PRODUCTIVITY GROWTH AND INNOVATION SUPPORT

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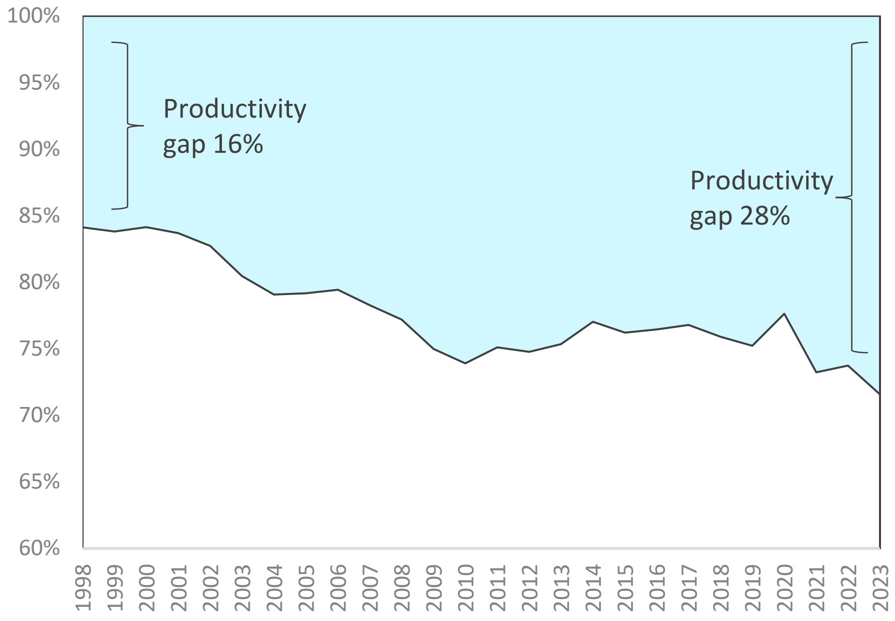
WEAK PRODUCTIVITY HAS BEEN A PERENNIAL ISSUE IN CANADA

- Canadian productivity growth has been lagging the U.S. on average over the past several decades.
- Our productivity gap with the U.S. has widened from 16% to 28%.

Canada's labour productivity gap with the US has grown over the past 25 years

GDP per hour worked relative to the US (US=100%)



