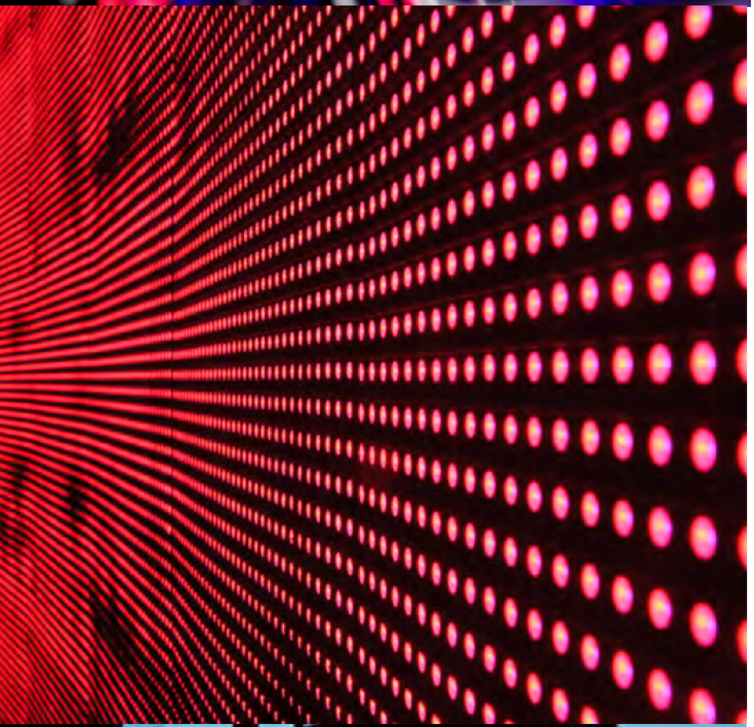


The Economic Impact of R&D Tax Incentives: Evidence using Regression Discontinuity Design

Report

Russell Thomson,[1] Trevor Kollmann,[1] and Nobuaki Yamashita[1,2]

Centre for Transformative Innovation

swinburne.edu.au/cti

The Economic Impact of R&D Tax Incentives: Evidence using Regression Discontinuity Design

Russell Thomson,[1] Trevor Kollmann,[1] and Nobuaki Yamashita[12]

Abstract: We employ a regression discontinuity design to estimate the causal impact of R&D tax incentives, exploiting a feature of the Australian policy which provides a higher level of support for companies with a turnover below A$20m.We estimate the policy generates an additional $1.61 R&D per dollar of tax revenue foregone. To understand the economic impact of this spending, we estimate the effect of own and external R&D stock on firm productivity, then use the estimated marginal product coefficients to calculate the implied economy wide marginal social return. Our results imply that $1 of eligible R&D generates an additional $3.10 via higher economy-wide production. Putting these together, we arrive at a net present value of the economy-wide benefit of the R&D tax incentive policy of $4.99 per dollar of revenue forgone.

[1] Centre for Transformative Innovation, Swinburne University of Technology, Melbourne, Australia

[2] School of International Politics, Economics and Communication, Aoyama Gakuin University, Tokyo, Japan

1. Introduction

R&D tax incentives are among the most common policy tools to promote innovation and foster economic growth. In 2022, 33 out of the 38 OECD member countries offered tax incentives for R&D expenditures (OECD, 2023). Measuring the economic benefits of such subsidies requires an estimate of both the extent of additional private investment in R&D as well as the ensuing productivity benefits. It is notoriously difficult to statistically identify the causal impact of tax incentives because, by design, equivalent firms investing in equivalent research activity are eligible for the same level of effective subsidy. We provide new evidence of the causal impact of the R&D tax incentive program in Australia using regression discontinuity design (RD design) at the A$20 million turnover threshold that determines eligibility for a higher incentive rate. To assess the economy wide impact of R&D supported by the scheme we estimate productivity impact of eligible R&D spending using the approach proposed by Bloom *et al.,* (2020). We find that each dollar of tax revenue forgone induces an additional $1.61 R&D investment which results in $4.99 total economic benefit.

The efficacy of R&D tax incentives has been heavily studied, though until recently compelling causal design has seldom been forthcoming. A key benefit of tax incentives, relative to competitive grants, is market-based allocation of effective subsidy; all firms undertaking eligible activity can benefit. Identification is difficult because firm-level data typically reflect little exogenous variation in the rate of subsidy. Identification in some contexts, including the US, has faced the additional complication that tax credits have been targeted at incremental R&D

spending.[2] In these contexts, identification has been based on 'internal' style instrumenting approaches (Hall, 1992; Dagenais *et al.,* 1997); cost of financial capital (Thomson 2010); and more recently, changes in the tax code (Rao, 2016). An alternative approach has been to use variation in tax policy between countries (or states) over time to identify the effect of tax incentives on aggregate cross-country (or state) R&D (Bloom *et al.,* 2002; Guellec & Van Pottelsberghe, 2003; Falk, 2006; Wilson 2009; Thomson and Jensen, 2013).[3] This cross-jurisdiction approach also lacks a formal causal design to compellingly separate the effect of (relatively infrequent) policy reform from other contemporaneous factors driving variation in R&D.

More recently, the application of quasi-experimental approaches has made important inroads in identifying the causal effect of R&D tax subsidies. Difference-in-Differences (DID) has been applied to reforms in the UK in 2008 (Guceri and Liu 2019); the Canadian small business tax incentive, targeted at firms with turnover below C$500,000 (Agrawal *et al.,* 2020); reform to the Australian R&D tax code in 2012 (Holt *et al.,* 2021) and shift to a threshold for eligibility small firm tax benefit in in India in 2011 (Ivus *et al.,* 2021).

Regression discontinuity design (RD design) provides a compelling causal design for entitlement policies that feature specific subsidies for small firms, a common feature of policy design. RD design allows for an unbiased and consistent causal estimate within the neighbourhood of the cut-off so long as participants cannot precisely manipulate their position vis-à-vis the

[2] Incremental investment refers to the component of R&D spending that is over and above some historic base level of investment, typically operationalized as expenditure over and above a moving average spend in the preceding years. Early schemes in the US, Australia and initially Canada embodied this design feature.

[3] Thomson (2017) proposed an alternative industry-by-country level approach, combining cross-industry variation in R&D capital intensity with cross-country variation in tax policy.

threshold (Lee 2008).[4] Dechezleprêtre *et al.,* (2023) implement a fuzzy RD design based on changes to the size threshold determining eligibility for more generous support in the United Kingdom. Using both traditional RD design and difference-in-discontinuity, the authors focus on the impact of the R&D tax incentives on patenting behaviour.

A principal disadvantage of RD design relates to external validity; estimates are valid proximate to the policy threshold considered. In this regard, the cut-off threshold for the policy studied by Dechezleprêtre *et al.,* (2023) is the margin between medium and large firms, defined as employing 499 employees and either balance sheet under €86 (US$90) million assets or €100 (US$105) million turnover.[5] Although firms above this threshold are responsible for a great share of business expenditure on R&D, there is considerable interest in also understanding the efficacy of tax incentives on smaller firms, which are often the targets of focused innovation policy. Small firms are often considered to be crucial incubators of radical science intensive technology and are particularly sensitive to the cost of capital (Rosen 1991; Schneider and Veugelers 2010; Cohen 2010; Veuglers *et al.,* 2019). Perhaps equally pertinent, Dechezleprêtre *et al.,* (2023) data span the period immediately after the 2008 global financial crisis which was characterised by an extreme credit constrained environment. It is widely understood that the magnitude of the effect of R&D subsidies is likely conditional on a firms' financial constraint (see e.g., Dechezleprêtre *et al.,*2023).

[4] Several key prior studies have employed RD design to examine the effects of government grants on business R&D (Bronzini and Piselli, 2016; Howell, 2017).

[5] An implication of this threshold is that the authors' main result rests on only 200 patenting firms which claim the subsidy. See Dechezleprêtre *et al.* (2023), Table A7.

More generally, it is well recognized that technology policy impact can be contingent on macroeconomic conditions (Guceri and Albinowski 2021).[6]

We apply a sharp RD design to evaluate and measure the additionality achieved by the R&D tax incentive policy in Australia. The R&D tax incentive program in Australia provides a higher rate of benefit to small firms, defined by a turnover below A$20 million (US$13.5 million). The Australian context embodies several features which make it in some ways an ideal context for the implementation of RD design. The policy relies solely on current year business turnover to determine eligibility for the higher rate of incentive. Turnover is readily observable and relatively difficult to manipulate over a sustained period.[7] Moreover, as we are comparing two levels of effective subsidy, the likelihood of conflating change in real R&D investment with reclassification of existing expenses is minimal. By definition, spurious reclassification has negligible real cost so it is unlikely that a marginally higher rate of subsidy will induce additional reclassification. Our study also considers a period of relative macroeconomic stability.

