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Innovation or Commercialization? Evidence from Firm-Level Staggered Entry into Technology Development Areas in Türkiye

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Research Article

Keywords: Technology Development Areas, Innovation Policy, Staggered Difference-in-Differences, Commercialization

Posted Date: February 3rd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-8725619/v1

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Additional Declarations: No competing interests reported.

Version of Record: A version of this preprint was published at The Journal of Technology Transfer on October 10th, 2026. See the published version at https://doi.org/10.1007/s10961-026-10396-x.

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Abstract

This paper evaluates the causal impact of Technology Development Areas (TDAs) on firm-level innovation and commercialization in Türkiye. Exploiting staggered firm entry into TDAs and rich microdata from the Ministry of Science, Industry and Technology's 2012 Impact Evaluation Survey, treatment effects are estimated using the cohort-specific Difference-in-Differences framework of Callaway and Sant'Anna (2021), which is robust to heterogeneous treatment timing. The study examines multiple stages of the innovation process, including project completion, product development, patenting, and domestic and international sales. The results show that entry into a TDA has no statistically significant effect on patenting activity in the short run. In contrast, TDA participation leads to sizable and economically meaningful increases in applied innovation and commercialization outcomes, particularly completed projects, developed and sold products, and turnover. These effects emerge quickly after entry and are robust to alternative specifications and controls. The findings suggest that TDAs primarily enhance the efficiency with which existing innovative capabilities are translated into market outcomes, rather than immediately expanding firms' upstream inventive capacity.

Keywords: Technology Development Areas; Innovation Policy; Staggered Difference-in-Differences; Commercialization

JEL Codes: O31; O38; R58; C23

1. Introduction

Since the early 2000s, Türkiye has pursued a place-based innovation strategy centered on Technology Development Areas (TDAs), established under Law No. 4691 to support R&D activity, technology transfer, and university-industry collaboration. Over time, this initiative has evolved into a nationwide innovation infrastructure. By 2025, more than 90 TDAs were in operation, hosting over 12,000 firms and employing over 110,000 R&D personnel (Ministry of Industry and Technology, 2025). This scale underscores the central role of TDAs within Türkiye's innovation ecosystem and raises a core policy question: does participation in TDAs causally strengthen firm-level innovation and commercialization, or does it mainly concentrate activity among firms that were already more innovation-oriented?

The prominence of TDAs in Türkiye reflects a broader international shift toward innovation-driven growth strategies. Across developed and emerging economies, governments increasingly rely on place-based instruments – such as science parks and technology zones, and related innovation hubs – to stimulate knowledge creation and facilitate commercialization. These policies are grounded in arguments emphasizing spatial proximity, localized knowledge spillovers, and coordination as mechanisms for mitigating market failures in R&D investment and innovation finance. Consequently, such programs have proliferated worldwide, often supported by substantial public expenditure and targeted fiscal incentives.

Despite widespread adoption, empirical evidence on the effectiveness of innovation hubs remains mixed. While some studies report positive effects on firm-level innovation and growth, others find limited or statistically insignificant impacts once heterogeneity, selection, and pre-treatment dynamics are accounted for (Albahari et al., 2023). Moreover, recent work distinguishes innovation quantity from innovation quality and shows that increases in observable outputs – such as patent counts – do not necessarily imply sustained technological progress or productivity gains (Cheng et al., 2024). These findings highlight the importance of rigorous identification strategies and outcome measures that capture multiple stages of the innovation process.

Within this context, Türkiye provides a particularly informative setting for empirical analysis. Alongside the expansion of TDAs and complementary innovation institutions such as TÜBİTAK, the country has experienced substantial growth in observable innovation outputs, including patent applications and the number of R&D-oriented firms. Nevertheless, Türkiye continues to lag behind many OECD countries in key innovation inputs, most notably

R&D researcher density and longer-run innovation capacity (Ünsal, 2025). This combination of strong policy commitment and uneven alignment between policy ambition and inputs motivates a closer examination of whether TDAs generate additional innovation or primarily reinforce existing capabilities among selected firms.

To place Türkiye's innovation performance in comparative perspective, Figure 1.1 plots the country's position relative to the OECD average along three dimensions: innovation outputs (resident patent applications), human inputs (R&D researchers per million people), and financial inputs (R&D expenditure as a share of GDP). The figure reveals a persistent asymmetry in Türkiye's convergence path. Since the mid-2000s, R&D expenditure has increased rapidly, reaching roughly two-thirds of the OECD average by the late 2010s. In contrast, growth in R&D researcher density has been considerably slower and remains well below OECD levels. Patent activity has expanded sharply over the same period, broadly tracking improvements in financial inputs, yet it remains closer to human-capital convergence than to R&D spending. This divergence suggests constraints related to absorptive capacity and the accumulation of research personnel, and it motivates micro-level evidence on the channels through which innovation policy operates.

This pattern points to what may be described as a Türkiye innovation imbalance. While financial commitments to R&D and observable outputs have expanded rapidly, the accumulation of R&D human capital has lagged behind. As a result, improvements in innovation performance may reflect efficiency gains, institutional support, and concentration of activity among capable firms rather than broad-based capacity deepening. Viewed through this lens, TDAs may operate less as instruments that expand the economy's underlying innovation capacity and more as mechanisms that improve the efficiency with which existing inputs are translated into commercially relevant outputs. Determining whether TDAs contribute to firm-level innovation beyond selection and concentration effects is therefore both policy-relevant and empirically challenging.

