R&D Expenditures, Rents, and Wage Inequality: Evidence from an R&D Tax Credit

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Abstract

This paper examines the impact of R&D tax credits on firm-level and worker-level outcomes, using the Scientific Research and Experimental Development (SRED) tax credit in Canada. Leveraging a regression kink design and matched employer-employee tax records, I estimate a large and statistically significant increase on 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, surplus per worker, after-tax income per worker, and wages while non-R&D-intensive firms show minimal changes. These gains disproportionately benefit high-skill, older, and long-tenured workers, exacerbating wage inequality both between and within firms. High-skill workers experience the largest earnings gains, with a 10 percent increase in EL leading to a 1.6 percent rise in their earnings, while low-skill workers see no significant changes. These findings provide evidence of rent-sharing mechanisms and highlight the role of R&D tax credits in contributing to wage inequality. Robustness checks confirm the stability of the results across different model specifications.

JEL Classification: E24, J31, L25

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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 R&D tax credits, are designed to promote innovation. Understanding how these policies influence economic growth and labor dynamics in innovative firms is crucial for policy-making. Meanwhile, extensive empirical research demonstrates that firms contribute significantly to both between-firm and within-firm wage inequality (Card et al., 2014, 2018; Kline et al., 2019; Song et al., 2019; Saez et al., 2019; Carbonnier et al., 2022). R&D activities as a source of firm productivity heterogeneity (Griffith et al., 2004) – which drives higher-quality products, better innovation processes, and greater tacit knowledge among workers – can affect firm size distribution, wage premiums, and the sorting of skill groups across firms (Card et al., 2018). Therefore, government policies could help narrow the recent growing productivity gap within industries (Autor et al., 2020) and reduce wage inequality, or, if they fail to stimulate innovation in small and medium-sized firms, they could worsen wage inequality.

This papers studies the impacts of an R&D tax credits on firm-level outcomes, and how the tax-credit-induced shocks to firm performance affect the worker-level outcomes. I use the special design of a tax policy named Scientific Research and Experimental Develop (hereafter, 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. SRED is a two-tier tax credits which provides an investment tax credits at the general rate of 20 percent for all firms.[1] 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 (hereafter, EL) which is a function of eahc firm's lagged taxable income. I exploit the cross-sectional variation of firms' EL in a regression kink (RK) design to identify the impact of the tax credits.

I first examine the effects of the tax credits on firm-level R&D expenditures. I find that a \$100k increase in EL leads to an average \$5,976 annual increase in R&D expenditure. In elasticity terms, a 10 percent increase in EL translates into a 2.3 percent increase in annual R&D expenditures. R&D tax credits are designed to encourage innovation, but the effects on firms vary depending on their initial R&D intensity (Agrawal et al., 2020; Dechezleprêtre et al., 2023). Specifically, firms that are already R&D-intensive tend to respond more strongly, while firms with little prior R&D activity show limited changes.

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

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. Prior research has shown that a small response along the extensive margin can lead to increased gaps in productivity between firms (Czarnitzki and Delanote, 2015). Exploiting the detailed firm-level data, I define two measure of R&D intensity: (i) R&D expenditure scaled by revenue, and (ii) total amount of wages and salaries paid to R&D workers scaled by total payroll. Using either measure, I find significant heterogeneous response among firms based on their R&D intensity. The results demonstrate that firms in the top 25th percentile 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, these firms experience significant improvements in profitability, surplus per worker, and after-tax income per worker, while non-R&D-intensive firms show smaller or no changes in these metrics. I show that these results are not attributable to changes in worker composition, as the share of female employee, average age, and share of high-skill workers remains stable across firms. Rising R&D expenditures, surplus, and wages suggests tax credits exacerbates between-firm wage inequality through a larger takeup by R&D-intensive firms.

The regression kink (RK) design exploits the presence of a kinked schedule in the relationship between lagged taxable income (the running variable) and EL (the assignment variable) to identify the impact of a more generous tax credits. 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 (no-kink assumption) (Card et al., 2017). I provide graphical and empirical tests to show that the p.d.f of number 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.