Our second key contribution is to measure the economy wide benefits of the R&D tax incentive scheme by estimating the productivity benefits of eligible R&D spending. Empirical estimates of the productivity enhancing effect of R&D tax incentives are surprisingly rare with most evaluations focusing on the amount of additional R&D induced, reporting either the tax price elasticity or ‘value for money’ ratio. We use confidential firm-level data for the population of

---

[6] More generally, how R&D investments change in periods of economic crisis period has been extensively studied (e.g. Nicholas 2008; Gordon 2018; Yamashita 2021).

[7] Opportunistic timing of asset disposal to inflate earnings.

Australian firms to estimate the productivity effect of investment funded via the R&D tax incentive policy using the approach developed by Bloom *et al.,* (2013).

We find that the higher refundable offset induces statistically and economically significant additional R&D investment relative to the lower non-refundable offset. Our results suggest that the higher rate of subsidy provided to firms with a turnover below A$20 million induces investment of an additional A$1.61 of R&D per dollar of tax revenue foregone. We estimate that an increase of A$1 in the stock of R&D generates an additional A$0.46 output. Putting these together, we arrive at a net present value of the economy-wide benefit of R&D tax incentive policy of $4.99 per dollar of revenue forgone.

2. Policy Context and Data Sources

Australian tax incentives aimed to foster private R&D were initially introduced in 1985 and have since been adjusted and reformed many times.[8] Our analysis focuses on the policy introduced in 2011,[9] called the R&D Tax Incentive Program (R&DTI). The R&DTI is a large-scale government initiative; in the 2019-20 financial year, the program registered A$12.7 billion in R&D expenditures from 14,040 businesses (Industry Innovation and Science Australia, 2021). In the same year, the impact of the scheme on the government revenue was A$2.7 billion (DISER, 2021). The R&DTI has received several minor changes since its inception, summarized in Table 1.

[8] Information on earlier schemes can be found in Thomson, (2010).

[9] A financial year in Australia is from 1 July through 30 June.

The R&DTI program comprises a 45 percent offset for small companies (defined as firms with an aggregate current year turnover under A$20 million) and a 40 percent offset for large companies (aggregate turnover exceeding A$20 million). The 45 percent R&D tax offset is refundable, which means that companies with eligible expenditure and no tax liabilities can receive a reimbursement corresponding to any unused offset amount. The 40 percent R&D tax offset is non-refundable, however any residual balance can be carried forward against future tax liability.[10]

[Table 1]

Data

Our data come from the Australian Bureau of Statistics (2021), Business Longitudinal Analysis Data Environment (BLADE). The data modules within BLADE contain integrated financial, innovation and business characteristics for more than 2 million active businesses in Australia.[11] Financial information comes from tax returns lodged with the Australian Taxation Office via quarterly Business Activity Statements and annual Business Income Tax statements. Financial data is provided to the ABS at the Australian Business Number level, which informally corresponds to a single establishment, or branch in the case of large complex companies. R&D expenditures are based on the eligible expenditures provided by the Australian Taxation Office. Additional robustness and falsification tests use financial data from Business Income Tax as well as Pay-As-You-Go (PAYG) statements from the Australian Taxation Office. Alternative innovation

[10] The value of non-refundable offsets therefore depends on the firm's idiosyncratic discount rate and the number of years before the firm generates a taxable profit.

[11] This statistic is based on the number of ABNs reporting financial information to the Australian Tax Office (ATO) during the period of study.

outcomes - patents, trademarks and design rights are drawn from IP Australia.[12] We include businesses whose aggregate turnovers fall within a neighbourhood (described below) around the refundable offset eligibility cut-off of A$20 million.[13]

For complex (multi-subsidiary) businesses, eligibility for the small firm incentive rate is based on aggregate turnover. Ownership relationships are not generally coded in administrative tax databases. We use two available approaches to identify group membership. First, the Australian Bureau of Statistics maintains a population of 'profiled' businesses, recording their legal structure and provide unique Enterprise Group identifiers. Unfortunately, not all ownership relationships are captured by the profiled population.[14] To identify non-profiled complex firms, we take advantage of a feature of the Australian tax code that allows complex firms with common ownership to report consolidated sales for Goods and Services Tax (GST Group).[15]

Our main focus is firms with non-zero R&D expenditures in any of the fiscal years between 2012-13 and 2019-20. Foreign controlled firms[16] were removed from the sample, because it is not possible to verify the aggregate turnover of foreign owned firms, as business activity outside Australia is not recorded by the Australian Taxation Office. Since the data come from company

---

[12] IP Australia Intellectual Property Longitudinal Research Data (IPLORD)

[13] Aggregate turnover was based on turnover supplied by the firms within their reported BAS which are filed quarterly with the ATO.

[14] ABS the population of profiled firms is determined by ABS based on principles that: (a) they operate through multiple legal entities (b) over $250m in turnover or $25m wages annually (as a group of entities) and (b) not be able to accurately represent themselves as individual ABN units for statistical purposes (ABS pers comm.)

[15] Firms are incentivized to report as a GST Group as it allows sales of goods and services between GST group members to not be subject to GST. These firms must have at least 90 per cent common ownership. We exploit the ABS procedure which apportions group financials equally to identify GST group members.

[16] Operationalized as firms with 10 percent or more foreign shareholding.

tax returns, they are subject to the usual legal accounting standards. Nonetheless, data were cross verified between available information within each company tax return. For example, observations were dropped if the value of offset claimed did not match the total reported R&D expenditure.[17] We also removed firms which claimed the lower (large firm) tax offset rate but reported aggregate turnover below $20 million which is understood to reflect incomplete aggregation of financials for complex company groups.[18] After cleaning, our primary regression is based on the 3,736 unique firms which claimed the incentive over the period and 9,661 firm-year observations.

3. Empirical Strategy

The R&DTI has a well-defined treatment discontinuity for firms at an aggregate turnover of $20 million. We use the following equation as our baseline to estimate the treatment effects of being eligible for the refundable R&D tax offset rate:

$$Log\ R\&D_i = \alpha + \tau[1|Turnover < \$20million] + f(Log\ Turnover) + \varepsilon_i \qquad (1)$$

where $Log\ R\&D_i$ is firm i's Log R&D spending, $[1|Turnover < \$20million]$ is an indicator if a firm's turnover is under $20 million and thus eligible for the refundable higher R&D tax offset rate, and $f(\cdot)$ a polynomial which is a function of the running variable, Log Turnover. We estimate this using OLS and as our sample pools observations over the period between 2012-13 and 2019-20, we cluster the standard errors at firm-level. The optimal asymmetric bandwidth for each model

---

[17] This affected 8 percent of potential firms. Based on advice from Department of Industry, Science and Resources and the ATO we understand this may reflect a revision to part of the tax return.

[18] Errors in aggregation can occur where firms have not been included in ABS profiled population and choose not to report via GST groups. This can also occur due to timing inconsistencies between corporate income tax reporting and merger and acquisition activity. We drop all observations for any firm that reports an inconsistency in any year, not solely the affected year, this affects 10 percent of our potential population of firms. The converse situation, errors whereby firms with observable turnover above $20 million claim the small firm rate occurs only 2.6 percent of firms.

was selected using methods developed by Imbens and Kalyanaraman (2012) and Calonico *et al.,* (2014).

Causal inference in regression discontinuity design requires that firms are not able to manipulate their treatment status (Lee 2008). The Australian policy change that we focus on is based only on the turnover criteria which renders little room for manipulation of the eligibility for generous tax benefits. Additionally, we undertake non-parametric discontinuity in density test procedure described by Cattaneo *et al.,* (2020). Results of these, presented in regression Table 2, suggest no significant discontinuity in the density around the cut-off point.

Firms within the refundable offset group spend A$821 thousand on average on R&D. On average, firms above the turnover threshold which are eligible for the offset rate spend more on R&D; an average of $1,264 thousand per firm. The positive association between turnover and R&D expenditure is consistent with well-known patterns and does not violate the assumption of RD design.

4. Results

We first consider visual inspection of the expected discontinuity at A$20 million turnover threshold. Figure 1 depicts the relationship between turnover and R&D (both in logs) for the primary regression sample. It is not possible to graph individual firms due to confidentiality restrictions on company tax return data. Each observation on Figure 1 therefore represents the average R&D spend for groups of firms within turnover bins with a fixed width of 0.04 log points. Each bin represents on average 172 firms. The fitted lines illustrate the predictions from locally weighted scatterplot smoothing (LOWESS)[19] regression on either side of the A$20 million discontinuity. The LOWESS regression lines reveal a steady positive relationship between turnover and R&D as turnover increases toward the threshold followed by a sharp decrease in average R&D followed by a return to a positive relationship, albeit at a steeper gradient. The provides a priori evidence of a discontinuity at the A$20 million threshold for eligibility for the more generous subsidy rate which we formally interrogate using econometric RD design.