A central challenge lies in identification. Firms enter TDAs in different calendar years, treatment is permanent once entry occurs, and firms differ substantially in their pre-entry innovation trajectories. Moreover, treatment effects may be heterogeneous across firms and evolve over time. Much of the earlier science-park literature relies on matched comparisons and conventional two-way fixed effects (TWFE) Difference-in-Differences models, which can be biased under staggered adoption when treatment effects are heterogeneous. In TWFE, already-treated units can serve as inappropriate controls for later-treated units, obscuring causal interpretation.

This study addresses these challenges by providing a causal evaluation of TDAs in Türkiye using firm-level data and methods designed for staggered policy adoption. Drawing on the 2012 Impact Evaluation Survey for TDAs conducted by the Turkish Ministry of Science, Industry, and Technology, the analysis exploits detailed information on firms' innovation activities in the years surrounding TDA entry. This structure allows construction of firm-specific treatment timelines and estimation of treatment effects across outcomes spanning innovation activity, product development, and commercialization.

The paper contributes to the literature on innovation policy and science-park evaluation in several ways. First, it provides one of the first causal assessments of TDAs in Türkiye using firm-level longitudinal data that combine retrospective pre-entry information with post-entry outcomes. Second, by examining multiple innovation margins—including completed projects, product development, sales, and turnover—the analysis moves beyond single-indicator approaches and provides a more comprehensive view of how TDAs shape firms' innovation processes. Third, the paper applies the cohort-specific Difference-in-Differences estimator of Callaway and Sant'Anna (2021), aligning the empirical strategy with staggered TDA entry and avoiding biases associated with TWFE models. Finally, the findings speak to debates on place-based innovation policies in emerging economies by clarifying which stages of the innovation process respond most to TDA participation.

2. Literature Review

2.1 Innovation Measurement and the Role of Patents

Despite well-documented limitations – including strategic patenting, heterogeneity in patent quality, and cross-country institutional differences – patents remain one of the most widely used indicators of innovation output in empirical research (Jaffe & Lerner, 2004; Fang et al., 2017). Their continued use reflects both data availability and their ability

to capture codified technological knowledge generated through R&D processes. However, recent studies emphasize that patent counts alone may provide a misleading picture of innovation performance, particularly in environments where policy incentives encourage filing behavior without necessarily improving technological quality.

This insight has important implications for evaluating place-based innovation policies such as Science and Technology Parks (STPs) and Technology Development Areas (TDAs). While these policies are often credited with boosting patenting activity, a growing literature stresses the need to examine multiple innovation margins – including R&D projects, product development, and commercialization outcomes – to distinguish genuine technological upgrading from strategic or low-quality patenting. Accordingly, recent empirical studies increasingly adopt multi-dimensional measures of innovation performance rather than relying exclusively on patent counts (Ferguson & Olofsson, 2004; Lindelöf & Löfsten, 2003, 2004).

2.2 Theoretical Mechanisms of Innovation Hubs and Agglomeration

TDAs can be conceptualized as non-spontaneous agglomerations deliberately created through public policy to foster innovation and entrepreneurship. Unlike organic industrial clusters, TDAs are designed to generate knowledge spillovers, facilitate technology transfer, and reduce coordination failures between firms, universities, and research institutions. Theoretical contributions highlight several mechanisms through which these hubs may influence firm-level innovation and research activity (Albahari et al., 2023; Furman et al., 2006; Jaffe et al., 1993).

First, TDAs operate as learning and validation environments by providing firms with access to managerial know-how, technical expertise, and shared infrastructure. Such environments can accelerate experimentation and allow firms to identify unviable projects at an early stage, thereby reallocating resources toward more promising innovations (Yee & Choi, 2025). Second, innovation policies embedded in TDAs may reinforce path dependence and technological specialization, as firms and policymakers build on existing capabilities to minimize uncertainty and sunk costs. Rather than promoting diversification, TDAs may therefore deepen specialization within specific technological trajectories (Liu et al., 2024).

Third, TDAs may enhance firms' absorptive capacity – the ability to identify, assimilate, and exploit external knowledge – through proximity to universities and peer firms (Bone et al., 2019; Yee & Choi, 2025). These channels suggest that TDA participation may affect different dimensions of innovation unevenly, strengthening some outcomes (e.g., product development) while leaving others (e.g., patenting) unchanged.

2.3 Global Empirical Evidence on TDA Effectiveness

Empirical evidence on the effectiveness of science and technology parks (STPs) and TDAs remains mixed. While several studies report positive associations between park location and firm-level innovation, growth, and survival, others find limited or statistically insignificant effects once firm heterogeneity, selection into parks, and pre-existing innovation capacity are taken into account. Recent systematic reviews emphasize that these divergent findings often reflect differences in data scale, identification strategies, and outcome measurement (Albahari et al., 2023).

Early evidence is largely descriptive and focuses on comparisons between on-park and off-park firms. Using UK data, Westhead (1997) compares firms along a range of R&D inputs and outputs and finds no statistically significant differences. Similar conclusions emerge from Swedish studies. Lindelöf and Löfsten (2003, 2004), employing matched-pair comparisons, report no significant differences in patenting or new product introduction between science-park and non-science-park firms, attributing observed performance differences largely to selection. Ferguson and Olofsson (2004) likewise find no significant differences in sales or employment growth.