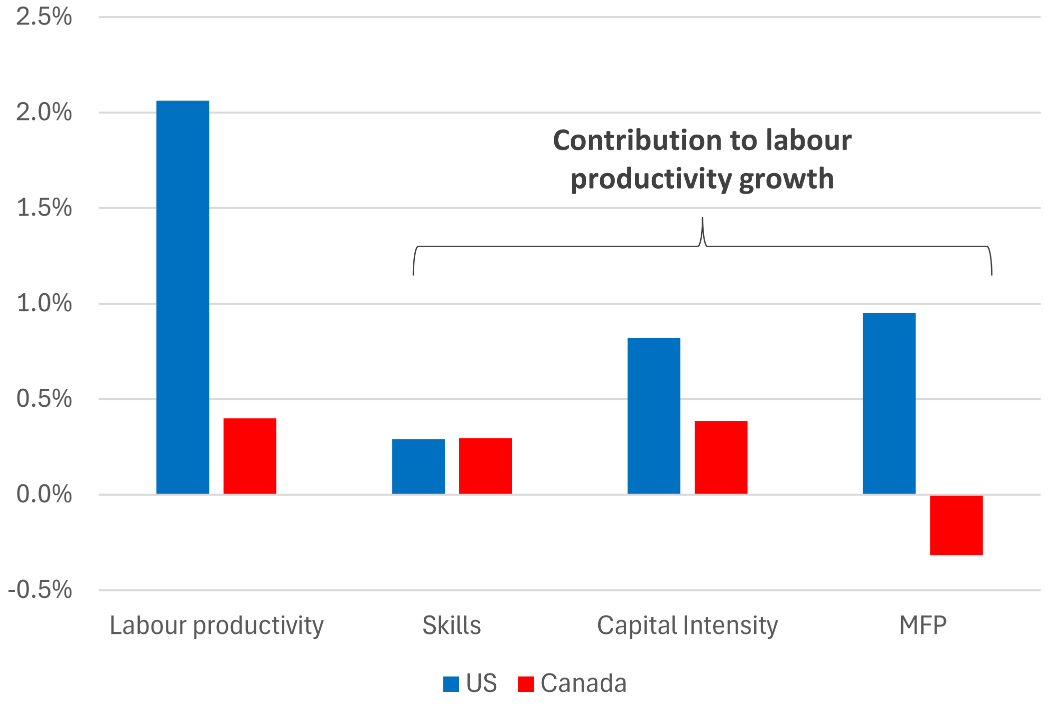
Source: OECD

LACK OF INNOVATION REMAINS A DRIVING FACTOR

- Decomposing labour productivity growth shows that Canada's primary weakness lies in Multi-factor Productivity (or MFP).
    - (MFP) is a broad measure of efficiency that reflects the impact of **innovation, economies of scale, and workplace organization**, and other factors.
    - Weak MFP performance points to **lower investment in innovation**.
    - This includes both **technical innovation** (e.g., R&D, tech adoption) and **non-technical innovation** (organizational improvements).

MFP driving gap in labour productivity

Labour productivity growth: Canada vs. the U.S., 2019-2023

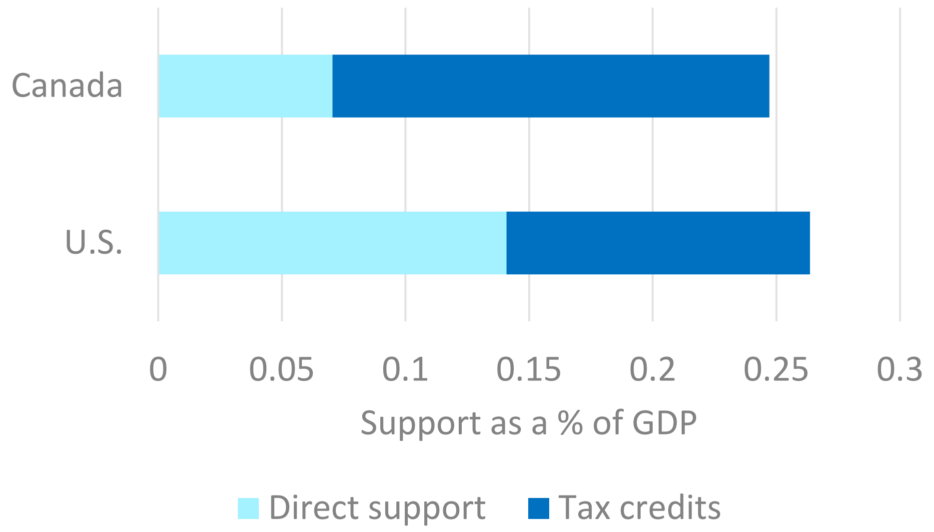


Source: Statistics Canada; Bureau of Labor Statistics

CONCERN CANADIAN INNOVATION SUPPORT GETS LESS BANG-FOR-THE-BUCK

- **Canada does not gain as much from innovation** (as suggested by aggregate MFP).
- Yet, Canada's support to business R&D exceeds the OECD average and is comparable to the U.S.
  - Canada also supports non-R&D innovation through various programs, though international comparisons are limited.
- A key knowledge gap remains: how Canada's mix of support mechanisms translates into business outcomes like productivity.

Canada and the U.S. provide similar support for R&D, but through different mechanisms
Government support for business R&D, 2021



Source: OECD

MAIN RESEARCH QUESTIONS

Do innovation direct support recipients invest more, grow faster, become more productive?

Do we see heterogeneity in impacts among different programs or support mechanisms? Among different types of businesses?

What is the broader relationship between innovation support and productivity growth? Are there spillovers from support?

THE BIGS INITIATIVE

- Since 2018, the BIGS initiative (between TBS and Statcan) has collected administrative data to enhance impact assessments for growth and innovation-related programming.
- A program stream is deemed **in scope** of BIGS if it satisfies at least one of the 13 criteria adopted from the OECD-Oslo Manual 2018 including innovation, growth and community spillovers.
- BIGS program streams offer diverse supports such as Grants & Contributions (Gs&Cs), advisory services, R&D investments, commercialization, and export initiatives.