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, 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. A way to control for this problem is to compare two groups of similar firms who have different EL schedules, so that the kinks occur at different points along the support of the running variable. Last, I perform a semi-parametric test inspired by the literature on detecting structural breakpoints in time series analysis, as outlined by Bai and Perron (2003). The test's core idea is to non-parametrically identify the location of the kink by searching for the point that minimizes the residual sum of squares, or equivalently, maximizes the R-squared value.

Given the evidence of rising R&D expenditures, surplus, and wages at R&D-intensive firms, I focus on how these developments contribute to within-firm wage inequality. To do so, I focus on the impact of R&D tax credits on incumbent workers at R&D-intensive firms. I show that treated workers experience a 1.1 log points increase in annual earnings, with a 10 percent increase in EL translating to a 0.7 percent rise in annual earnings. High-skill workers, measured through worker fixed effects or within-firm earnings distribution, benefit the most from increased R&D spending – with earning elasticities around 1.6 with respect to EL – while low-skill workers see no significant change. Additionally, high-tenure and older workers, especially those in their 40s and 50s, experience larger gains in earnings, with earning elasticities ranging from 1.2 to 1.9 percent with respect to EL. These findings align with the rent-sharing framework, where workers with more general and firm-specific knowledge capture a larger share of the rents induced by R&D expenditure. , and the paper explores how these findings contribute to within-firm wage inequality, particularly among high-skill, older, and long-tenured workers.

[700] This paper also contributes to a growing evidence in labor economics that study the role of firms in wage setting and wage inequality (Saez et al., 2019; Kline et al., 2019; Carbonnier et al., 2022; Howell and Brown, 2023). In this paper I contribute to the literature on firm-level drivers of wage inequality. I show that R&D expenditures exacerbate both between-firm and within-firm wage inequality. Heterogeneous ability of firms to benefit from R&D tax credits drives the between-firm wage inequality and rent sharing with high-skill, high-wage, and high-experience employees drives the within-firm wage inequality.

2 Institutional Background

The Scientific Research and Experimental Development (SR&ED) is the main federal tax incentive program to encourage all companies to conduct research and development in Canada. SR&ED is a two-tier tax credits which provides an investment tax credits on qualifying expenditure[2] 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 taxable income and prior-year taxable capital employed in Canada.[4] The function, in each year, 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:

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

where EL_{jt} is firm j's Expenditure Limit at year t, $TI_{j(t-1)}$ is lagged taxable income. Figure (1) illustrates this function. I exploit the kink in the relationship between the EL and lagged taxable income, which provides a credible exogenous variation in tax credits generosity, in my empirical design. Unlike Agrawal et al. (2020); Dechezleprêtre et al. (2023) that exploit 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).

As shown in Figure (1), there are two kink points in the relationship between lagged taxable income and the EL: Top kink at z_t^{top*} and the bottom 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

[2]To qualify for SR&ED tax incentive, the expenditures must meet the following two requirement: (i) The work must be conducted for the advancement of scientific knowledge or for the purpose of achieving a technological advancement, (ii) the work must be a systematic investigation or search that is carried out in a field of science or technology by means of experiment or analysis. The link provide more details.

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

[4]Since taxable capital is only relevant for a small share of firms in the analysis sample, I abstract it from my formulation. In appendix !!!, I show robustness results by considering the prior-year taxable capital

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

[100] 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 $z_j = 0$. [5]

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

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

where X_j is a set control variables such as lagged dependent variable, firm age, industry fixed effects, and province fixed effects.[6] 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

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

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 (no-kink assumption).

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.[7] 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

[6]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.”

[7]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.

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. The change in the first-order derivative is !!! (p-value = !!!) which 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 no-kink 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 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 two 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, hereinafter), 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 top 25 percentile of worker fixed effects distribution as *high skill*, and workers in the bottom 75 percentile 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.

[500] Comparison between incumbent and entrant at t=-1: The average incumbent workers' earnings is larger than average payroll at the firm the year before the treatment which suggests workers joining the firms the year before the treatment have lower earnings than the average incumbent in the sample.

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 !!! with a standard deviation, which suggests !!! percent as the mean percentage change in EL.

4.1 Firms Increase their SRED Expenditures

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 **??**, 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. 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.[8] Indeed, I find significant heterogeneity in firms' responses to eligibility for tax credits.