Econometric studies attempt to move beyond descriptive comparisons but face substantial endogeneity challenges. Siegel et al. (2003), using UK data, estimate negative binomial models of research output and find modest productivity differences that are sensitive to controls for internal R&D capacity. Audretsch et al. (2012), using German data, show that proximity to universities and regional competitiveness positively affect patenting, particularly in high-tech industries. Liberati et al. (2016), analyzing Italian science parks, find no general improvement in innovative or

financial performance following park entry. Together, these studies underscore the difficulty of disentangling location effects from firms' underlying innovative capabilities.

2.4 Innovation Policy and the "Turkish Paradox"

Türkiye provides a particularly informative case for evaluating TDAs. Since the early 2000s, the country has implemented a systematic innovation policy framework anchored by institutions such as TÜBİTAK and the Technology Development Zones Law of 2001. These efforts have coincided with rapid expansion of TDAs and growth in certain innovation indicators, yet Türkiye's overall performance relative to OECD peers remains uneven.

Comparative evidence points to a distinctive innovation paradox. While Türkiye performs relatively well in generating "new-to-the-market" innovations, it lags behind peers in incremental innovation and in the sustained accumulation of R&D inputs, particularly human capital (Ünsal, 2025). Figure 1.1 illustrates a part of this imbalance: although R&D expenditure has increased markedly, growth in R&D researcher density has been considerably slower. As a result, innovation outcomes appear driven more by efficiency gains and novelty than by deep capacity accumulation.

Micro-level evidence indicates that firms operating in TDAs exhibit higher average productivity levels, yet the marginal effect of TDA entry on conventional innovation outputs – such as patenting – often appears weak (Ünsal, 2025). This pattern is consistent with the interpretation that TDAs primarily support downstream stages of the innovation process, particularly product development, commercialization, and market access, rather than upstream inventive activity. Such a role aligns closely with the design of Türkiye's development plans, which emphasize applied R&D and commercialization.

2.5 Methodological Challenges and Recent Econometric Advances

A large share of the empirical literature evaluating science parks, technology zones, and place-based innovation policies relies on comparison-of-means analyses (Ferguson & Olofsson, 2004; Lindelöf & Löfsten, 2003, 2004), R&D production functions that treat park location as a time-invariant treatment status (Siegel et al., 2003), or conventional two-way fixed effects (TWFE) Difference-in-Differences estimators (Liberati et al., 2016), typically using matched samples of on- and off-park firms. In comparison-based approaches, the impact of TDA entry cannot be identified because firm outcomes are not observed both before and after entry. Moreover, these studies implicitly pool firms entering innovation zones at different points in time, thereby masking potential heterogeneity in treatment effects across cohorts.

While Siegel et al. (2003) provide valuable exploratory evidence on differences in research productivity between on-park and off-park firms, they do not explicitly model staggered entry into science parks or heterogeneous treatment effects. Similarly, Liberati et al. (2016) estimate TWFE models that combine early and late entrants within a single treatment effect. As shown in recent econometric work, such estimators mechanically compare already-treated units to later-treated units under staggered adoption, producing coefficients that may represent mixtures of incomparable states rather than well-defined causal parameters, even when parallel trends hold and samples are carefully matched. These concerns are particularly salient in the context of TDAs, where treatment is permanent and innovation responses are likely to vary across cohorts and over time.

To address these issues, recent studies increasingly adopt staggered Difference-in-Differences estimators that explicitly account for treatment timing heterogeneity. Among these, the framework developed by Callaway and Sant'Anna (2021) has emerged as a leading approach. By estimating cohort-specific treatment effects and restricting comparisons to not-yet-treated units at each point in time, this method restores causal interpretability and allows for dynamic responses. These advances are especially relevant for evaluating TDAs, where firms enter at different times and innovation responses may evolve gradually (Callaway & Sant'Anna, 2021; Borusyak, 2024).

Accordingly, a growing number of applied policy evaluations with staggered implementation have moved away from conventional TWFE estimators toward cohort-based DID designs. Applications span regional and place-based policies (Goldsmith-Pinkham et al., 2020; De Chaisemartin & d'Haultfoeuille, 2023), public health interventions (Marcus & Sant'Anna, 2021), and corporate regulation (Baker et al., 2022). Some studies acknowledge staggered adoption

concerns as a robustness consideration, even when conventional estimators remain the primary specification as in the case of labor market regulations study of Cengiz et al. (2019).

A small but growing strand of the science-park literature explicitly adopts staggered DID designs. Anton-Tejon et al. (2024) evaluate the medium-term regional effects of Science and Technology Parks in Spain using variation in establishment timing and find positive but heterogeneous innovation effects that emerge gradually across cohorts. Similarly, Ancona and Ceci (2025) treat entry into international science-park networks as a staggered intervention and show that network membership strengthens entrepreneurial ecosystems over time. In related settings, studies of national high-technology zones exploit staggered policy rollout across cities and find increases in firm innovation and productivity alongside spatial reallocation effects (Chen & Liu, 2022).

Together, these studies highlight that science parks and technology zones are characterized by permanent treatment and heterogeneous entry timing, making cohort-specific Difference-in-Differences approaches particularly appropriate. By adopting such a framework at the firm level, the present study builds on this emerging literature and provides new evidence on how TDAs affect different stages of the innovation process, from project development to commercialization.