[Figure 1]

Table 2 reports baseline RD design estimates. Recall that firms with a turnover under A$20 million are eligible for the higher value of refundable R&D tax offset. All regressions control for a linear term of the running variable (Turnover), an interaction between Turnover and treatment status (i.e., Turnover under A$20 million) and year fixed effects. We also implemented the local polynomial method suggested by Cattaneo *et al.,* (2020) which implements a data-driven technique to select the optimal bandwidth. To see the sensitivity of the chosen bandwidth, we also report a set of alternative bandwidths as a robustness check, described below and reported in Table 4. For each regression sample, we undertake the test for discontinuity in distribution proposed by Cattaneo *et al.,* (2020) and in each case we fail to reject the null hypothesis, suggesting that firms were not able to significantly manipulate their turnover to obtain a higher offset rate.

Column 1 of Table 2 reveals an estimated coefficient on this discontinuity is 0.257. This translates into a 29% increase in R&D expenditure for those firms below the cutoff as compared

---

[19] A local linear regression using a tri-cube weighting function (Cleveland 1979)

to those above the cutoff.[20] To further examine the robustness to functional form assumption we augment the model with higher order terms in the running variable and their interaction with firm treatment status (Cook 2008). Results are presented in columns 2 include the quadratic term and in column 3 we also add the cubic term.

Almond and Doyle (2011) propose applying a ‘doughnut method’, whereby observations within 5% of threshold are removed from the estimating sample to accommodate any possible manipulation around the cutoff point. Results using this approach are reported in column (4). In column (5), we perform the nonparametric robust bias-corrected inference method (Calonico *et al.,* 2014). As shown, the estimated coefficient on the assignment variable remains largely unchanged.

We also investigate the extent to which our results may be driven by the behaviour of firms whose turnover fluctuates such that they qualify for the higher rate of incentive in some years but do not qualify in others. To do this, we re-run the baseline regression excluding firms having crossed the cutoff more than once. Results are presented in column (6), and show the estimated treatment effect virtually remains almost the same as the baseline results in column (1). In column (7) we re-estimate the RD design based on the sample of firms which did cross the eligibility threshold more than once. We note that the estimated coefficient is slightly larger, perhaps reflecting some opportunistic behaviour among those firms, although not statistically significantly different than the coefficient estimates reported in column (6).

[Table 2]

---

[20] Percentage change: $e^{0.257} - 1$

Bandwidth Selection

To ensure that our results are not excessively sensitive to the choice of bandwidth, we conducted a grid search of the bandwidth window, varying the upper and lower bandwidth in increments of 0.15 log points (from 0.3 to 2.25) in Table 3. Results show that the estimated coefficient is reasonably stable across relevant windows of bandwidth (Table 3). In particular, the results are robust with symmetric bandwidth, as was common in older RD design applications.

[Table 3]

Extensive Margin

The results presented above document a positive impact of the more generous tax offset on R&D expenditure. We also consider whether this policy impact induces increases in the extensive margin – that is, whether eligibility to the more generous rebate incentivizes firms to become R&D active. Column 1 of Table 4 shows the results of a linear probability model with an indicator variable which takes the value to 1 if a firm report any R&D expenditures and zero otherwise. The estimating sample includes all firm-year observations for all Australian firms within the turnover bandwidth. Column 2 uses the nonparametric robust bias-corrected inference method (Calonico *et al.,* 2014). Both results indicate that the higher offset rate induces a 2 percentage point increase in the likelihood of firms engaging in qualifying R&D activities. We note that this finding contrasts with Dechezleprêtre *et al.,* (2023) who find tax incentives have no impact on the extensive margin for R&D, but that they do effect the extensive margin for patenting.

In column (3), we combine the sample of intensive and extensive margins by setting the dependent variable as the log R&D for the full sample of firms within BLADE, rather than just the firm-years for firms with positive R&D expenditures.[21] Using the full sample, the coefficient estimates remain quite stable when compared to the results of Table 2.

[Table 4]

Impact on Measures of Research Output

Table 5 reports estimates for analogous RD Design models using alternative outcome measures which might be anticipated to be influenced by R&D tax incentives, including patents, trademarks and design rights. To account for the lead time required to convert R&D expenditures to IP registrations we consider aggregate registrations of each IP application over three years periods. Estimations reveal no statistically significant coefficient estimates on the treatment assignment variable. We speculate that the lack of observable policy impact on these outcome measures may reflect that the quantum of R&D induced may not translate to an observable difference in registrations such as patenting, especially since additional R&D is anticipated to result in increased IP registrations after a stochastic lag, adding further noise. Though we also note that firms at our margin of interest are not intensive applicants of patents or design rights owing to their size.[22]

[Table 5]

Falsification Tests

We undertake two common falsification tests. The first is to estimate analogous models of alternative outcome variables which are not expected to exhibit discontinuity at the cutoff, namely

---

[21] To account for firms reporting zero, R&D, we do a standard adjustment of adding $1 to R&D prior to the log transformation.

[22] The share of R&D active firms within the bandwidth which register any patents, trademarks and design rights over a three year period are 0.08, 0.26 and 0.04, respectively.

wages, employment, and tangible investment. Results are presented in Table 6. In all cases, we do not find any statistically significant treatment effect of being below the cutoff. This result also supports the assumption of RD design that firm characteristics are similar at the cut-off.

[Table 6]

Our second falsification test is to test for structural breaks in R&D at alternative turnover thresholds (where no policy discontinuity applies). We implement this approach using the local polynomial optimal bandwidth estimator discussed by Calonico *et al.,* (2014). To avoid potential contamination with the actual treatment effect we use only the treated observations when artificial cut-offs are below the true cut-off of A$20 million and only control observations for artificial cut-offs above (Cattaneo *et al.,* 2020). Figure 2 reports the coefficient estimates of interest and their corresponding 90% confidence intervals. The only statistically significant coefficient estimate is at the true cut-off of A$20 million. Coefficients at all other artificial cut-offs are not statistically different from zero. These results demonstrate that the only observable discontinuity in R&D falls at the treatment threshold.[23]

[Figure 2]

Value for Money Ratio

To interpret the magnitude of the causal estimate for R&D tax incentives, we calculate the 'value for money' ratio, which is sometimes referred to as the additionality ratio defined as the amount of additional R&D for every dollar of tax revenue forgone. We estimate the additionality of the

[23] Estimating the same models using OLS yields consistent results.

refundable 45 percent offset as compared to the non-refundable 40 percent offset. To make the calculation tractable, we assume that the amount of induced R&D is entirely attributable to the higher rate of offset, not to earlier access to benefits for firms with exhausted tax liabilities under the rebate scheme.[24]

The main estimate in Section 4 suggests a treatment effect of 29 percent greater claimable R&D expenses. As we estimate the treatment effect in dollars of R&D (rather than, for example, a count of additional patents), we can directly obtain the additionality ratio (value for money ratio) as:[25]

$$\frac{\Delta R\&D}{\Delta Tax\ Revenue\ Forgone} = \frac{\Delta R\&D}{\Delta Offset \times R\&D + \Delta R\&D \times Offset} = \frac{0.29}{\$0.05 + 0.29 \times \$0.45} = 1.61 \quad (2)$$

Note that the first term in the denominator reflects the cost of subsidizing inframarginal R&D (R&D already being undertaken at the lower subsidy level sub subject to the higher rate of subsidy) and the second term reflects the cost to revenue of the marginal (induced) R&D. If the estimated effect is attributed to the higher offset rate, it amounts to the additionality (value for money ratio) of 1.61 for R&D per dollar of tax revenue foregone. Based on the difference in tax price between

[24] Firms with no tax liabilities in a claiming year are able to carry forward unused tax credits to future years. This means the effective value may be discounted depending on the firm's discount rates as well as the number of years before the firm earns a taxable profit.

[25] Second, we have not explicitly modelled the difference in refundability between the large and small firm policy. For those large firms with exhausted tax liabilities, non-refundable offsets can be carried forward to reduce future tax liabilities, using population average delays and representative discount rates suggests a small difference in value; though we acknowledge this may be larger for firms with high idiosyncratic discount rates.

the small and large firm scheme (40 vs 45 percent credit) the implied tax price elasticity of R&D is equal to 3.5.[26]

This estimate is reasonably similar to the previous literature. Though we note it is somewhat smaller than estimated by Dechezleprêtre *et al.,* (2023) who find a tax price elasticity of 4.1 and a value for money ratio of 2.34. This difference may reflect that smaller firms analyzed here are intrinsically less responsive to R&D tax incentives. Alternatively, it may reflect heightened sensitivity to liquidity due to the global financial crisis concurrent with the latter study.

