Radical Innovation and Firm Productivity Growth

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PRIN Final Workshop
February 5, 2026

BACKGROUND

- Extensive literature studies how innovation is **measured**, what **drives** it, and how it affects firm **performance** (Castellacci & Zheng, 2010; Bontempi & Mairesse, 2015; Ugur et al., 2016)

- Despite many empirical studies, measuring innovation's effect on firm-level productivity reveals no consensus on its magnitude (Hall et al. 2009).

- While **innovation** is associated with **positive long-run** productivity effects, **short-run impacts** are often more nuanced (Hall et al., 2010; Chappell & Jaffe, 2018)

- Organizational adjustments, learning dynamics, and implementation lags can generate temporary productivity declines, consistent with a **J-curve effect** (Chappell & Jaffe, 2018; Brynjolfsson et al., 2021)

IMPACTS OF INNOVATION

- Innovation measurement relies on both **input indicators** (R&D expenditures) and **output measures** (patents) (Griliches, 1990; Crépon et al., 1998)
- **Patent indicators** are useful for identifying most technically and commercially valuable innovations (Carpenter et al., 1981; Trajtenberg, 1990; Albert et al., 1991)
- High-quality patents affect **firms' performance** (Lanjouw and Schankerman, 2004) or **market value** (Hall et al., 2005)
- Citation-weighted patents outperform raw patent counts in explaining differences in **labour productivity** among firms (Bloom and Van Reenen, 2002)

RADICAL INNOVATION as NOVELTIES

- Radical innovations are **novel** from the existing technological base and also **impactful** as they affect future innovations (Dahlin and Behrens, 2005, Cohen, 2010, Archibugi et al., 2013)

- Measuring and assessing the impact of radical innovation is a challenging task

- To detect radical innovation **ex-ante,** we define **radical innovations as novelties**

- Economically: **Novelties** can create a technological discontinuity that breaks existing knowledge trajectories and reshapes firms' competitive positions. (Verhoeven et al., 2016).

This paper in a nutshell

Objectives:

- Investigate the dynamic effects of radical innovation on firm productivity growth
- Identify the main transmission channels

Data Source:

- Panel data for Italian firms between 2012 to 2020 from Moody's Orbis Intellectual Property (IP) database

Empirical strategy:

- Development of a radical innovation metric using text mining on patent text
- Event study to assess the dynamic effects of radical innovation on labor productivity
- Decomposing labour productivity growth into output growth and employment growth to identify transmission mechanisms
- Robustness checks to address causality concerns

Baseline Specification

Panel data for Italian firms spanning from 2012 to 2020.
Lower cases variables in logs:

$$\Delta lp_{it} = \beta N_{it} + \gamma x_{it} + \alpha_i + \mu_{jt} + \epsilon_{it}$$

- Δlp_{it} is the annual log change in labour productivity
- N_{it}= treatment dummy equal to 1 from the year of introduction of a radical innovation onward and 0 otherwise
- β = average post-treatment effect of a radical innovation
- x_{it} a vector of controls:
  - Lagged level of labor productivity;
  - Capital labor ratio;
  - Firm’s patent portfolio;
  - Financial ratios: cash-flow, intangible assets, debt;
  - Competition effects: number of patenting firms operating in the same region–sector pair as the focal firm;
  - Knowledge spillovers: number of patent applications filed in the same region–sector pair as the focal firm
- μ_{jt} sector-year fixed effect ; α_i firm fixed effects

Data Sources

Panel of **28,611 Italian firms** over the period **2012-2020** taken from **Moody's Orbis Intellectual Property (IP) database**

ORBIS IP DATASET

BALANCE SHEET DATA

Dependent Variable:
- Labour productivity: value added (or sales) per employee

Control Variables:
- Capital stock per employee
- Financial ratios: cash-flow, intangible assets, debt
- Competition effects: number of patenting firms operating in the same region–sector pair as the focal firm
- Knowledge spillovers: number of patent applications filed in the same region–sector pair as the focal firm

PATENT DATA

29,332 patent applications with English-language titles and abstracts.