3. Data

The empirical analysis uses firm-level microdata collected by the Turkish Ministry of Industry and Technology through its 2012 Impact Evaluation Survey of Technology Development Areas. The survey provides retrospective information on firms' innovation inputs, activities, outputs, and commercialization outcomes, together with the exact calendar year of entry into a Technology Development Area (TDA). This entry-year information is central to the empirical strategy, as it enables the construction of a staggered treatment design in which firms enter TDAs at different points in time and remain treated thereafter.

The analysis focuses on firms that entered a TDA between 2010 and 2013 and for which innovation outcomes are observed during the 2008–2012 period. Restricting attention to these cohorts ensures that each treated firm contributes at least two pre-treatment, allowing for an examination of the parallel trends assumption (Equation 1), and that valid not-yet-treated comparison firms are available within the same calendar years (Equation 2). The resulting dataset forms an unbalanced firm–year panel, reflecting cohort-specific entry timing and unequal pre- and post-entry observation windows. The final sample consists of 1,040 firms, distributed across entry cohorts as follows: 203 firms entered in 2010, 323 in 2011, 409 in 2012, and 105 in 2013 (Table 3.1).

3.1 Treatment Definition and Entry into Technology Development Areas

Treatment is defined as a firm's entry into a Technology Development Area. Article 3 of the Technology Development Zones Law (Law No. 4691) defines eligible activities in functional terms, emphasizing R&D and innovation orientation, but does not prescribe standardized quantitative performance criteria for firm admission, such as minimum patent holdings, firm size, or R&D production thresholds (Republic of Türkiye, 2001).

During the period under study (2010–2012), entry into TDAs followed an application-based process administered by TDA management companies in accordance with the legal framework established by Law No. 4691 and its implementing regulation. Firms seeking admission were required to submit an R&D, software, or technology development project describing the technical content and objectives of their proposed activities within the zone. Applications were evaluated to assess compliance with the statutory requirement, often with input from academic or technical committees. Consistent with the law, admission decisions were based on project eligibility and activity type rather than on ex ante measures of innovation performance.

This institutional design implies that selection into TDAs reflects eligibility conditions defined by the nature of firms' activities rather than formal performance-based thresholds. While firms engaged in non-R&D activities were excluded by design, firms meeting the basic statutory criteria were generally eligible for admission. University collaboration was encouraged and often viewed favorably in the evaluation process, but it was not a legal requirement for entry (Republic of Türkiye, 2001; Ministry of Industry and Technology, 2025). Accordingly, entry into TDAs is not random,

and the empirical strategy does not rely on random assignment but on a parallel trends assumption conditional on observables and cohort-specific timing.

To account for the gradual nature of innovation responses, treatment timing is defined conservatively. The year of entry into a TDA is treated as a pre-treatment period, and treatment is assumed to begin in the first full calendar year following entry. This convention reflects the institutional reality that firms typically require time to relocate, initiate projects, and begin R&D activities within the TDA, and it reduces the risk that contemporaneous adjustments in the entry year contaminate post-treatment trends (Table 3.2).

3.2 Definitions for inputs and outputs

The analysis examines multiple outcomes capturing distinct stages of the innovation process, as summarized in Table 3.2. Innovation inputs are measured using the number of R&D personnel and R&D expenditure, both of which enter the analysis as controls in selected specifications. Innovation activities are proxied by the number of completed innovation projects. Innovation outputs include the number of developed products, sold products, and national patents. Commercialization outcomes are measured using turnover from domestic sales and turnover from international sales.

Several of these variables exhibit strong right skewness and a high prevalence of zero values. To retain zero observations while mitigating distributional concerns, all innovation and commercialization variables are transformed using the inverse hyperbolic sine (IHS) transformation. Estimated coefficients should therefore be interpreted as semi-elasticities rather than changes in levels.

Time-varying controls used in augmented specifications include R&D personnel and R&D expenditure, while firm and calendar-year fixed effects are included throughout to absorb time-invariant firm characteristics and common macroeconomic shocks.

Monetary variables – R&D expenditure, domestic turnover, and international turnover – are expressed in real 2010 Turkish lira. Variables originally reported in Turkish lira are deflated using the Turkish Consumer Price Index (CPI, 2010 = 100). International turnover, reported in U.S. dollars, is first converted into Turkish lira using annual average USD/TRY exchange rates and subsequently deflated using the same CPI series. CPI and exchange rate data are obtained from World Bank indicators.

3.3 Descriptive Statistics

Table 3.3 reports baseline firm characteristics measured at event time zero. The average firm in the sample is relatively young, with a mean age of just over four years at entry. Most firms are domestically owned, with foreign-owned or foreign-partnered firms accounting for less than five percent of the sample.

The dataset includes a university-industry collaboration index, capturing the extent of a firm's formal engagement with universities prior to or during TDA participation. The index ranges from zero to six, with higher values indicating more intensive collaboration across dimensions such as joint projects, academic involvement, and knowledge exchange activities. A value of zero corresponds to no observed collaboration. This measure is used to describe baseline firm characteristics and to explore heterogeneity in selected outcomes.

Approximately one-quarter of firms are owned by an academic, and the majority operate as standard private firms rather than incubator firms or spin-offs. Differences in the number of observations across characteristics reflect missing information for some firms and the unbalanced structure of the panel.