5. Economic Impact

The first order impact of R&D tax incentives is to induce firms to invest more in R&D. Productivity spillovers arising from such R&D are the most common justification for public support of private R&D (Bloom *et al.,* 2019). Measuring the total economic benefit of R&D tax subsidies requires an estimate of productivity gains from induced R&D (the private rate of return) and their spillover effects on the adjacent firms (the external rate of return). Yet, empirical work which include estimates of the productivity enhancing effect of R&D supported by R&D tax incentives is surprisingly rare, with most economic evaluations of R&D tax incentives focusing on the impact of implicit subsidies on R&D spending.[27]

---

[26] The tax price elasticity is calculated ratio 0.29 to the proportional difference in the user cost of capital, where the user cost or R&D capital is given by $\frac{(1-A)}{(1-\tau)}(r+\delta)$ where A is the value of credits and deductions on R&D & τ is the corporate income tax rate.

[27] For grant-based subsidies, Crespi *et al.,* (2020) estimate the direct and spillover effects of two separate R&D grant schemes designed to promote firm-level research and development (R&D) investment in Chile on firm productivity of other non-participating firms.

To estimate the overall economic impact of the R&D tax incentive in Australia we complement our estimate of value for money ratio with bespoke estimates of the economic returns to eligible expenditure (all spending claimed against the policy) using data covering the population claiming firms over the period 2002-2019. To do this, we first estimate the effect of own and external R&D stock on firm productivity, then use the estimated marginal product coefficients to calculate the implied economy wide marginal social return (MSR) – i.e., the increase in aggregate output generated by a marginal increase in firm i's R&D stock – following the approach of Bloom *et al.,* (2013). We outline the key results and their implications here; additional details of the data and estimation are included in the appendix.

To estimate productivity effect of the stock of eligible R&D investment (henceforth referred to as R&D stock) we follow the common two-stage procedure whereby we first estimate firm-level total factor productivity (TFP) and then estimate the effect of own and external R&D stock on this. To derive the total factor productivity (TFP) for each firm in each year we use the control function approach of Ackerberg, Caves and Frazer (2015) (ACF). The ACF approach accommodates simultaneity of inputs and endogenous exit using a control function based on purchases of intermediate inputs. We allow for parameter heterogeneity by estimating separate production functions for firms in each of the 15 industry divisions.[28] Data used for these production function estimates are defined and summarized at Table A2. We report a full set of resulting input coefficients estimated using both ACF and OLS at appendix A1.

[28] We omit mining (B), financial services (K), public administration (N) and administrative support (O) based on relevance or the fact that production functions estimated for resulted in unreasonable input coefficients, e.g., a complexity in mining productivity is ore quality & financial services face complexities with separating tangible from financial capital.

In a second step we model the effect of own and external R&D stock on firm-level TFP. Following Bakhtiari and Breunig, (2018) we focus on R&D spillovers within the same state. The estimating equation is given at equation (3).

$$TFP_{it} = \theta_1 r_{it-1} + \theta_2 s_{it-1}^{intra} + \theta_3 s_{it-1}^{inter} + \alpha_j + \lambda_t + u_{it} \tag{3}$$

where TFP_{it} r_{it} and s_{it} reflects firms own and external stock of R&D for firm i in year t. External R&D stock (S_{it}) is further decomposed to allow for separate estimate of intra- and inter-industry spillovers. Specifically, we include the unweighted sum of R&D stock of firms in the same 2 digit industry (intra-industry) in the same State $\left(s_{it-1}^{intra}\right)$ and the unweighted sum of R&D stock with other industries in the same State $\left(s_{it-1}^{inter}\right)$.[29] The parameters of interest for our analysis are θ_1 (own R&D elasticity of output) and θ_2 ($i$ntra-industry spillovers) and θ_3, (inter-industry spillovers). We include state, industry and year fixed effects to control for specific technological opportunity, *inter alia*. Following Bloom et al (2013) we also include four-digit industry time-varying controls, defined as the annual average turnover in each industry, to capture common transitory shocks that might affect industry level unit cost of R&D.

Estimates are reported in Table 7. Column (1) present a simple baseline OLS log-linear Cobb Douglas production function incorporating the R&D stock measures where the dependent variable is value added. Column (2) models TFP, via a first stage using ACF for the pooled sample. Column (3) models TFP which has been estimated via 15 industry-specific production functions estimated using ACF. Finally, Column (4) augments the model by including industry average real

[29] We use the unweighted measure of a pool of external R&D stock since symmetric of inter-industry impact is an assumption for approximating rate of return from output elasticities (see Bloom *et al.,* 2013).

value added, suggested by Bloom *et al.* (2013). Estimates of the output elasticity of own R&D stock range from 0.035 to 0.066; estimated elasticity of external intra-industry R&D stock spillovers range from 0.013 to 0.017; and our estimates of the output elasticity of external inter-industry R&D stock range from 0.056 to 0.065. Our finding that intra-industry R&D spillover are greater than inter-industry R&D spillovers is consistent with the literature and is typically argued to reflect that the spillovers from R&D by firms within the same industry are tempered by business stealing effects.

[Table 7]

Bloom *et al.,* (2013) show that under specific simplifying assumptions,[30] the social rate of return of R&D can be derived from the productivity coefficients, via the following formula:

$$MSR = \frac{Y}{R}(\theta_1 + \theta_2 + \theta_3) \tag{4}$$

Where Y/R is the ratio of output to R&D Stock. It is well recognised that this ratio $\left(\frac{Y}{R}\right)$ is biggest wild card in converting elasticities into marginal benefits. Following Bloom *et al.,* (2013) we use the median ratio of value added over R&D stock for firms in the regression sample.[31] Using the coefficient estimate for R&D-outputs elasticity in Table 7, and the corresponding ratio of median value-added to the firm's own R&D stock (3.97, Table A4) we arrive at an estimated MSR

---

[30] The simplifying assumptions include that firms are symmetric with the same size of output and R&D stock, and the same technological linkage as well as the absence of strategic complementarity between internal stock of R&D and the specific industry mix of external R&D available to each firm.

[31] In the review by Hall, Mairesse and Mohnen (2010, Tables 2a and 2b), this was assumed to lie in the 1 to 14 range. Bloom, Schankerman and Van Reenen (2013, pp 1383) use the median value of the ratio of sales to R&D stock, which is 2.48. Kim and Lester (2019) have chosen Y/K instead of Y/R. In Goto and Suzuki (1989, Table 4) the assumed value added to R&D stock lay in the range of 8 to 100 depending on the 2-digit industry (this implies that the sales to R&D stock ratio would be higher).

of 0.46.[32] Assuming a depreciation rate of 15 percent (consistent with construction of our R&D stock measures) this implies the net present value (NPV) of the discounted stream of economic benefits arising from a dollar of R&D stock is then given by:[33]

$$\frac{MSR}{\rho} = \frac{0.46}{0.15} = 3.10 \tag{5}$$

This estimate is reasonably consistent with the extant literature. In the Australian context, Wynn *et al.,* (2022) apply the method by Jones and Summers (2020) report a lower bound estimate of the economy wide benefits of a dollar of R&D of \$3.50. Drawing together our estimate of the NPV of additional eligible R&D stock (\$3.10) and the additional R&D per dollar of tax revenue for every dollar of tax revenue forgone (\$1.61) suggests net present of total economic value generated by each dollar of revenue forgone by the R&D tax incentive is \$4.99.

6. Conclusion

Tax incentives have garnered almost universal favour as policy for encouraging private sector research and innovation. To identify the causal effect of the R&DTI, we employ regression discontinuity design at the \$20 million turnover threshold that determines firms' eligibility for the higher refundable offset value. We provide three main findings regarding the effectiveness of R&D tax incentives. First, our analysis reveals that for every dollar of tax revenue forgone, there is an additionality effect of \$1.61 in additional R&D expenditure. In other words, these incentives yield

[32] We consider estimates reported in column 3 a representative midpoint. Corresponding estimates using alternative estimates of output elasticities can be calculated similarly. Using the median output elasticities we have: $MSR = 3.97 \times (0.042 + 0.015 + 0.060) = 0.46$.