Table (5) 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. The first measure, R&D expenditure scaled by revenue, is commonly used in the literature (see, for instance, Bøler (2015)). For the second measure, I leverage detailed firm-level data, specifically the total amount of 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. Columns (1) and (4) show that R&D-intensive firms—those in the top 25th percentile 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 (5) reveal 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 (6) show that the average wage at R&D-intensive firms increases significantly, whereas the change in average wages at other treated firms is small and statistically insignificant. 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 Surplus. Table (**??**) 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.

[8] 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.

While non-R&D-intensive firms also see a statistically significant increase in profitability, the magnitude is smaller compared to R&D-intensive firms. Columns (2) and (5) reveal that R&D-intensive firms also experience a large and statistically significant increase in their surplus per worker, defined as the sum of EBITDA and total payroll, scaled by the number of workers, whereas non-R&D-intensive firms do not experience any change in their average surplus. Similarly, Columns (3) and (6) show R&D-intensive firms also experience a large and statistically significant increase in their after-tax-income per worker, whereas non-R&D-intensive firms do not experience any change in their average after-tax-income per worker. Comparing the estimates from Table (5) and (**??**), I find a pass-through of tax-credit-induced surplus of !!!.

Worker Composition. The increase in average wages may be driven by changes in worker composition rather than changes in worker compensation. Table (6) 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 (5) 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.

Motivated by the concurrent increase in R&D expenditure, surplus per worker, and average wages, 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 changes in worker composition, I focus on incumbent workers with at least one year of tenure at their (R&D-intensive) firms. Table (7) 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 their original firm. On average, treated incumbent workers experience a 1.1 percentage 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, 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. A way to control for this problem is to compare two groups of similar firms who have different EL schedules, so that the kinks occur at different points along the support of the running variable. Assuming that the functional dependence between y and w_1 is consistent across the two groups, the average treatment effect can be identified and estimated using a "double-difference regression kink design." (Landais, 2015). [To Be Included !!!]

Lastly, I perform a semi-parametric test inspired by the literature on detecting structural breakpoints in time series analysis, as outlined by Bai and Perron (2003). The test's core idea is to non-parametrically identify the location of the kink by searching for the point that minimizes the residual sum of squares, or equivalently, maximizes the R-squared value. [To Be Included !!!]

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 25th percentile 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 lack of 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 (8) 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 point 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 (9) 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.

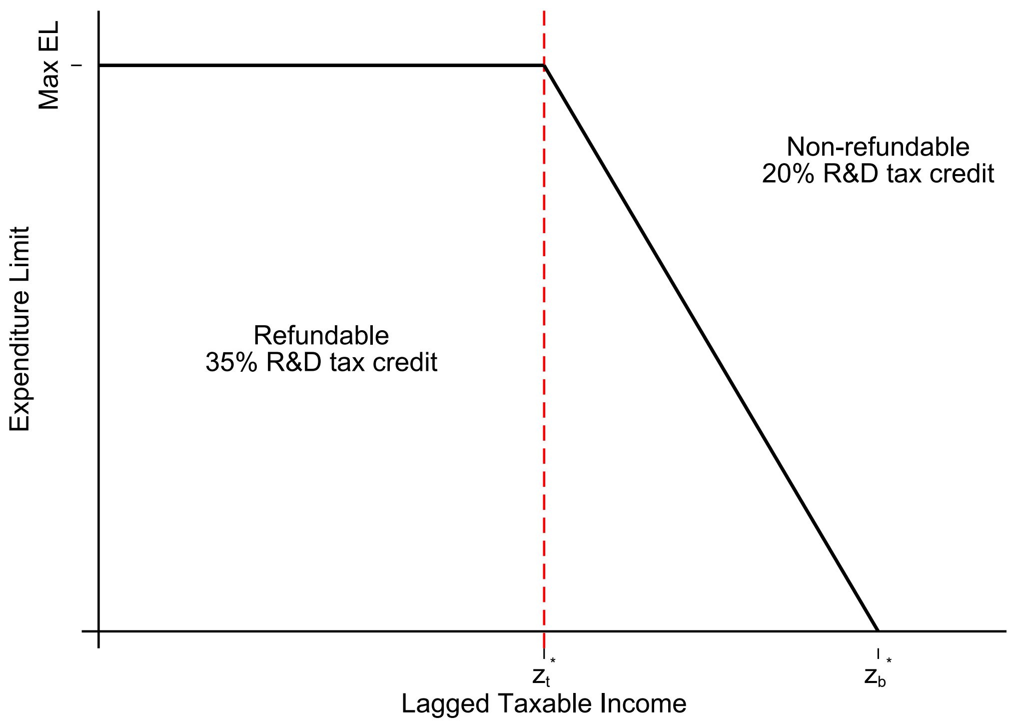
5.2 General Experience and Firm-Specific Experience

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 (10) 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 (11) 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.