Table 3.4 presents descriptive statistics for innovation-related variables measured in the year immediately preceding TDA entry (entry year − 1) for treated firms, alongside statistics for not-yet-treated firms observed in the same calendar years. Firms that have already entered a TDA in a given year are excluded from the comparison group. Because the table pools observations across different years, group counts are not mutually exclusive at the firm level: a given firm may appear as not-yet-treated in earlier years and as an "entry year – 1" observation in a later year. This structure

reflects the staggered nature of TDA entry and is fully consistent with the comparison framework used in staggered Difference-in-Differences designs.

Across all outcomes, treated firms exhibit slightly higher levels of innovation inputs and activities prior to entry, suggesting anticipation of TDA admission. However, differences in pre-treatment outcomes are generally modest, and key commercialization indicators – such as turnover and patenting – are broadly comparable across treated and not-yet-treated observations. These patterns suggest that while selection into TDAs is associated with greater engagement in innovation-related activities, treated and control firms operate in similar innovation environments prior to entry. Finally, Table 3.5 documents the distribution of key outcomes before and after entry, demonstrating that the results are not driven by extreme values or outliers.

Table 3.4: Descriptive Statistics: Innovation Outcomes

Panel A. (TDA entrants: entry year − 1)				
Variable	**Description**	**Mean**	**SD**	**N**
ihs_rdpersonnel	R&D personnel	1.21	1.31	935
ihs_rdexpenditure_real2010	R&D expenditure (real 2010 TL)	4.73	6.15	935
ihs_project	Completed projects	0.41	0.73	935
ihs_dev_product	Developed products	0.12	0.37	935
ihs_sold_product	Sold products	0.33	0.76	935
ihs_patent_nat	Nationally registered patents	0.38	1.09	935
ihs_turnover_nat_real2010	Domestic turnover (real 2010 TL)	0.05	0.28	935
ihs_turnover_int_real2010	International turnover (real 2010 TL)	7.66	7.11	935
Panel B. (Not-yet-treated: same year wt entrants)				
Variable	**Description**	**Mean**	**SD**	**N**
ihs_rdpersonnel	R&D personnel	1.05	1.29	942
ihs_rdexpenditure_real2010	R&D expenditure (real 2010 TL)	4.03	5.88	942
ihs_project	Completed projects	0.35	0.73	942
ihs_dev_product	Developed products	0.10	0.38	942
ihs_sold_product	Sold products	0.28	0.70	942
ihs_patent_nat	Nationally registered patents	0.32	1.15	942
ihs_turnover_nat_real2010	Domestic turnover (real 2010 TL)	0.02	0.17	942
ihs_turnover_int_real2010	International turnover (real 2010 TL)	6.51	7.17	942

Notes: All outcomes are inverse-hyperbolic-sine transformed. Descriptive statistics are reported for firm–year observations measured in the year prior to entry into a TDA (entry year − 1) for treated cohorts. The comparison group consists of firms that are not yet entered a TDA in the same calendar years, firms already treated in a given year are excluded. For Panel A and B, N refers to the number of firm–year observations. Because the table pools observations across multiple years, group counts reflect observations rather than mutually exclusive firm sets.

3.4 Implications for Identification

The combination of staggered TDA entry, firm-specific pre-treatment information, and detailed innovation outcomes makes this dataset particularly well suited for cohort-specific Difference-in-Differences analysis. At each point in time, a subset of firms remains untreated, allowing later entrants to serve as valid comparison units for earlier cohorts. Although the retrospective design limits the length of observed post-treatment periods, the institutional features of TDA entry and the availability of multiple pre-treatment observations support the credibility of the identifying assumptions underlying the empirical strategy.

4. Methodology

This study evaluates the causal impact of participation in Technology Development Areas (TDAs) on firm-level innovation outcomes using a Difference-in-Differences framework tailored to staggered treatment adoption. Firms enter TDAs in different years, and treatment is absorbing once entry occurs, generating heterogeneous exposure lengths and an unbalanced panel across entry cohorts. To accommodate these features, the empirical analysis relies primarily on the cohort-specific estimator proposed by Callaway and Sant'Anna (2021), which identifies Average Treatment Effects on the Treated (ATT) by comparing treated firms to not-yet-treated firms within the same calendar years. This approach allows treatment effects to vary across cohorts and over time, while avoiding the biases associated with conventional two-way fixed effects (TWFE) estimators in staggered settings.

The analysis considers multiple outcomes capturing distinct stages of the innovation process, including inventive activity, product development, and commercialization. Given the data structure, event-time estimates are used to assess the plausibility of the parallel trends assumption and to illustrate short-run post-entry response patterns, rather than to characterize long-run dynamic effects.

4.1 Baseline Model: Two-Way Fixed Effects DID

Let Y_{it} denote an innovation outcome of firm i in year t, such as national patent registrations, completed R&D projects, developed or commercialized products, or sales of R&D outputs. Let $D_{it} = 1$ indicate that firm i has entered a TDA by year t, and $D_{it} = 0$ otherwise. The baseline empirical specification adopts a TWFE Difference-in-Differences framework:

$$Y_{it} = \alpha_i + \lambda_t + \beta^{TWFE} D_{it} + X_{it}'\gamma + \varepsilon_{it},$$

where α_i and λ_t denote firm and year fixed effects, respectively, and X_{it} includes time-varying firm characteristics such as R&D employment and R&D expenditures. Under parallel trends in untreated outcomes and homogeneous, time-invariant treatment effects, β^{TWFE} identifies the average causal effect of TDA participation.

