag{9}$$

To estimate this equation requires an additional moment, as ξ_{jt} and l_{jt} are not orthogonal. A standard option is to assume lagged employment is orthogonal to the error term $\xi_{jt} + \eta_{jt}$. This implies the parameters β_l and β_k can be computed by a generalized methods of moments estimator:

$$E\left[(\xi_{jt} + \eta_{jt})\begin{pmatrix} k_{jt} \\ l_{j,t-1} \end{pmatrix}\right] = 0$$

which yields estimates for $\hat{\beta}_k$ and $\hat{\beta}_l$. The estimates of productivity ω_{jt} can then be retrieved as:

$$\hat{\omega}_{jt} = y_{jt} - \hat{\beta}_k k_{jt} - \hat{\beta}_l l_{jt}$$

Table A1: Evolution of Small Business Deduction Threshold and SRED Tax Credit Threshold

Year	SBD Limit	Top Kink	Bottom Kink
2001 - 2002	200	200	400
2003	225	200	400
2004	250	300	500
2005	300	300	500
2006 - 2007	300	400	600
2008	400	400	700
2009 - 2019	500	400	700

Notes: This table report the changes in Small Business Deduction threshold and it coincidence with the top kink and bottom kink of the tax credits schedule across the 2001-2019 period.