Key BIGS Organizations

Natural Sciences and Engineering Research Council (NSERC)	Innovation, Science and Economic Development (ISED)
Global Affairs Canada (GAC)	National Research Council (NRC)
Natural Resources Canada (NRCan)	Regional Development Agencies (RDAs)*
Employment and Social Development Canada (ESDC)	Environment and Climate Change Canada (ECCC)

Flagship BIGS Programs**

Industrial Research Assistance Program (IRAP) *NRC*	**Strategic Innovation Fund (SIF)** *ISED*
GAC **Trade Commissioner Service (TCS)**	*RDAs* **Business Scale-up and Productivity (REGI)**

For the BIGS initiative, a **program stream** is a business-facing program that provides **funding** or **services** to recipients. A program stream is uniquely distinguishable to its target audience by aspects such as name, purpose, and service delivery model.

*including ACOA, CanNor, CEDQ, FedDev, FedNor, PacifiCan, and PrairiesCan

** **Flagship Programs** refers to the largest BIGS programs that were identified as focal points in the 2017 innovation and skills plan

HOW DO BIGS PROGRAMS INCREASE PRODUCTIVITY ?

Direct Effects

BIGS

- Support improves firm capabilities (e.g., tech adoption, R&D)
- Encourages capital deepening, upgrading skills, and knowledge creation
- Leads to productivity gains within supported firms

PRODUCTIVITY

Indirect Effects

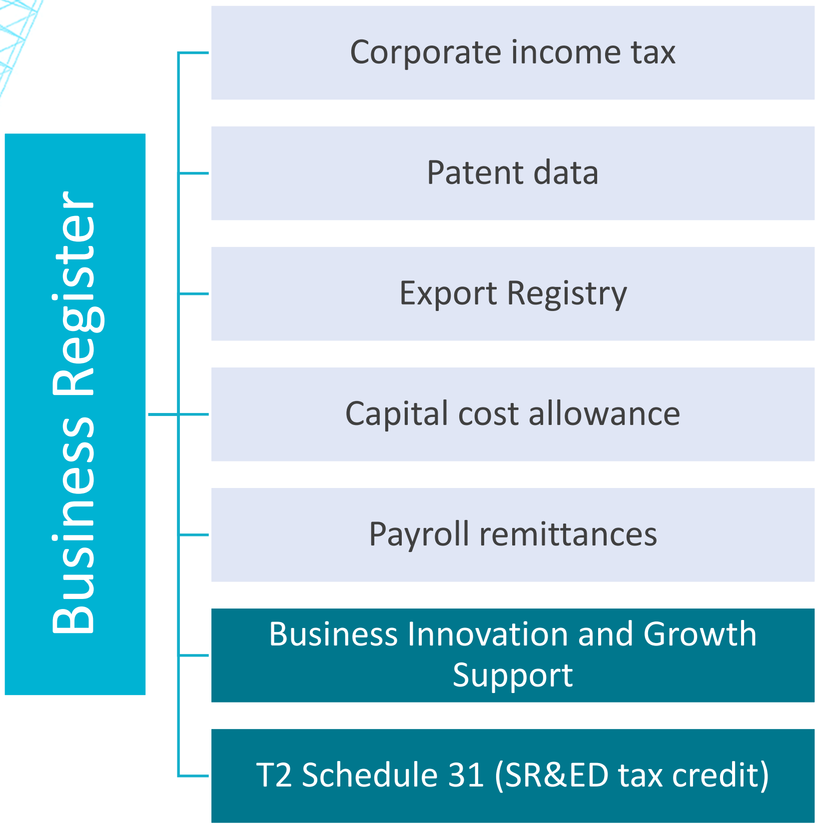
BIGS

- Enhances spillovers to non-supported firms (e.g., knowledge diffusion, workforce upskilling)
- Supports sector-wide productivity growth via network and clustering effects

THRIVING ECOSYSTEM

PRODUCTIVITY

STATISTICS CANADA ADMINISTRATIVE DATA



- Data links BIGS program data and SR&ED ITC files to key administrative data sources covering growth, investments, patenting, exporting, R&D performance.

- Population includes all BIGS program beneficiaries from 2008-21.

- Control population of non-BIGS beneficiaries from across the economy, excluding agriculture, education, and government services.

KEY OUTCOMES

- Past studies show positive effects on growth, but **links to productivity are less consistent**.
  - This may reflect delayed impacts—e.g., "growing pains" before gains materialize.