[33] $\lim_{n\to\infty} \sum_{t=0}^{n} r\left(\frac{1-\rho}{1+\pi}\right)^t = \frac{r}{1-\frac{1-\rho}{1+\pi}} = \frac{r(1+\pi)}{\pi+\rho}$ ρ is depreciation and π is the discount rate, assumed to be zero. The appropriate discount rate for society wide benefits is typically considered the real risk-free rate benchmark (such as government bonds).

almost twice the amount in R&D activity compared to the fiscal resources foregone. Second, when calculating the marginal social rate of return, we found that each dollar invested in R&D generates spillover effects of $0.46 for the broader economy annually over the entire lifespan of the technological asset resulting from the R&D activity. This underscores the positive externalities and long-term economic benefits associated with R&D investments. Lastly, our assessment of the net present value (NPV) of economy-wide benefits stemming from eligible R&D expenditures indicates a total NPV of $4.99 for each $1 of tax revenue foregone. This figure represents the cumulative economic value generated by each dollar of revenue forgone due to the R&D tax incentive.

A few caveats remain to be acknowledged. First, as in the case of all such evaluations, it is not possible to categorically rule out possible relabelling or input price inflation (i.e., paying more for the same inputs).[34] Nonetheless, our productivity estimates confirm that in aggregate eligible expenditure augments the productivity on average of both the recipient firm and others in the same state. Finally, whereas RD design is a powerful analytical technique for identifying causal effects for firms proximate to the policy cut-off, it has well-known untestable limitations in external validity. To this end, our analysis focuses on a heavily populated margin of medium sized enterprises (A$20m turnover) often targeted for innovation policy.

[34] See Goolsbee (1998) and Thomson and Jensen (2013) for evidence on R&D subsidies and input price inflation.

Acknowledgements

The authors have received a funding from the Australian Government Department of Industry, Science, Energy and Resources for related analysis resulting in reports delivered in 2015 and 2022. We express our gratitude in particular to Malcom Jones from Department of Industry, Science, Energy and Resources who provided expert advice regarding details of the tax program. We also gratefully acknowledge the Australian Bureau of Statistics for making available the unique data, without which this analysis would not be possible. Thanks to Talei Parker as well as Molly Chapman, Humaira Khan, Laura Brazier, Rashmin Chitale at the ABS who contribute to the vital operation of BLADE. We would also like to thank Alfons Palangkaraya and Beth Webster, Bob Breunig, Alicia Rambaldi and Jongsay Yong for comments and suggestions on related analysis. Any remaining errors and any opinions expressed remain solely the responsibility of the authors.

Data disclaimer: This study uses data supplied to the ABS under the Taxation Administration Act 1953, A New Tax System (Australian Business Number) Act 1999. Legislative requirements to ensure privacy and secrecy of these data have been followed. See https://www.abs.gov.au/statistics/microdata-tablebuilder/datalab/using-datalab-responsibly. For access to BLADE data under Section 16A of the ABS Act 1975 or enabled by section 15 of the Census and Statistics (Information Release and Access) Determination 2018, source data are de-identified and so data about specific individuals has not been viewed in conducting this analysis. In accordance with the Census and Statistics Act 1905, results have been treated where necessary to ensure that they are not likely to enable identification of a particular person or organisation.

Reference

Ackerberg, D. A., Caves, K., & Frazer, G. , 2015. Identification properties of recent production function estimators. *Econometrica*, 83(6), 2411–2451.

Agrawal, A., Rosell, C. and Simcoe, T., 2020. Tax credits and small firm R&D spending. *American Economic Journal: Economic Policy*, 12(2), pp.1-21.

Almond, Douglas, and Joseph J. Doyle. 2011. "After Midnight: A Regression Discontinuity Design in Length of Postpartum Hospital Stays." *American Economic Journal: Economic Policy*, 3 (3): 1-34.

Australian Bureau of Statistics (ABS) 2021, Microdata: Business Longitudinal Analysis Data Environment, accessed 2023

Bakhtiari, S. and Breunig, R. (2018). “The role of spillovers in research and development expenditure in Australian industries”, Economics of Innovation and New Technology, 27(1), 14–38.

Balaguer, A., Palangkaraya, A., Talgaswatta, T. and Webster, E. (forthcoming), ‘R&D external benefits in Australian industries’, Research Paper, Office of the Chief Economist, Australian Government Department of Industry, Innovation and Science.

Bloom, N., Griffith, R. and Van Reenen, J. (2002), ‘Do R&D Tax subsidies Work? Evidence from a Panel of Countries 1979–1997’, Journal of Public Economics, 85, 1–31.

Bloom, N., Schankerman, M. and Van Reenen, J. (2013), ‘Identifying technology spillovers and product market rivalry’, Econometrica 81(4), 1347–1393.

Bloom, N., Van Reenen, J., and Williams H. (2019), "A Toolkit of Policies to Promote Innovation." Journal of Economic Perspectives, 33 (3): 163-84.

Bronzini, R., Piselli, P., 2016. The impact of R&D subsidies on firm innovation. Research Policy 45, 442–457.

Calonico, S., Cattaneo, M.D. and Titiunik, R., 2014. Robust nonparametric confidence intervals for regression‐discontinuity designs. Econometrica, 82(6), pp.2295-n2326.

Cattaneo, N., Idrobo,. N., and Titiunik, R. (2020), ‘A Practical Introduction to Regression Discontinuity Designs: Foundations’, Cambridge University Press.

Cleveland, William S. 1979. ‘‘Robust Locally-weighted Regression and Smoothing Scatterplots.’’ Journal of the American Statistical Association 74:829--836.

Cook, Thomas D. 2008. “‘Waiting for Life to Arrive’: A History of the Regression-Discontinuity Design in Psychology, Statistics and Economics.” Journal of Econometrics, 142 (2): 636–54.

Crespi, Gustavo, Lucas Figal Garone, Alessandro Maffioli, and Ernesto Stein. 2020. “Public Support to R&D, Productivity, and Spillover Effects: Firm-Level Evidence from Chile.” World Development 130 (June): 104948.

Dagenais, M., Mohnen, P. and Therrien, P. (1997), 'Do Canadian Firms Respond to the Fiscal Incentives to Research and Development', Scientific Series. Centre Interuniversitaire de Recherche en Analyse des Organisations (CIRANO), Montreal.

Dechezleprêtre, A., Einiö, E., Martin, R., Nguyen, K.T. and Van Reenen, J. (2023), Do Tax Incentives Increase Firm Innovation? An RD Design for R&D, Patents, and Spillovers, American Economic Journal: Economic Policy (forthcoming).

Department of Industry, Science, Energy and Resources (2021), '2021-22 Science, Research and Innovation (SRI) Budget Tables'. https://www.industry.gov.au/sites/default/files/2021-12/2021-22-sri-budget-tables.xlsx

Falk, M. (2006), 'What Drives Business Research and Development (R&D) Intensity Across Organisation for Economic Co-Operation and Development (OECD) Countries?', Applied Economics, 38, 533–47.

Goolsbee, A., 1998. Does government R&D policy mainly benefit scientists and engineers?.

Gordon, R. J. (2018). Declining American economic growth despite ongoing innovation. Explorations in Economic History, 69, 1-12

Goto, A. and Suzuki, K. (1989) R&D Capital, Rate of Return on R&D Investment and Spillover of R&D in Japanese Manufacturing Industries. Review of Economics & Statistics, 71,555-564.https://doi.org/10.2307/1928096

Guceri, I., and Liu, L. (2019), 'Effectiveness of Fiscal Incentives for R&D: Quasi-experimental Evidence', American Economic Journal: Economic Policy, 11: 266-91.

Guceri, I., and Albinowski, M. (2021), 'Investment responses to tax policy under uncertainty'. Journal of Financial Economics 141, 1147–1170.

Guellec, D. and Van Pottelsberghe, B. (2003), 'The Impact of Public R&D investment on Business R&D', Economics of Innovation and New Technology, 12, 225–43.

Hall, B. (1992), 'R&D Tax Policy During the Eighties: Success of Failure', Working Paper No. 4240, NBER, Cambridge, MA.

Hall, B. and Van Reenen, J. (2000), 'How effective are fiscal incentives for R&D? A review of the evidence.' Research Policy, 29, 449-469.

Hall, B. H., Mairesse, J. and Mohnen, P. (2010), 'Measuring the returns to R&D', in B. H. Hall & N. Rosenberg (eds.), Handbook of the economics of innovation, Volume 2, Chapter 24, North-Holland: Amsterdam, The Netherlands.

Heckman, J., Ichimura, H., and Todd, P. (1997), "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme", Review of Economic Studies, 64(4), 605-654.

Holt, J., Skali, A. and Thomson, R. (2021), 'The additionality of R&D tax policy: Quasi-experimental evidence', Technovation, 107, 102293.

Howell, Sabrina T. 2017. "Financing Innovation: Evidence from R&D Grants." American Economic Review, 107 (4): 1136-64.

Imbens, G. and Kalyanaraman, K., 2012. Optimal bandwidth choice for the regression discontinuity estimator. The Review of Economic Studies, 79(3), pp.933-959.