Figure 1: Expenditure Limit Schedule



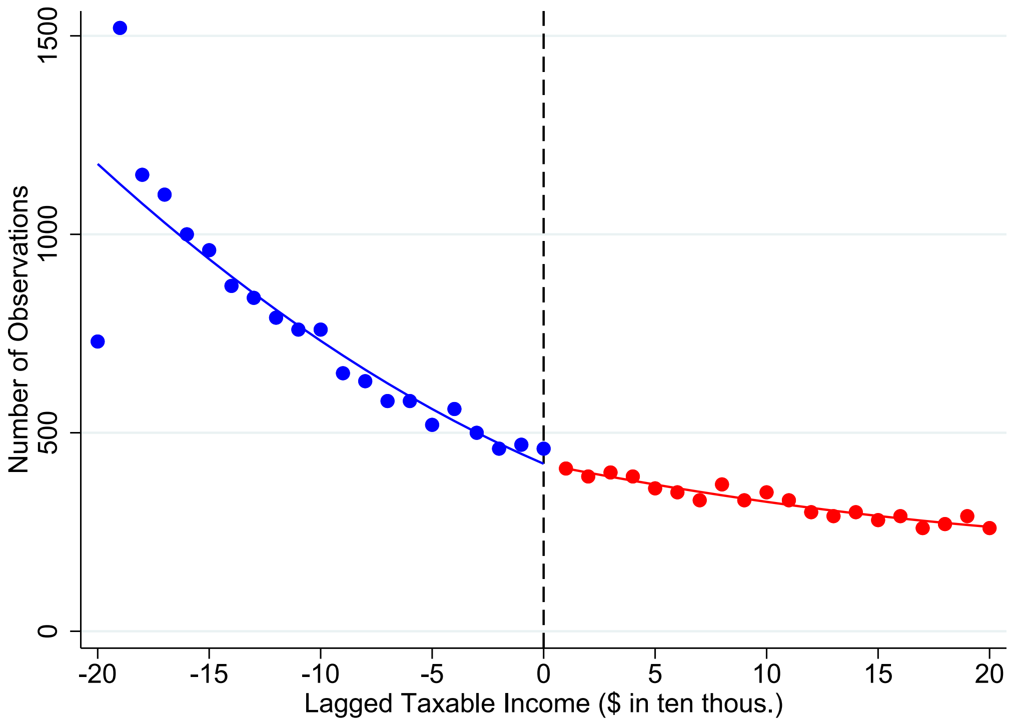
Notes:

Table 1: No-Kink Assumption Test

	(1)	(2)	(3)	(4)
Dependent Variable	R&D Exp.	R&D Wages	Employment	Average Wage
Eligible × 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	4880	4880	4870	4870