- Our approach extends previous work by:
  - Controlling for pre-support investment activities;
  - Analyzing post-support investment in productivity-enhancing asset classes;
  - Leveraging more robust productivity metrics.

Performance Metrics

Growth & Innovation
- Sales
- Employment
- Exports
- Patents
- R&D expenditures

Investment New
- Total capital investment
- M&E investment
- Intangible investment

Productivity New
- Labour productivity
- Multi-factor productivity

PRODUCTIVITY ESTIMATION

Labour Productivity

Calculation:

- $LP_{it} = \frac{Y_{it}}{L_{it}} = \frac{W_{it}+R_{it}}{N_{it}}$
- Where:
  - Y : Output
  - L : Labour input
  - W : Labour income
  - R : Capital income
  - N : # of employees

Deflators:

- We use KLEMS and the National Accounts to construct industry specific price deflators, including:
  - Gross output
  - Capital investment
  - Labour
  - Intermediate inputs
  - R&D expenditures

Multi Factor Productivity (industry specific models)

Production Function (Log-Linear):

- $y_{it} = \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \varepsilon_{it}$
- y :output | k, l: inputs | ω: unobs. TFP | ε: i.i.d. error

Identification via Proxy:

- Endogeneity: k_{it}, l_{it} correlated with ω_{it}
- Proxy: m_{it} (intermediates) → $\omega_{it} = h_t(m_{it}, k_{it})$

MFP Evolution Assumption:

- $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$

Estimation Strategy:

- $y_{it} = \beta_k k_{it} + \beta_l l_{it} + g\big(h_{t-1}(m_{it-1}, k_{it-1})\big) + \xi_{it} + \varepsilon_{it}$

GMM estimation using lagged inputs as instruments

- $E[\xi\_it + \varepsilon\_it \mid Z\_it] = 0$

MFP Recovery:

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

MORE PRODUCTIVE FIRMS SEEK SUPPORT

- BIGS beneficiaries outperform other businesses in their industry across a variety of metrics:
  - Sales growth
  - Labour productivity
  - MFP
  - Investment
- Accordingly, need to control for these underlying differences to assess impact of support.

Beneficiaries invest more and are more productive

BIGS beneficiaries vs general population

$$Y_{it} = \beta_0 + \beta_1 BIGS_{it} + \sum_{j=1}^{J-1} \gamma_j NAICS_{j,i} + \sum_{t=1}^{T-1} \delta_t Year_t + \varepsilon_{it}$$

Dependent variable	Coeff
Sales growth	0.083 ***
Labour productivity	0.316 ***
Labour productivity growth	0.036 ***
Multi-factor productivity	0.392 ***
Multi-factor productivity growth	0.016 ***
Investment per employee	1.779 ***
M&E investment per employee	1.919 ***
Intangible investment per employee	0.523 ***

Note: Sample includes BIGS supported firms in the year(s) they receive support and businesses not receiving BIGS support during the sample period (2008-2021); productivity variables are up until 2020. All regressions include time fixed effects and industry fixed effects (NAICS 3-digit), which are not reported. Growth rates are calculated as $\ln(X_t)-\ln(X_{t-1})$. Investment variables are in the inverse hyperbolic sine transformation to account for 0 values. Standard errors are clustered at the business level. *** p<0.01

STAGE 1: PROPENSITY SCORE MATCHING

- Defining the treatment group:
  - Businesses receiving support for the first time.
  - Limit to cohorts allowing post-treatment analysis.

- Use propensity score matching to select the control group:
  - Limit control pool for each treatment to businesses in the same NAICS 3-digit industry
  - Select nearest neighbour with replacement based on propensity score.