Industry Innnovation and Science Australia (2021). Annual Report 2020-21. Department of Industry, Science, Energy and Resources.

Ivus, O., Jose, M., Sharma, R., 2021. R&D tax credit and innovation: Evidence from private firms in india. Research Policy 50, 104128.

Jones, B.F., Summers, L.H., 2020. A Calculation of the Social Returns to Innovation, NBER working paper series. National Bureau of Economic Research, Cambridge, Mass.

Jones, C. & J. Williams (1998), "Measuring the Social Return to R&D", The Quarterly Journal of Economics, 113(4):1119-35.

Kim, M. and Lester, J. (2019), 'R&D spillovers in Canadian industry: Results from a new micro database', CSLS Research Report 2019-02. Available at https://ssrn.com/abstract=3469865

Lee, D. (2008), "Randomized experiments from non-random selection in U.S. House elections", Journal of Econometrics, 142(2): 675-697.

Nicholas, Tom. (2008) "Does Innovation Cause Stock Market Runups? Evidence from the Great Crash." American Economic Review 98, no. 4, pp.1370–1396.

OECD 2023 OECD R&D tax incentives database, 2022 edition, accessed July 2023 https://www.oecd.org/innovation/tax-incentives-RD-innovation/ Palangkaraya, A., Balaguer, A., Shavazi, A., Talgaswatta, T., Tuhin, R., Webster, E., (2021). R&D external benefits in Australia by fields of research, Report prepared for the Australian Government Department of Industry Innovation and Science Office of the Chief Economist.

Parisi, M. L., and Sembenelli, A. (2003), 'Is Private R&D Spending Sensitive to its Price? Empirical evidence on panel data for Italy', Empirica, 30, 357-377.

Parsons, M., and Phillips, N. (2007), 'An Evaluation of the Federal Tax Credit for Scientific Research and Experimental Development', Department of Finance Canada Working Paper

Rao, N., 2016. Do tax credits stimulate R&D spending? The effect of the R&D tax credit in its first decade. *Journal of Public Economics*, 140, pp.1-12.

Scheerer, F.M. (2010), Pharmaceutical innovation, Chapter Chapter 12 in Handbook of the Economics of Innovation, vol. 1, pp 539-574

Thomson, R. (2010), 'Tax Policy and R&D Investment by Australian Firms', The Economic Record, 86, 260–80.

Thomson, R. (2017), The effectiveness of R&D tax credits, Review of Economics and Statistics, 99(3): 544–549.

Thomson, R., and Jensen, P.H. (2013), 'The effects of public subsidies on R&D employment: Evidence from OECD countries', National Tax Journal, 66, 281-310.

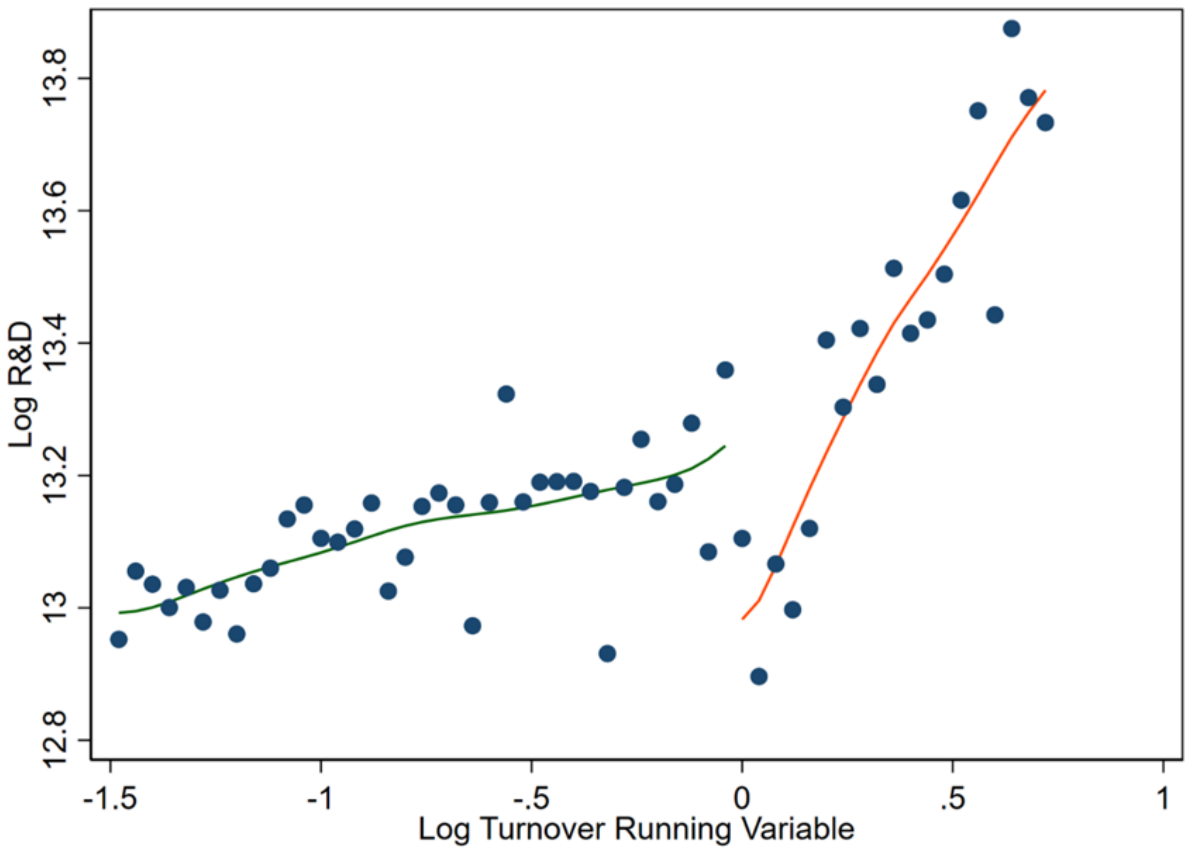
Van Beveren, I. , 2012. Total factor productivity estimation: A practical review. Journal of Economic Surveys, 26(1), 98–128. https://doi.org/10.1111/j.1467-6419.2010.00631.x

Wilson, D.J. (2009), 'Beggar Thy Neighbour? The In-state, Out-of-state, and Aggregate Effects of R&D Tax subsidies', Review of Economics and Statistics 91, 431–436.

Wynn, K., Liu, M. and Cohen, J., 2022. Quantifying the economy‐wide returns to innovation for Australia. Australian Economic Papers, 61(3), pp.591-614.

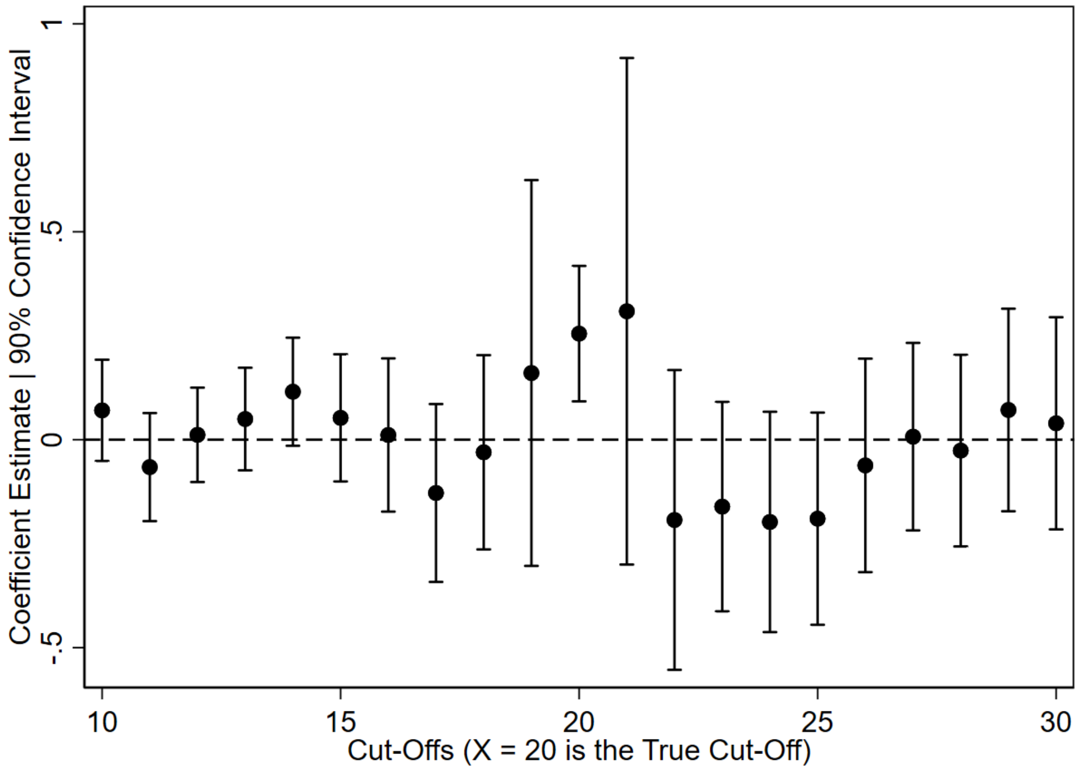
Yamashita, N., 2021. Economic crisis and innovation capacity of Japan: Evidence from cross-country patent citations. Technovation 101, 102208.