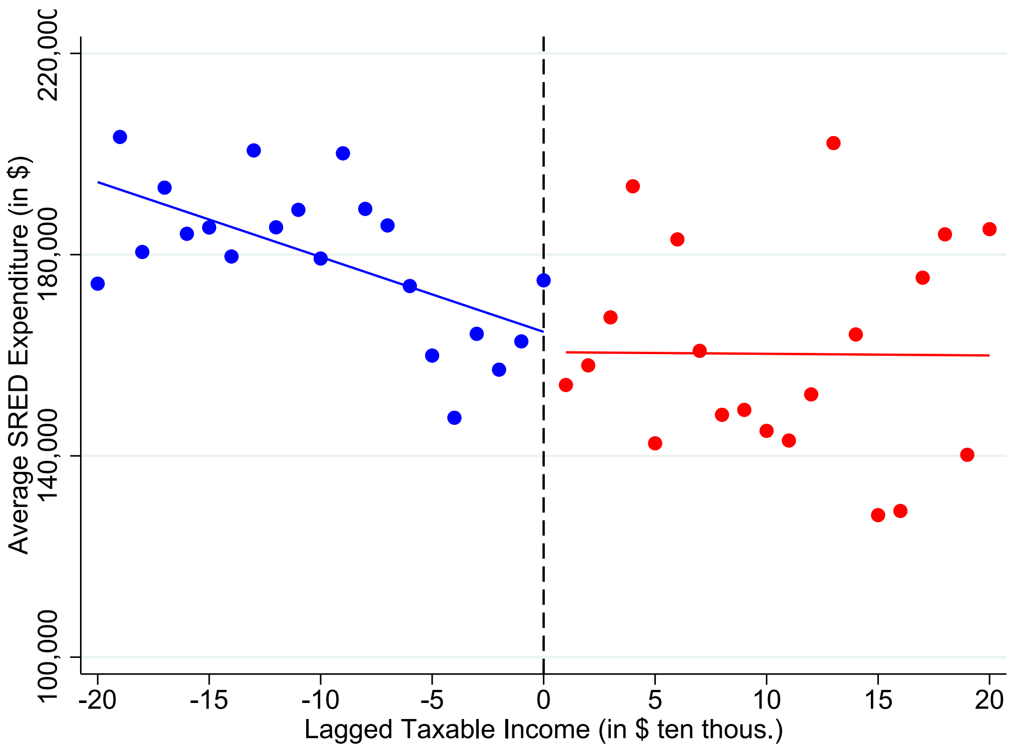
Notes:

Figure 2: McCrary Test For No Manipulation at the Kink



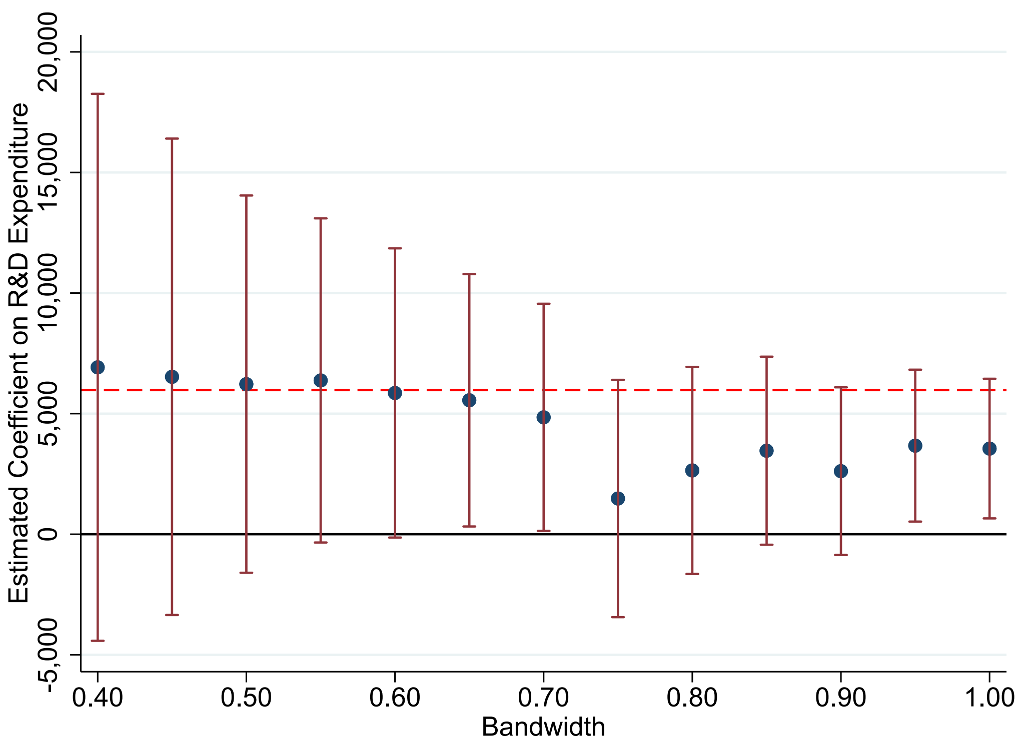
Notes: This figure reports the McCrary test for discontinuity in distribution of lagged taxable income at the normalized kink point. Estimation sample includes CCPC firms with lagged taxable income within $200k of the kink point. Section 3 describe the sample selection criteria.