Estimate Propestiy Score from Logistic Model

$$\Pr(Support_i = 1) = \alpha + \alpha_{ind} + \beta X_i + \varepsilon_i$$

Controls (X_i) include 1 year lag of:

- Labour productivity;
- Multi factor productivity;
- Investment past 3 years (M&E, intangible);
- Total Assets;
- Sales;
- Employment;
- Average Wages;
- Retained Earnings;
- R&D Expenditures;
- Exporter;
- Age;
- Prior sales growth (dummy categories)

COHORTS BALANCED ACROSS SEVERAL KEY COVARIATES

Kolmogorov-Smirnov equality of distribution tests

	Before matching					After Matching				
	2012	2013	2014	2015	2016	2012	2013	2014	2015	2016
Employment	***	***	***	***	***		**	**	***	**
Employment2	***	***	***	***	***		**	**	***	**
Sales dummy										
Sales	***	***	***	***	***			***		
M&E invest 3yr dummy	***	***	***	***	***					
M&E investment 3yr	***	***	***	***	***			**		*
Intangible invest 3yr dummy	*	*								
Intangible investment 3yr	*	**								
R&D dummy	***	***	***	***	***					
R&D expenditures	***	***	***	***	***	**				
Labour productivity	***	***	***	***	***			*		
Multi-factor productivity	***	***	***	***	***					
age	***	***	***	***	***					
Export dummy	***	***	***	***	***					
Exports	***	***	***	***	***	*	***	*		**
High growth dummy	***	***	***	***	***					
Growth dummy	***	**		*						
Shrink dummy	***	***	***	***	***					
Nascent dummy	***	***	***	***	***					
Propensity score	***	***	***	***	***					

*** P<0.01; ** P<0.05; * P<0.1

STAGE 2: STAGGERED DIFFERENCE-IN-DIFFERENCES

- We use the Callaway and Sant'Anna (2021) DiD estimator.
- For each support cohort, the model cycles through all appropriate two-group, two-period comparisons.
  - Ensures that only truly untreated units serve as controls, avoiding bias that arises when already-treated units are inappropriately compared to new adopters.
- Combines the *ATT(g,t)* estimates across cohorts and time using weights that reflect sample size and data structure.

Estimating event–study ATT

Define relative time e = t - g where g is the cohort's treatment start (e=0 at treatment).

Event-study function pools estimates for all cohorts at the same relative time e.

$$ATT_{event}(e) = \sum_{g} w(g,e) \cdot ATT(g, g+e)$$

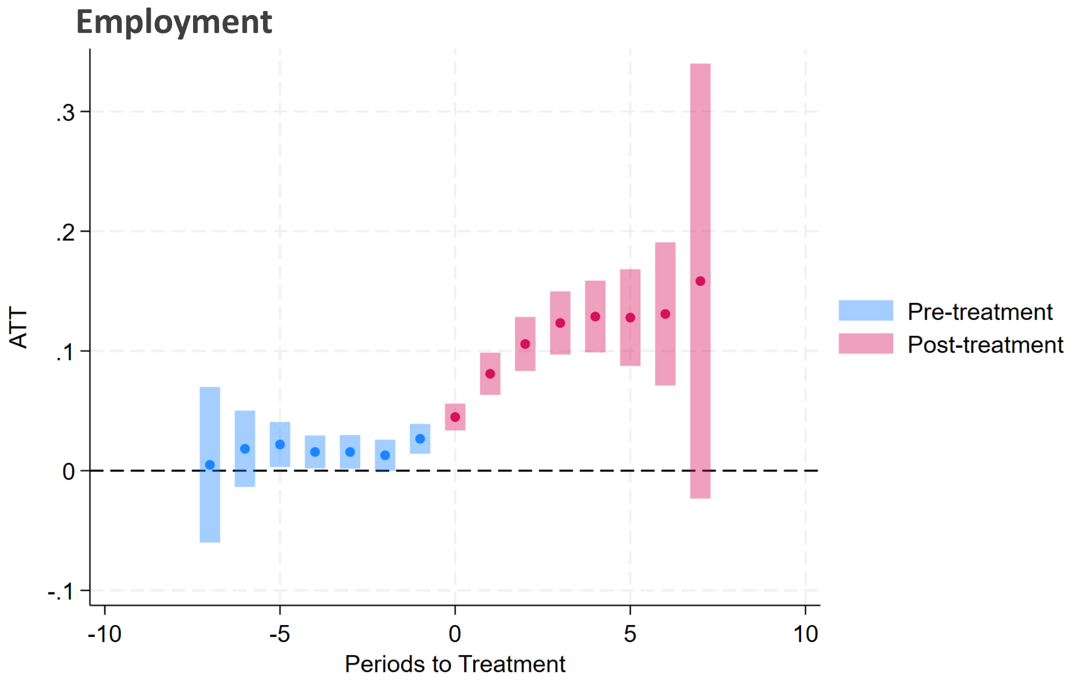
Results can be displayed by period, or aggregated to an event window (e.g., 5 years):

$$\hat{\theta}(g) = \frac{1}{5} \sum_{e=1}^{5} ATT(g, g+e)$$

BIGS SUPPORT LINKED WITH BUILDING CAPACITY

- BIGS support is most consistently associated with firm growth through employment expansion.
- Employment effects emerge quickly after support and strengthen over time, indicating sustained impact.