Figure 1: Scatterplot of Log R&D on turnover



Notes: Figure 1 depicts the relationship between turnover and R&D (both in logs) for the primary regression sample. Each observation represents the average R&D spend for groups of firms within a turnover bin with a fixed width of 0.04 log points. Each bin represents on average 172 firms. The fitted lines illustrate the predictions from locally weighted scatterplot smoothing (LOWESS) regression on either side of the A$20 million discontinuity.

Figure 2: RD design Estimation for True and Artificial Cut-Offs



Notes: Each of these results is based on regression discontinuity estimates by local polynomial robust bias-corrected inference methods (Calonico *et al.,* 2014). The bars represent the 90% confidence intervals. Bandwidth is selected using a data-driven technique to select the optimal bandwidth separately across each side of the cut-off (Calonico *et al.,* 2014). Following Cattaneo *et al.,* (2020), we use only the treated observations when artificial cut-offs are below the true cut-off of $20 million as well as only the control observations for artificial cut-offs are above.

Table 1: Overview of Key Recent Reforms

Year	Policy Event
2011-12	• R&D Tax Incentive (R&DTI) replaces the R&D Tax Concession (RDTC). • Available to companies that are resident in Australia for tax purposes, and foreign companies in certain circumstances. • Refundable 45 percent tax offset available to companies with turnover of less than A$20 million, providing a benefit of 15 to 45 cents in the dollar for these companies. • Non-refundable 40 percent tax offset available to other companies, resulting in a benefit of 10 cents in the dollar for these companies.
2015-16	• A$100 million R&D expenditure threshold introduced. Companies expending more than A$100 million on R&D can receive a tax offset at the corporate tax rate for the R&D expenditure in excess of A$100 million.
2016-17	• R&DTI rates lowered to 43.5 percent and 38.5 percent for small and large firms, respectively.

Source: Australian Taxation Office (ATO various years), Department of Industry, Innovation and Science.

Table 2: Baseline Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Quadratic	Cubic	Doughnut	Robust	Single Crossers	Multi Crossers
Turnover under A$20 million (=1)	0.257***	0.252**	0.270*	0.252**	0.255***	0.208**	0.421**
	(0.090)	(0.122)	(0.157)	(0.102)	(0.099)	(0.100)	(0.209)
Number of observations (total)	9,661	9,661	9,661	9,460	9,610	9,216	445
Number of observations (treatment)	8,341	8,341	8,341	8,247	8,276	8,035	306
Number of observations (control)	1,320	1320	1,320	1,213	1,334	1,181	139
R-squared	0.0200	0.0202	0.0202	0.0204	n.a.	0.0207	0.0168
Bandwidth (Lower)	1.480	1.480	1.480	1.480	1.473	1.480	1.480
Bandwidth (Upper)	0.780	0.780	0.780	0.780	0.788	0.780	0.780
Local Polynomial Density (p-value)	0.4654	0.4654	0.4654	0.5445	0.4617	0.2965	0.1763

Notes: Columns (1) to (4) and (6) to (7) are based on regression discontinuity estimates using OLS from data spanning between 2012-13 and 2019-20. In column (5), we perform the local polynomial robust bias-corrected inference method to estimate the regression discontinuity estimate (Calonico *et al.,* 2014). Bandwidth (Lower/Upper) is selected by a data-driven technique to select the optimal bandwidth (Calonico *et al.,* 2014). Local polynomial density (p-value) by Cattaneo *et al.,* (2020) provides a check on the continuity of the running variable. OLS regressions also control for a linear term of the running variable (Turnover), an interaction between Turnover and Treatment status (ie. Turnover under A$20 million), year fixed effects. Estimates in columns (2) and (3) include the quadratic for the running variable and interaction term while column (3) adds a further cubic term for the running variable and interaction term. In column (4), we apply the doughnut method of Almond and Doyle (2011) whereby observations within 5% of threshold are removed from the estimating sample. In column (6), we re-run the baseline regression excluding firms having crossed the cutoff more than once. The sample used in column (7) includes only those firms that have crossed the cutoff more than once.

Table 3: Bandwidth sensitivity

		Upper Bandwidth (Control Group)													
		0.3	0.45	0.6	0.75	0.9	1.05	1.2	1.35	1.5	1.65	1.8	1.95	2.1	2.25
Lower Bandwidth	0.3	0.371**	0.309**	0.302**	0.276**	0.239*	0.211*	0.156	0.131	0.096	0.059	0.050	0.046	0.052	0.074
(Treatment Group)	0.45	0.312**	0.249**	0.243**	0.216*	0.180*	0.152	0.097	0.072	0.036	0.000	-0.010	-0.014	-0.007	0.014
	0.6	0.282**	0.220*	0.213**	0.187*	0.150	0.122	0.067	0.042	0.007	-0.030	-0.039	-0.043	-0.037	-0.015
	0.75	0.316***	0.253**	0.247**	0.220**	0.184*	0.156*	0.101	0.076	0.040	0.004	-0.006	-0.010	-0.003	0.018
	0.9	0.326***	0.263**	0.257**	0.231**	0.194**	0.166*	0.111	0.086	0.051	0.014	0.004	0.001	0.007	0.029
	1.05	0.314***	0.252**	0.245**	0.219**	0.182**	0.154*	0.099	0.074	0.039	0.002	-0.007	-0.011	-0.005	0.017
	1.2	0.339***	0.276***	0.270***	0.243***	0.206**	0.179**	0.123	0.098	0.063	0.026	0.017	0.013	0.020	0.041
	1.35	0.348***	0.285***	0.279***	0.253***	0.216**	0.188**	0.133	0.108	0.073	0.036	0.026	0.023	0.029	0.051
	1.5	0.356***	0.293***	0.287***	0.261***	0.224**	0.196**	0.141*	0.116	0.081	0.044	0.034	0.031	0.037	0.059
	1.65	0.364***	0.302***	0.295***	0.269***	0.232***	0.204**	0.149*	0.124	0.089	0.052	0.043	0.039	0.045	0.067
	1.8	0.384***	0.322***	0.316***	0.289***	0.252***	0.224***	0.169**	0.144*	0.109	0.072	0.063	0.059	0.066	0.087
	1.95	0.394***	0.332***	0.326***	0.299***	0.262***	0.234***	0.179**	0.154**	0.119	0.082	0.073	0.069	0.076	0.097
	2.1	0.388***	0.326***	0.319***	0.293***	0.256***	0.228***	0.173**	0.148*	0.113	0.076	0.067	0.063	0.069	0.091
	2.25	0.408***	0.346***	0.339***	0.313***	0.276***	0.248***	0.193**	0.168**	0.133*	0.096	0.087	0.083	0.090	0.111

Notes: Each cell provides a set of coefficient estimates based on regression discontinuity estimates using OLS from data spanning between 2012-13 and 2019-20. The lower bandwidth used is found in the row, while upper bandwidth is found in the column. All regressions control for a linear term of the running variable (Turnover), an interaction between Turnover and Treatment status year fixed effects. Recall that the optimal bandwidth in the preferred estimates is 1.48 in lower bandwidth (Treatment Group) and 0.78 in upper bandwidth (Control Group) (column 1 of table 3)

Table 4: Extensive Margin

	(1)	(2)	(3)	(4)
Dependent Variable	R&D (1/0)	log(R&D)	R&D (1/0)	log(R&D)
Estimator	OLS	Nonparametric	OLS	Nonparametric
Turnover under $20 million	0.020***	0.020***	0.282***	0.229***
	(0.004)	(0.004)	(0.040)	(0.042)
Number of observations (treatment)	372194	372194	306212	306212
Number of observations (control)	19821	19821	21811	21811
Bandwidth (Lower)	2.501	2.501	1.790	1.790
Bandwidth (Upper)	0.967	0.967	0.474	0.474

Notes: Columns (1) and (3) are based on regression discontinuity estimates using OLS from data spanning between 2012-13 and 2019-20. In columns (2) and (4), we perform the local polynomial robust bias-corrected inference method to estimate the regression discontinuity estimate (Calonico *et al.,* 2014). These sets of regressions include all firm-year observations irrespective if they claim any R&D tax incentive. The dependent variable is indicated in the column head. Bandwidth (Lower/Upper) is selected by a data-driven technique to select the optimal bandwidth (Calonico *et al.,* 2014). OLS regressions also control for a linear term of the running variable (Turnover), an interaction between Turnover and Treatment status (ie. Turnover under A$20 million), year fixed effects and firm fixed effects.