This TWFE formulation generalizes the canonical two-group/two-period DID model:

$$Y_{it} = \alpha + \beta_1 \text{Treated}_i + \beta_2 \text{Post}_t + \beta^{DID}(\text{Treated}_i \times \text{Post}_t) + X_{it}'\gamma + \varepsilon_{it},$$

where Treated_i indicates firms that ever participate in a TDA, Post_t denotes the post-treatment period, and the interaction term captures treatment exposure. In this canonical setting, β^{DID} measures the average treatment effect on the treated by comparing outcome changes for treated firms before and after treatment to those of never-treated firms, conditional on parallel trends.

Recent econometric research (Goodman-Bacon, 2021; Sun & Abraham, 2021; Callaway & Sant'Anna, 2021) shows that when treatment adoption is staggered and treatment effects are heterogeneous across cohorts or evolve over time, TWFE estimators may combine multiple comparisons that do not correspond to valid counterfactuals. In particular, the estimator can implicitly compare earlier-treated firms with later-treated firms, generating "forbidden comparisons" and, in some cases, negative implicit weights on cohort-time treatment effects. Because firms enter TDAs in different years and may exhibit heterogeneous post-entry innovation responses, TWFE estimates in this context should be interpreted with caution and are not used as the primary basis for causal inference.

Although the analysis does not include a never-treated group, TWFE estimates are reported as a benchmark to facilitate comparison with earlier studies that evaluate place-based innovation policies using conventional DID specifications.

4.2 Staggered Adoption and the Potential Outcomes Framework

Let $Y_{it}(1)$ denote the potential outcome for firm i at time t if treated (i.e., after entering a TDA), and $Y_{it}(0)$ the outcome if untreated. The observed outcome satisfies:

$$Y_{it} = D_{it}Y_{it}(1) + (1 - D_{it})Y_{it}(0)$$

Define the firm's treatment adoption year as:

$$G_i = \min\{t: D_{it} = 1\},$$

with $G_i = \infty$ for firms not treated within the sample window. Firms in the same adoption year g form a cohort. Treatment is absorbing:

$$D_{it} = 1\{t \geq G_i\}.$$

The causal parameter of interest is the group-time average treatment effect for each treated cohort g and time $t \geq g$:

$$ATT(g,t) = \mathbb{E}[Y_{it}(1) - Y_{it}(0) \mid G_i = g].$$

This estimand can vary across cohorts (g) – early vs. late entrants may differ in absorptive capacity, technological readiness, or innovation strategy – and across time (t), treatment effects may accumulate or dissipate. The unbalanced structure of the data, arising from cohort-specific entry timing and differing observation windows, further motivates estimators that allow for cohort-specific dynamics. All reported estimates focus on the Average Treatment Effect on the Treated (ATT), consistent with voluntary program participation.

4.3 Identification: Cohort-Specific Parallel Trends

For identification, Callaway & Sant'Anna (2021) impose a cohort-specific parallel trends assumption:

$$\mathbb{E}\big[Y_{it}(0) - Y_{i,t-1}(0) \,\big|\, G_i = g\big] = \mathbb{E}\big[Y_{it}(0) - Y_{i,t-1}(0) \,\big|\, i \in C_t(g)\big] \quad (1)$$

for all $t < g$, where $C_t(g)$ is the control group for cohort g at time t. A key element of the framework is the construction of $C_t(g)$, which may include:

- not-yet-treated firms (future entrants untreated at time t);
- never-treated firms, if available; or
- any combination of the above.

This structure allows estimation even when all firms are eventually treated, provided that at every period there exist a subset of firms that remains untreated. This condition holds in our setting because later-entering firms serve as valid controls for earlier entrants.

4.4 Estimation of Group-Time $ATT(g,t)$

Callaway and Sant'Anna (2021) propose several estimators – outcome regression, inverse probability weighting, and doubly robust procedures – each generating consistent estimates of $ATT(g,t)$ under the identification assumptions. A generic estimator takes the form:

$$\widehat{ATT}(g,t) = [\widehat{\mathbb{E}}(Y_{it} \mid G_i = g) - \widehat{\mathbb{E}}(Y_{i,t-1} \mid G_i = g)] - [\widehat{\mathbb{E}}(Y_{it} \mid i \in C_t(g)) - \widehat{\mathbb{E}}(Y_{i,t-1} \mid i \in C_t(g))] \quad (2)$$

Dynamic effects may be expressed in event time by indexing $k = t - g$, so that:

$$ATT_k = ATT(g, g + k),$$

which traces responses at entry ($k = 0$) and in subsequent years, subject to data availability.

4.5 Aggregation of $ATT(g,t)$

Because $ATT(g,t)$ is estimated separately by cohort and year, an overall effect is obtained through explicit weighting:

$$ATT^{overall} = \sum_{g\in\mathcal{G}} \sum_{t\in T_g} w_{g,t} ATT(g,t), \qquad w_{g,t} \geq 0, \qquad \sum w_{g,t} = 1.$$

The cohort-specific framework allows aggregation using transparent and economically meaningful weighting schemes. For example, effects can be weighted by cohort size (giving greater weight to larger entry cohorts), by calendar time (ensuring balanced representation across years), or by event time (emphasizing short-run or longer-run responses). This transparency contrasts with TWFE estimators, which may produce implicit, non-convex weights under staggered adoption.