BIGS support association with rising employment

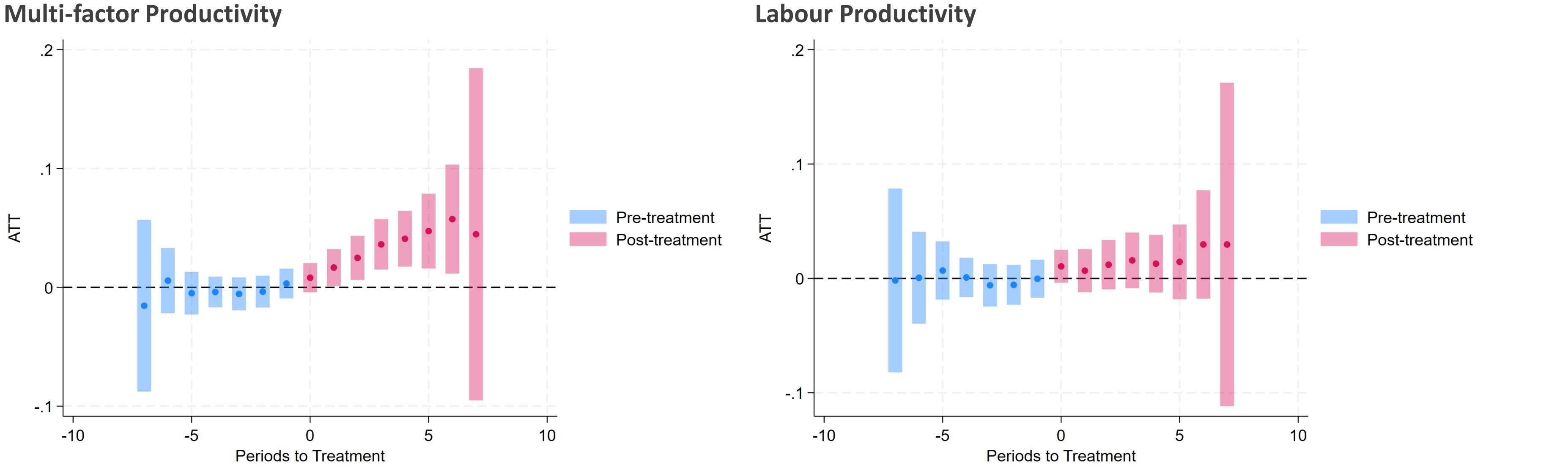


Notes: Points show estimated average treatment effects on the treated (ATTs) by event time (first year of BIGS support); bars denote 95% confidence intervals. Negative values indicate pre-treatment periods. Estimates are relative to otherwise similar matched control firms.

PRODUCTIVITY IMPACTS DIFFER BY MEASURE

- Results show **statistically significant gains in multi-factor productivity (MFP), but no robust effects on labour productivity**.
- This pattern is consistent with innovation support improving technical and organizational efficiency (captured by MFP) while firms simultaneously expand employment, scale operations, or invest in intangible capacity, **dampening short-run gains in output per worker**.