Figure 3: Kink in Average SRED Expenditure



Notes: This figure reports the average R&D expenditure for firms within each $10k bins around the normalized kink point. Section 3 describe the sample selection criteria.

Figure 4: Tax Credits Impact by Bandwidth



Notes: This figures plots the estimated tax credits impact on R&D expenditures using a wider selection of bandwidth around the kink point. The bandwidth selection is ranging from \$40k to \$100k with \$5k steps. The bandwidth suggested by Calonico et al. (2014) is \$67,600 for R&D expenditure.

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 Payrolls ('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		
Construction	0.05	0.06		
Manufacturing	0.53	0.52		
Wholesale Trade	0.11	0.11		
Transportation	0.01	0.01		
Information	0.02	0.02		
Services	0.12	0.12		
Other	0.14	0.14		

Notes:

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:

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	5428.635**	5704.000**	5975.525**	6161.955**	6100.196**
	(2362.402)	(2413.529)	(2473.874)	(2533.813)	(2520.095)
Mean at t = -1	170536.49	170536.49	170536.49	167664.51	167664.51
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: Tax Credits Impacts based on R&D Intensity

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Intesity:	R&D Exp. Scaled by Revenue			R&D Wages Scaled by Total Payroll		
Dependent Variable:	R&D Exp.	R&D Wages	Average Wage	R&D Exp.	R&D Wages	Average Wage
Eligible × Z (R&D Intensive = 0)	629.517	916.295	-309.273	1488.433	871.658	-271.743
	(1705.552)	(1112.263)	(235.528)	(1807.181)	(1114.967)	(230.275)
Eligible × Z (R&D Intensive = 1)	24424.313***	18489.948***	1511.357***	20184.479**	16488.121***	1414.295***
	(8859.997)	(5750.897)	(449.999)	(8266.623)	(5583.712)	(463.781)
Difference:	23942.972***	17663.600***	1831.372***	19001.476**	15860.544***	1687.324***
	(8959.456)	(5860.852)	(495.894)	(8482.798)	(5735.897)	(510.551)
Mean at t = -1 (R&D Intensive = 0)	71547.97	47611.48	46582.86	77410.63	44560.56	46313.83
Mean at t = -1 (R&D Intensive = 1)	474536.28	292138.8	54738.58	442493.67	291083.9	52926.52
Adj. R squared (R&D Intensive = 0)	0.438	0.397	0.620	0.457	0.445	0.657
Adj. R squared (R&D Intensive = 1)	0.504	0.507	0.649	0.536	0.507	0.596
Observations (R&D Intensive = 0)	3,770	3,770	3,750	3,900	3,900	3,890
Observations (R&D Intensive = 1)	1,260	1,260	1,250	1,300	1,300	1,300

Notes:

Table 6: Worker Composition

	(1)	(2)	(4)	(5)	(6)	(8)
Measure of Intensity:	R&D Exp. Scaled by Revenue			R&D Wages Scaled by Total Payroll		
	Share Female	Average Age	Share High-Skill	Share Female	Average Age	Share High-Skill
Eligible × Z (R&D Intensive = 0)	0.001	-0.002	-0.000	0.001	-0.016	-0.000
	(0.001)	(0.039)	(0.001)	(0.001)	(0.040)	(0.001)
Eligible × Z (R&D Intensive = 1)	0.004**	-0.012	0.001	0.003	0.044	0.001
	(0.002)	(0.070)	(0.003)	(0.002)	(0.070)	(0.003)
Difference:	0.004*	-0.007	0.001	0.002	0.063	0.001
	(0.002)	(0.079)	(0.003)	(0.002)	(0.081)	(0.003)
Mean at t = -1 (R&D Intensive = 0)	0.28	39.27	0.32	0.28	39.15	0.32
Mean at t = -1 (R&D Intensive = 1)	0.28	37.94	0.38	0.29	38.06	0.37
Adj. R squared (R&D Intensive = 0)	0.907	0.784	0.751	0.905	0.784	0.749
Adj. R squared (R&D Intensive = 1)	0.87	0.755	0.729	0.858	0.756	0.723
Observations (R&D Intensive = 0)	3,740	3,740	3,740	3,870	3,870	3,870
Observations (R&D Intensive = 1)	1,240	1,240	1,240	1,290	1,290	1,290