4.6 Summary of Empirical Strategy

The empirical analysis proceeds in three steps. First, a conventional TWFE DID model is estimated as a transparent benchmark and to facilitate comparison with earlier evaluations of place-based innovation policies. These estimates exploit within-firm variation over time while controlling for firm and year fixed effects.

Second, our primary causal estimates are obtained using the cohort-specific Difference-in-Differences framework proposed by Callaway and Sant'Anna (2021) (CSDID). This approach is designed for staggered treatment adoption and delivers valid group–time average treatment effects by comparing treated firms to not-yet-treated firms within the same calendar period. The resulting ATTs form the core empirical results.

Third, the temporal pattern of treatment effects is examined using event-time estimates. Given data limitations, this analysis focuses on a narrow window around TDA entry (two pre-treatment periods and one post-treatment period). Accordingly, the event-time estimates are interpreted as diagnostic checks for pre-treatment trends and short-run post-entry responses rather than evidence on long-run dynamics.

Finally, heterogeneity is explored along a key institutional dimension – university–industry collaboration – by estimating cohort-specific ATTs separately for collaborating and non-collaborating firms. This analysis provides insight on whether TDA participation differentially affects innovation and commercialization depending on firms' engagement with academic partners.

Taken together, this empirical strategy prioritizes credible identification and transparent aggregation, providing causal estimates of short-run innovation and commercialization effects while clearly delineating the scope imposed by the available data.

5. Estimation and Results

This section presents the empirical results. Before estimating treatment effects, the plausibility of the identifying assumptions underlying the staggered Difference-in-Differences (CSDID) framework is assessed. In particular, it is examined whether firms that enter Technology Development Areas (TDAs) exhibit similar pre-treatment dynamics to firms that have not yet entered, conditional on cohort-specific treatment timing. Establishing comparable pre-entry trends is essential for the causal interpretation of the estimated effects.

5.1 Assessment of Parallel Trends Assumption

Before presenting the DID estimates, the plausibility of the parallel trends assumption is examined using cohort-specific pre-treatment comparisons. Given the staggered timing of entry into TDAs, the assessment relies on not-yet-treated firms as controls within the same calendar years, excluding firms that are already treated in a given year.

Figure 5.1 displays pre-entry trends for nationally registered patents and R&D inputs for the 2010 and 2011 entry cohorts. For national patents the pre-treatment trajectories of treated and not-yet-treated firms are broadly similar, with no systematic divergence in the years immediately prior to entry. Although level differences exist, there is limited evidence of sharply differential pre-trends, supporting the use of DID methods for these outcomes.

By contrast, R&D inputs – particularly R&D expenditure and R&D personnel – exhibit more pronounced pre-treatment divergence. Treated firms display steeper pre-entry increases, consistent with anticipatory investment behavior. This pattern suggests that R&D inputs may be endogenous to the TDA entry decision and therefore are more appropriately treated as controls (or mechanisms) than as primary outcomes of the policy.

Taken together, the graphical evidence supports the identifying assumptions more strongly for innovation outputs than for input measures. Accordingly, the baseline specifications focus on outputs and commercialization outcomes as primary endpoints, while treating R&D inputs as controls. These considerations further motivate the use of CSDID estimators that explicitly account for treatment-timing heterogeneity.

5.2 Two-Way Fixed Effects Estimates

Tables 5.1 and 5.2 present TWFE estimates of the impact of entry into TDAs on firm-level innovation and performance outcomes. All specifications include firm and year fixed effects and exploit within-firm variation over time. Effects are reported in inverse-hyperbolic-sine (IHS) units and can be interpreted as semi-elasticities; for larger values, coefficients approximate percentage changes.

Table 5.1: Baseline TWFE estimates of TDA entry on firm outcomes

	(1) Patents	(2) Projects	(3) Developed products	(4) Sold products	(5) Domestic turnover	(6) International turnover
TDA entry	-0.005	0.143***	0.122***	0.176***	1.505***	0.322
	(0.019)	(0.046)	(0.039)	(0.061)	(0.338)	(0.208)
FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No
Firm–year obs.	3,028	3,024	3,023	3,023	3,027	3,027

Notes: All outcomes are inverse-hyperbolic-sine transformed. The treatment indicator equals one in years strictly after TDA entry. FE is firm and year fixed effects. Standard errors clustered at the firm level in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 5.2: TWFE estimates with firm-level controls

	(1) Patents	(2) Projects	(3) Developed products	(4) Sold products	(5) Domestic turnover	(6) International turnover
TDA entry	-0.005	0.139***	0.118***	0.168***	1.490***	0.355*
	(0.019)	(0.044)	(0.037)	(0.062)	(0.334)	(0.208)
FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm–year obs.	3,010	3,010	3,010	3,010	3,010	3,010

Notes: All outcomes are inverse-hyperbolic-sine transformed. The treatment indicator equals one in years strictly after TDA entry. FE is firm and year fixed effects. Controls include R&D personnel and R&D expenditure. Standard errors clustered at the firm level in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.

The baseline estimates in Table 5.1 reveal a clear pattern: TDA entry is not associated with changes in patenting activity, but it is linked to sizable and statistically significant increases in downstream innovation and commercialization outcomes. The estimated effect on national patents is essentially zero (−0.005, s.e. 0.019), while project completion increases by about 0.14 IHS units, developed products by 0.12, and sold products by 0.18. Commercial outcomes respond particularly strongly: domestic turnover rises by roughly 1.5 IHS units following TDA entry, while international turnover increases by about 0.32 IHS units, although the latter is estimated less precisely.