Mixed impact on productivity



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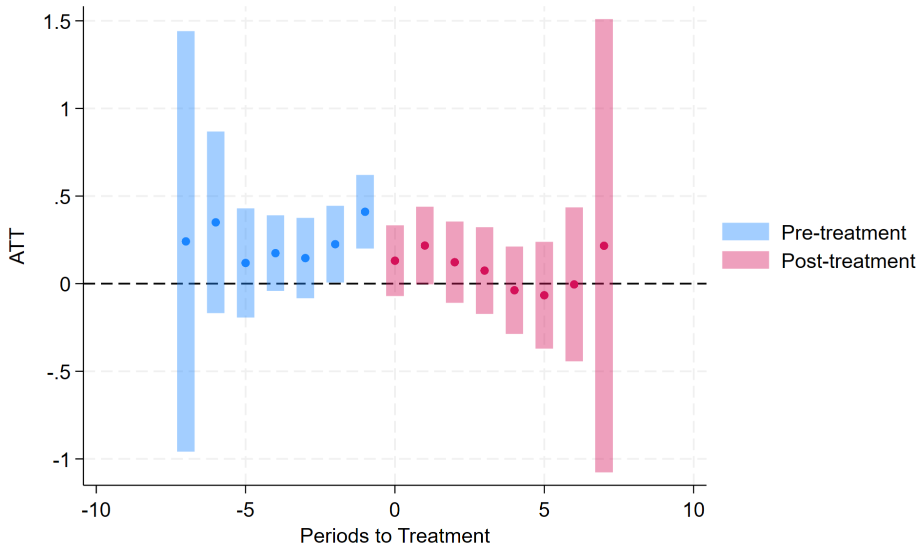
INVESTMENT RESULTS MIXED

- Fixed-effects models on matched data (with balanced pre-support investment levels) show positive and statistically significant impacts on investment.
- Our preferred specification, which **accounts for pre-support investment dynamics, does not find robust post-support effects**, reflecting investment ramp-up around the time of support.
- **This pattern is consistent with anticipatory behaviour or selection** into support among firms already undertaking investment projects.
- Investment's lumpy nature limits potential for full pre-treatment balance on its dynamics.

Support not associated with a change in investment trends, but may signal anticipatory behaviour

Capital Investment per employee



Notes: Points show estimated average treatment effects on the treated (ATTs) by event time (first year of BIGS support); bars denote 95% confidence intervals. Negative values indicate pre-treatment periods. Estimates are relative to otherwise similar matched control firms.

STAGE 3: HETEROGENEOUS PROGRAM IMPACTS

- Aggregate results mask substantial variation in impacts across firms and types of support.
- To understand how programs affect different businesses—and how firms interact with programs—we examine treatment effects across key subgroups.
- Treated firms are partitioned by support characteristics (e.g., financial vs non-financial, support intensity) and firm attributes (e.g., age, size, pre-support growth).
- For each subgroup, impacts are estimated relative to a matched control group drawn from the same comparison set, ensuring like-for-like comparisons.

Framework allows for testing statistical significance across different models and ATT estimates

- Differences in subgroup impacts are assessed using Recentered Influence Functions (RIFs) derived from the staggered DID estimator. More formally:

$$RIF_{ig} = \varphi(Y_{it}, D_{it}; \widehat{\theta_{g,t}})$$

Where φ is the influence function operator, Y is the outcome, D is the treatment indicator, and θ is the estimated ATT.

- RIFs provide linearized contributions of each observation to estimated ATTs, enabling formal tests of whether impacts differ across subgroups.

$$H_0: \widehat{ATT_1} = \widehat{ATT_2}$$

$$t = \frac{\widehat{ATT_1} - \widehat{ATT_2}}{\sqrt{\widehat{Var}(RIF_1)/N_1 + \widehat{Var}(RIF_1)/N_2}}$$

GROWING AND YOUNG BUSINESSES ASSOCIATED WITH BETTER OUTCOMES

- Estimated impacts vary meaningfully by firm characteristics.
- Firms with stronger pre-support growth show larger and more statistically significant impacts, consistent with greater capacity to leverage support.
- Younger firms also exhibit relatively large and significant effects, consistent with higher need of support.
- Firm size not associated with significant ATT heterogeneity.

Treatment effects by firm characteristic (5-year ATT)

	Pre-support growth (3 yr avg<10%)	Pre-support growth (3 yr avg >10%)	Difference test
Employment	1.2%	**26.5%** ***	***
Multi-factor productivity	0.3%	**6.6%** ***	***
Labour productivity	-0.5%	**3.8%** **	**
	Older (> 5 yrs old)	Young (< 5 yrs old)	Difference test
Employment	**5.3%** ***	**29.1%** ***	***
Multi-factor productivity	**2.3%** ***	**6.8%** ***	*
Labour productivity	0.5%	**9.9%** ***	***
	Micro (<=5 employees)	Non-micro (>5 employees)	Difference test
Employment	**7.8%** ***	**6.0%** ***	-
Multi-factor productivity	-0.2%	**2.5%** ***	-
Labour productivity	0.4%	0.6%	-

*** P<0.01; ** P<0.05; * P<0.1

Notes: Entries report average treatment effects on the treated (ATTs) over the five years following first receipt of support. Firms are partitioned by pre-support growth, age, and size as indicated in column headers. For each partition, treatment effects are estimated using separate difference-in-differences models, with control groups restricted to matched comparison firms corresponding to the treated firms in that partition.