Independent Variables:
- Novelty Text-Based
- Novelty Backward Cites

Measuring Radical Innovation

TEXT-BASED APPROACH

- Our N_{NLP} measure compares the titles and abstracts of 29,332 patents with those filed in the previous five years (from 2007 to 2020)
- Text analysis is applied to the title and abstract (text) of 51,705 patents
- Each patent text is converted into a numerical vector that captures how often each term appears $(TF_{p,w})$ and how distinctive it is based on its use in past patents $(PastIDF_w)$

$$TFIDF_{p,w} = TF_{p,w} \times PastIDF_w$$

$$PastIDF_w = \log\left(\frac{P+1}{1+d(w)}\right) + 1$$

where P is the bulk of patents filed in the five years preceding p , and $d(w)$ is the number of those patents containing term w

- N_{NLP} for patent p is the maximum textual distance from prior patents (Gerken and Moehrle, 2012)

$$\boxed{N_{NLP}(p) = 1 - \max_{q \in \{P\}} \rho_{p,q}}$$

where P is the bulk of patents filed in the five years preceding p , and $\rho_{p,q}$, is the cosine similarity between patents p and q.

- A high value of N_{NLP} indicates that the focal patent p diverges substantially from prior art
- A patent is classified as novel if its N_{NLP} score falls above the 90th percentile

Measuring Radical Innovation

BACKWARD CITATIONS

- For comparison purposes, we construct a measure of novelty based on backward citations, defined as follows (Ahuja and Lampert, 2001):

$$N_{BWC}(p) = 1 - \frac{BWC_p}{\max(BWC_t)}$$

Where BWC refers to the sum of the backward citations included in the focal patent p, t represents the filing year of patent p, while $\max(BWC_t)$ is the maximum number of backward citations observed among all patents filed in the same year (cohort) as the patent p

- A high value of N_{BWC} indicates that the focal patent p relies less from prior art
- A patent is classified as novel if its N_{BWC} score falls above the 90th percentile

Treated firms

All firms with at least one patent identified as radical innovation (novelty) over the period **2012-2020**

TEXT-BASED APPROACH

1,510

treated firms

(vs 27,101 control firms)

BACKWARD CITATIONS

2,337

treated firms

(vs 26,234 control firms)