Notes:

Table 7: 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	29230	29230	29230	29230	17060

Notes:

Table 8: Heterogeneity based on AKM Worker Fixed Effects

	(1)	(2)	(3)
Dependent Variable:	log(Earnings)		Retention
Sample:	All	Stayers	All
Eligible × Z (Low Skill)	0.000	0.002	-0.003
	(0.006)	(0.005)	(0.002)
Eligible × Z (High Skill)	0.016***	0.011**	0.007***
	(0.005)	(0.004)	(0.002)
Difference	0.017**	0.009	0.009***
	(0.008)	(0.007)	(0.002)
Mean at t = -1 (Low Skill)	10.03	10.03	1
Mean at t = -1 (High Skill)	10.9	10.9	1
Adj. R squared (Low Skill)	0.261	0.427	0.002
Adj. R squared (High Skill)	0.388	0.543	0.003
Observations (Low Skill)	16820	16820	16820
Observations (High Skill)	10750	10750	10750

Notes:

Table 9: Heterogeneity based on Within-Firm Earnings Distribution

	(1)	(2)	(3)
Dependent Variable:	log(Earnings)		Retention
Sample:	All	Stayers	All
Eligible × Z (1st Quartile)	-0.007	-0.007	-0.001
	(0.013)	(0.012)	(0.003)
Eligible × Z (2nd Quartile)	0.009	0.007	0.002
	(0.009)	(0.007)	(0.003)
Eligible × Z (3rd Quartile)	0.017**	0.014***	0.000
	(0.007)	(0.005)	(0.002)
Eligible × Z (4th Quartile)	0.016**	0.012***	0.006***
	(0.006)	(0.004)	(0.002)
Mean at t = -1 (1st Quartile)	9.43	9.43	1
Mean at t = -1 (2nd Quartile)	10.05	10.05	1
Mean at t = -1 (3rd Quartile)	10.45	10.45	1
Mean at t = -1 (4th Quartile)	11.04	11.04	1
Observations (1st Quartile)	4850	4845	4850
Observations (2nd Quartile)	7255	7255	7255
Observations (3rd Quartile)	8535	8535	8535
Observations (4th Quartile)	8595	8595	8595

Notes:

Table 10: Heterogeneity based on Tenure

	(1)	(2)	(3)
Dependent Variable:	log(Earnings)		Retention
Sample:	All	Stayers	All
Eligible × Z (Low Tenure)	0.007	0.005	0.003*
	(0.005)	(0.004)	(0.001)
Eligible × Z (High Tenure)	0.018**	0.020***	0.001
	(0.008)	(0.006)	(0.002)
Difference:	0.018*	0.019***	-0.002
	(0.010)	(0.007)	(0.002)
Mean at t = -1 (Low Tenure)	10.22	10.22	1
Mean at t = -1 (High Tenure)	10.84	10.84	1
Adj. R squared (Low Tenure)	0.355	0.522	0.002
Adj. R squared (High Tenure)	0.495	0.624	0.001
Observations (Low Tenure)	22990	22990	22990
Observations (High Tenure)	6240	6240	6240

Notes:

Table 11: Heterogeneity based on Worker Age

	(1)	(2)	(3)
Dependent Variable:	log(Earnings)		Retention
Sample:	All	Stayers	All
Eligible × Z (20s)	0.007	0.012*	-0.000
	(0.008)	(0.007)	(0.003)
Eligible × Z (30s)	-0.002	0.001	0.006**
	(0.008)	(0.006)	(0.002)
Eligible × Z (40s)	0.019**	0.012*	0.002
	(0.008)	(0.006)	(0.002)
Eligible × Z (50s)	0.024**	0.029***	0.005*
	(0.012)	(0.008)	(0.003)
Mean at t = -1 (20s)	10.08	10.08	1
Mean at t = -1 (30s)	10.54	10.54	1
Mean at t = -1 (40s)	10.62	10.62	1
Mean at t = -1 (50s)	10.62	10.62	1
Observations (20s)	7130	7130	7130
Observations (30s)	7930	7930	7930
Observations (40s)	7230	7230	7230
Observations (50s)	4300	4300	4300

Notes:

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:

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