Table 5: Alternative outcome variables of R&D outlays

	Filed Patents (Over Three Years)	Filed Trademarks (Over Three Years)	Filed Design Rights (Over Three Years)
Turnover under A$20 million (=1)	-0.035	0.396	0.131
	(0.111)	(0.303)	(0.094)
Number of observations	5238	5238	5238
Number of observations (treatment)	4528	4528	4528
Number of observations (control)	710	710	710
R-squared	0.0018	0.0125	0.0002
Bandwidth (Lower)	1.4800	1.4800	1.4800
Bandwidth (Upper)	0.7800	0.7800	0.7800
Local Polynomial Density (p-value)	0.5896	0.5896	0.5896

Notes: Each of these results is based on regression discontinuity estimates using OLS from data spanning between 2012-13 and 2019-20. Bandwidth (Lower/Upper) is selected by a data-driven technique to select the optimal bandwidth (Calonico *et al.,* 2014). Lower is the sample size of the treatment group, while Upper is that of the control group. Local polynomial density (p-value) by Cattaneo *et al.,* (2020) provides a check on the continuity of the running variable. All regressions control for a linear term of the running variable (Turnover), an interaction between Turnover and Treatment status (ie. Turnover under A$20 million), year fixed effects.

Table 6: Falsification test with the different outcome variables

	(1) Log Wages	(2) Log Headcount	(3) Log Capex	(4) Log Non-Current Assets
Turnover under A$20 million (=1)	-0.025	-0.017	0.004	-0.099
	(0.056)	(0.027)	(0.120)	(0.113)
Number of observations	159073	145930	168304	81251
Number of observations (treatment)	147166	134759	155601	74896
Number of observations (control)	11907	11171	12703	6355
R-squared	0.0288	0.1097	0.0130	0.0129
Bandwidth (Lower)	1.680	1.680	1.680	1.680
Bandwidth (Upper)	0.500	0.500	0.500	0.500
Local Polynomial Density (p-value)	0.4948	0.2688	0.8141	0.6831

Notes: Each of these results is based on regression discontinuity estimates by local linear regressions, using data from 2012-13 to 2019-20. The dependent variable is indicated in the column header. Bandwidth (Lower/Upper) is selected by a data-driven technique to select the optimal bandwidth (Calonico *et al.,* 2014). Local polynomial density (p-value) by Cattaneo *et al.,* (2020) provides a check on the continuity of the running variable. OLS estimates also control for a linear term of the running variable (Turnover), an interaction between Turnover and Treatment status (ie. Turnover under A$20 million), year fixed effects and firm fixed effects.

Table 7 Marginal Product of R&D Stock Estimates

	(1)	(2)	(3)	(4)
Dependent Variable Notes	Log Real Value Added	Pooled TFP Estimates using ACF in First Step	Industry Specific TFP Estimates using ACF in First Step	Industry Specific TFP Estimates using ACF in First Step
Lag Log Real Capital (BIT)	0.189***			
	(0.005)			
Log Headcount	0.799***			
	(0.009)			
Lag Log Real R&D Stock	0.066***	0.036***	0.042***	0.035***
	(0.005)	(0.004)	(0.005)	(0.005)
Lag Log Real Intra-Industry R&D Stock	0.013**	0.017**	0.015**	0.013*
	(0.007)	(0.007)	(0.007)	(0.007)
Lag Log Real Inter-Industry R&D Stock	0.065**	0.056*	0.060**	0.059**
	(0.030)	(0.030)	(0.030)	(0.030)
Log Real Industry Average Value-Added				0.068***
				(0.009)
Number of Observations	54329	54217	54217	54134
Number of Firms	12859	12832	12832	12824
R Squared	0.7833	0.0653	0.3721	0.3753

Appendix

Table A1. Variable definition

Name of variables	Data Source	Definition
Value-added A$ millions	BAS (Business Activity Statement data)	Value added = Total sales less Cost of sales for tax purposes
Assets A$ millions	BIT (Business Income Tax data)	Non-current derived assets comprise assets that the company holds for at least one year, e.g., cars, land, buildings, office equipment, computers, bonds, stocks, notes, patents, trademarks, and goodwill.
Employment headcount	PAYG	Number of persons working for this business during last pay period
Own R&D A$ millions	R&D Tax Incentive Program R&DTI of the Department of Industry Science, Energy and Resources DISER	R&D expenditure values from the program data
Own R&D stock A$ millions	R&D Tax Incentive Program R&DTI of the Department of Industry Science, Energy and Resources DISER	Standard perpetually inventory formulae: $R_{f,it-1} = (1-\rho)R_{f,it-2} + D_{f,it-1}$, where D is R&D spending
External R&D stock A$ millions	R&D Tax Incentive Program R&DTI of the Department of Industry Science, Energy and Resources DISER	R&D stocks of all other firms but the said firm weighted by the proportion of firm is industry inputs are supplied by firm js industry output. Various weights used.

Table A2: Summary Statistics, Data used for Productivity Estimates

Variable	Definition	Mean	SD
Log Real Value-Added (BIT)	Sales less cost of goods sold	14.74	2.02
Log Real Capital (BIT)	Total Assets less Current Assets	14.31	2.59
Log Headcount	Number of persons working for this business during last pay period	3.60	1.68
Log Real Cost of Sales (BIT)	Cost of direct inputs to production less change in inventory	14.69	2.45

Notes: prior to estimating production functions, we removed firms which reported key operating ratios outside 99th percentile for their industry. Ratios were capital-labour, sales per employee and sales per capital.

Table A3. First Stage Production Function Estimates

	OLS				ACF					
Div	*k*		*l*		*k*		*l*	*Se*	*N*	*N firms*
(1)	0.311	(0.019)	0.683	(0.026)	0.296	(0.033)	0.736	(0.059)	1785	377
(3)	0.229	(0.004)	0.784	(0.006)	0.187	(0.010)	0.876	(0.021)	23834	4092
(4)	0.386	(0.015)	0.649	(0.024)	0.34	(0.113)	0.756	(0.188)	664	149
(5)	0.254	(0.009)	0.719	(0.012)	0.238	(0.022)	0.772	(0.038)	4122	919
(6)	0.241	(0.006)	0.791	(0.009)	0.115	(0.032)	1.092	(0.105)	9488	1885
(7)	0.084	(0.010)	0.894	(0.013)	-0.050	(0.142)	1.236	(0.337)	2786	690
(8)	0.233	(0.022)	0.741	(0.023)	0.285	(0.059)	0.685	(0.245)	539	116
(9)	0.319	(0.021)	0.666	(0.025)	0.331	(0.122)	0.639	(0.409)	941	193
(10)	0.227	(0.012)	0.809	(0.020)	0.344	(0.051)	0.207	(0.269)	1773	449
(12)	0.209	(0.012)	0.785	(0.017)	0.2	(0.026)	0.801	(0.050)	2788	626
(13)	0.132	(0.005)	0.894	(0.009)	0.132	(0.035)	0.892	(0.201)	11965	2923
(16)	0.183	(0.041)	0.793	(0.060)	0.167	(0.579)	0.876	(1.173)	308	83
(17)	0.117	(0.023)	1.016	(0.030)	0.215	(0.230)	0.870	(0.611)	1051	223
(18)	0.216	(0.048)	0.752	(0.065)	0.308	(0.145)	0.696	(0.193)	270	64
(19)	0.058	(0.019)	0.874	(0.027)	0.129	(0.111)	0.809	(0.423)	1594	345
Pooled	0.215	(0.002)	0.795	(0.004)	0.162	(0.005)	0.912	(0.013)	63908	12905

Table A4 Summary Statistics for Regression Estimates of Equation (3)

Variable	Mean	SD	Median
Log Real Industry Average Value-Added	15.86	1.2	15.7
Total Factor Productivity (ACF Pooled)	9.12	1.21	9.2
Total Factor Productivity (ACF Industry Specific Estimates)	9.14	0.98	9.24
Log R&D Stock	12.97	1.96	13.02
Log Intra-Industry R&D Stock	18.72	1.82	18.94
Log Inter-Industry R&D Stock	22.75	0.81	22.93
VA to R&D Stock Ratio (Y/R)	156.50	8939	3.97

Notes: Number of firm-year observations is 53860. Variable definitions provided in table A2