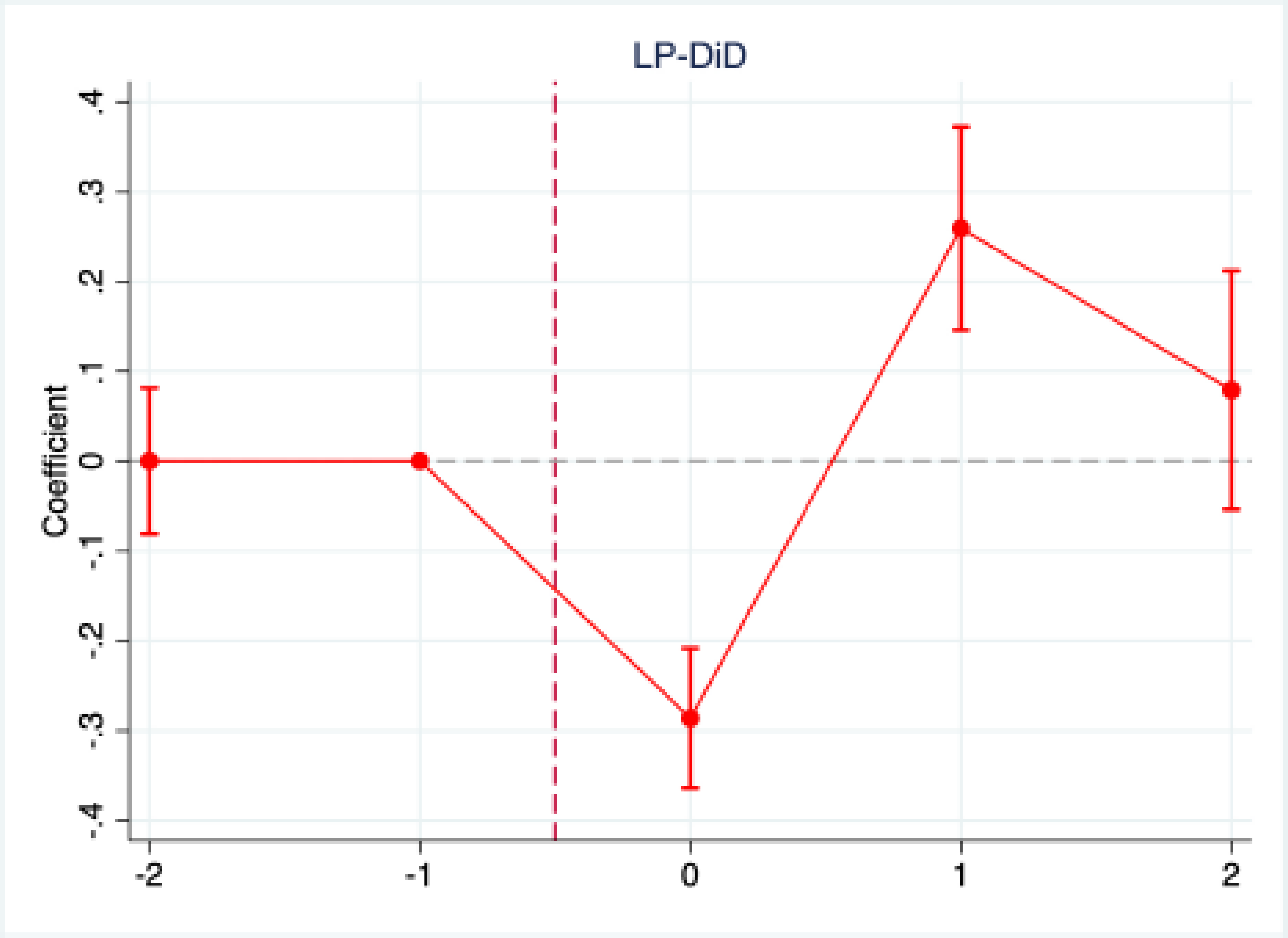
In line with Athey and Imbens (2022), we adopt an absorbing treatment framework: once a firm introduces a novelty, it remains treated for the remainder of the observation period

Dynamic Productivity Effects of Radical Innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Text					Backward cites				
Novelty (post × treatment)	-0.061***	-0.329***	-0.333***	-0.294***	-0.433***	-0.058***	-0.305***	-0.295***	-0.288***	-0.386***
	(0.019)	(0.031)	(0.036)	(0.043)	(0.043)	(0.022)	(0.033)	(0.038)	(0.045)	(0.046)
Novelty t-1		0.350***	0.304***	0.294***	0.486***		0.322***	0.254***	0.262***	0.361***
		(0.030)	(0.039)	(0.044)	(0.047)		(0.031)	(0.041)	(0.046)	(0.047)
Novelty t-2			0.081***	0.022	0.032			0.085***	0.062*	0.096***
			(0.023)	(0.031)	(0.030)			(0.026)	(0.036)	(0.033)
Novelty t-3				0.055**	0.058**				0.007	-0.016
				(0.024)	(0.023)				(0.027)	(0.025)
Novelty (cumulative)				0.076**	0.141***				0.044	0.055
				(0.034)	(0.030)				(0.039)	(0.035)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Labour productivity measure	Value added p.w.	Value added p.w.	Value added p.w.	Value added p.w.	Sales p.w.	Value added p.w.	Value added p.w.	Value added p.w.	Value added p.w.	Sales p.w.
Observations	189,802	189,802	166,431	142,493	179,304	189,802	189,802	166,431	142,493	179,304
R-squared	0.56	0.56	0.571	0.585	0.586	0.56	0.56	0.571	0.585	0.586