HIGHER SUPPORT AND MULTI-MODAL SUPPORT LINKED WITH BETTER OUTCOMES

- **Firms receiving higher levels of support show stronger outcomes**, including statistically significant gains in labour productivity.
- Grant and contribution (G&C) support is associated with better performance than non-financial support alone, with the **strongest results when combined with other supports**.
- Firms receiving higher-value or multiple forms of support overlap, reflecting greater support intensity and, **likely, stronger underlying firm capacity.**

Treatment effects by different support groups (5-year ATT)

	Non-financial support only	Support < $100K	Support > $100K
Employment	**3.4% ****	**16.7% *****	**22.5% *****
Multi-factor productivity	1.3%	**3.6% ****	**6.0% *****
Labour productivity	0.1%	1.0%	**4.9% *****
	Other support only	**G&Cs support only**	**G&Cs + other support**
Employment	**3.7% *****	**11.2% *****	**22.2% *****
Multi-factor productivity	1.5%	3.6%	**4.7% ***
Labour productivity	0.5%	1.6%	**2.6% *****

*** P<0.01; ** P<0.05; * P<0.1

Notes: Entries report average treatment effects on the treated (ATTs) over the five years following first receipt of support. Firms are partitioned by type of support received as indicated in column headers. The "Other support" category includes advisory, gov't services, procurement, and other / NA. For each partition, treatment effects are estimated using separate difference-in-differences models, with control groups restricted to matched comparison firms corresponding to the treated firms in that partition.

WORK IN PROGRESS

- Productivity decompositions
- Spillovers

PRODUCTIVITY DECOMPOSITIONS

- Innovation support is correlated with faster sales and employment growth.
- Accordingly, support could also affect aggregate productivity growth through **composition effects by reallocating market share to more productive firms.**

Basic Griliches-Regev Productivity Decomposition

$$\Delta P_{t,t-k} = P_t - P_{t-k} = \underbrace{\sum_{i \in C} \bar{\theta}_i \Delta p_i}_{\text{Within}} + \underbrace{\sum_{i \in C} \Delta\theta_i (\bar{p}_i - \bar{P})}_{\text{Between}} + \underbrace{\sum_{i \in N} \theta_{it}(p_{it} - \bar{P})}_{\text{Entry}} - \underbrace{\sum_{i \in X} \theta_{i,t-k}(p_{i,t-k} - \bar{P})}_{\text{Exit}}$$

Where P is firm-level labour productivity, and θ is firm market/employment share.

Calculated separately for supported vs non-supported businesses

ESTIMATING SPILLOVERS

- Support can boost productivity beyond recipients by driving innovation spillovers to non-supported firms.
- But too much support can backfire—crowding out private investment or causing resource congestion.

Spillover effects estimated using regressions inspired by zombie firm studies (e.g., Caballero et al 2008)

Combines recipient and non-recipient firms to assess whether support density affects the productivity of non recipients. More formally:

$$Y_{it} = \beta_1 I_{it} + \beta_2 I_{it} Share_{ind,t} + \beta_3 Firm\ contros_{it} + S'T + \varepsilon_{it}$$

Where I is a dummy indicating whether firm i did not receive support; *Share* is the share of total payroll of recipient firms in the same industry, and $S'T$ are vectors of industry and year fixed effects.

CONCLUSIONS

- Business support is associated with positive employment and mixed productivity outcomes on average, though estimated impacts vary substantially by firm characteristics, support type, and timing.
- Impacts tend to be larger and more statistically significant for young and growing firms, and where support is financial, more intensive, or combined across mechanisms (e.g., contribution + advisory).
- Program-level comparisons broadly reinforce aggregate results, suggesting that common support mechanisms and firm selection may play a larger role than individual program labels.
- Taken together, results are consistent with the view that more targeted and coordinated support—focused on firms with the capacity to absorb and scale—may yield higher returns.