The dependent variable is the annual rate of change of labour productivity. Parameter estimates are obtained from OLS regressions including firm and industry-by-year fixed effects. Controls (in logs) include lagged labour productivity, the capital–labour ratio, and patents per worker. Standard errors, reported in parentheses, are robust to heteroskedasticity and autocorrelation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Event Analysis



Trasmission Mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)
	Text			Backward cites		
	Output growth		Employment growth	Output growth		Employment growth
	Value added	Sales		Value added	Sales	
Novelty (contemp.)	0.029	-0.005	0.436***	-0.009	-0.019	0.383***
	(0.036)	(0.025)	(0.031)	(0.034)	(0.028)	(0.033)
Novelty (cumulative)	-0.0213	0.042*	-0.093***	-0.058*	0.031	-0.092***
	(0.040)	(0.025)	(0.021)	(0.041)	(0.028)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	146,901	179,708	196,896	146,901	179,708	196,896
R-squared	0.509	0.511	0.722	0.509	0.511	0.721

The dependent variable is the annual rate of change of output (value added or sales) and employment. Parameter estimates are obtained from OLS regressions including firm and industry-by-year fixed effects. Controls (in logs) include lagged labour productivity, the capital–labour ratio, and patents per worker. Standard errors, reported in parentheses, are robust to heteroskedasticity and autocorrelation.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Channels by Sectors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Manufacturing				Services			
	Labour productivity growth	Output growth		Employment growth	Labour productivity growth	Output growth		Employment growth
		Value added	Sales			Value added	Sales	
Novelty (contemp.)	-0.232***	0.032	0.035	0.334***	-0.519***	-0.017	-0.114*	0.746***
	(0.043)	(0.037)	(0.025)	(0.031)	(0.106)	(0.090)	(0.059)	(0.066)
Novelty (cumulatvie)	0.037	-0.008	0.027	-0.068***	0.167**	-0.06	0.079	-0.148***
	(0.034)	(0.032)	(0.024)	(0.016)	(0.082)	(0.075)	(0.048)	(0.039)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	82,956	85,400	102,582	109,889	59,537	61,501	77,126	87,007
R-squared	0.588	0.530	0.506	0.708	0.586	0.496	0.515	0.736

The dependent variable is the annual rate of change of output (value added or sales) and employment.Parameter estimates are obtained from OLS regression that includes firm fixed effects and time-by-industry fixed effects. Controls (in logs) include lagged labour productivity, the capital–labour ratio, and patents per worker. Standard errors, reported in parentheses, are robust to heteroskedasticity and autocorrelation.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Impacts of Firm Size

	(1)	(2)	(3)
	Small	Medium	Large
Novelty (contemp.)	-0.435***	-0.073*	-0.001
	(0.066)	(0.044)	(0.077)
Novelty (cumulative)	0.170***	-0.040	-0.027
	(0.051)	(0.040)	(0.071)
Controls	Yes	Yes	Yes
Obs.	105,185	26,578	9,165
R-squared	0.587	0.585	0.643

The dependent variable is the annual rate of change of labour productivity. Parameter estimates are obtained from the OLS regression, including firm fixed effects and time-by-industry fixed effects. Controls (in logs) include lagged labour productivity, the capital–labour ratio, and patents per worker. Standard errors, reported in parentheses, are robust to heteroskedasticity and autocorrelation.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Main findings

- With the launch of a novelty, labour productivity initially slows down but accelerates in the following years (**J CURVE EFFECT**)

- The cumulative effect of radical innovation is positive and significant: firms introducing novel technologies experience, on average, an **8%** faster rate of labour productivity growth

- We show that the impact of novelties on labour productivity growth is primarily driven by:
  - employment adjustments
  - service firms
  - small firms

- We demonstrate that text-based measures of patent novelty outperform citation-based indicators in identifying economically meaningful radical innovations

- Main Limitation: Exclusive use of patent data

THANK YOU FOR YOUR TIME

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