Table 5.2 augments the baseline specification with time-varying firm controls. The inclusion of controls leaves the overall pattern unchanged. Effects on projects (0.139), developed products (0.118), and sold products (0.168) remain positive and highly significant, and the estimated impact on domestic turnover remains large (1.49). International turnover continues to increase, with the coefficient rising modestly to 0.36 and attaining marginal statistical significance. As in the baseline specification, patenting remains unaffected. As firm-level controls (not reported in Table 5.2), R&D expenditure enters positively and significantly, while R&D personnel is insignificant, indicating that within-firm variation in innovation outcomes is more closely associated with financial inputs than with changes in research staff.

Overall, the TWFE results suggest that TDA participation primarily operates through applied innovation and commercialization channels rather than through formal inventive output. However, because firms enter TDAs in different years, TWFE estimates may combine cohort-specific and dynamic effects in potentially misleading ways under staggered adoption. Therefore these estimates are treated as benchmarks and turn next to cohort-specific Difference-in-Differences estimates designed for staggered treatment timing.

5.3 Cohort-Specific Difference-in-Differences Estimates

Table 5.3 presents Average Treatment Effects on the Treated (ATT) estimated using the cohort-specific difference-in-differences framework of Callaway and Sant'Anna (2021). This approach restricts comparisons to treated firms and not-yet-treated controls within the same calendar years, addressing biases inherent in TWFE models under staggered adoption. Given the limited observation window, the estimates should be interpreted as short-run effects of TDA entry. The estimated effects should be viewed as average treatment effects for firms that enter TDAs, rather than as the effect of offering TDA access to all firms.

The cohort-specific estimates closely mirror – but sharpen – the TWFE findings. TDA entry has no detectable effect on patenting (ATT = −0.003, s.e. 0.023), reinforcing the conclusion that formal patent output does not respond in the short run. In contrast, effects on applied innovation and commercialization are both economically meaningful and statistically significant. Project completion increases by about 0.11 IHS units, developed products by 0.10, and sold products by nearly 0.20.

Table 5.3: CSDID Average Treatment Effects on the Treated

	(1) Patents	(2) Projects	(3) Developed products	(4) Sold products	(5) Domestic turnover	(6) International turnover
ATT	-0.003	0.108**	0.099**	0.198***	2.343***	0.612***
	(0.023)	(0.051)	(0.045)	(0.066)	(0.376)	(0.226)
Firm–year obs.	2,702	2,698	2,698	2,698	2,702	2,702

Notes: All outcomes are inverse-hyperbolic-sine transformed. Average Treatment Effects on the Treated (ATT) are estimated using the cohort-specific difference-in-differences estimator of Callaway and Sant'Anna (2021). Treatment is defined as entry into a Technology Development Area (TDA), with treatment assumed to begin in the first full calendar year following entry. The control group consists of firms that have not yet entered a TDA in the same calendar year. Standard errors are clustered at the firm level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The largest responses again appear for turnover. Domestic turnover rises by approximately 2.34 IHS units following TDA entry. For firms near the median of the distribution, this magnitude corresponds roughly to a doubling of turnover, consistent with substantial commercialization gains. International turnover increases by about 0.61 IHS units. These magnitudes align with the event-study patterns in Figure 5.1, which show discrete post-entry gains rather than systematic pre-trends, particularly for commercialization outcomes.

Overall, the CSDID estimates confirm that the short-run impact of TDAs materializes primarily at later stages of the innovation process. By restricting attention to valid comparisons between treated and not-yet-treated firms, this framework provides a more credible assessment of the causal effects of TDA participation. The insignificant patent response may reflect timing (longer lags from R&D to patenting) rather than a true null effect.

5.3.1 Heterogeneity by University–Industry Collaboration

Table 5.4 explores heterogeneity in patenting responses by firms' university-industry collaboration status. Firms are divided into those with no collaboration and those reporting any collaboration, measured prior to or during TDA participation.

Point estimates differ modestly in sign across groups: firms without collaboration exhibit a small negative ATT (−0.008), while firms with collaboration display a positive ATT (0.019). However, both estimates are imprecise and statistically indistinguishable from zero. These results indicate no differential patent response to TDA entry along the collaboration dimension, consistent with the broader finding that TDAs do not immediately affect formal patenting.

Rather than contradicting the main results, the absence of heterogeneity reinforces their interpretation: TDAs appear to function primarily as platforms for applied development and market-oriented innovation, with limited short-run effects on patenting regardless of firms' pre-existing academic linkages.

5.4 Dynamic treatment effects and pre-trends

Figure 5.2 presents event-study estimates of the dynamic effects of TDA entry on innovation and commercialization outcomes based on the CSDID methodology. Given the short pre-treatment window available in the data, the event-study analysis is primarily used to assess the plausibility of the parallel trends assumption and to document short-run post-entry dynamics.

Across outcomes, pre-treatment coefficients are generally small and statistically indistinguishable from zero. Although some fluctuations occur in the pre-entry periods, these patterns are common when pre-treatment observations are limited and do not indicate systematic differential trends between treated and not-yet-treated firms. Overall, the absence of pronounced pre-treatment effects supports the identifying assumptions underlying the DID framework.

Post-entry dynamics reveal clear heterogeneity across innovation margins. For patenting activity, estimated effects remain close to zero throughout the post-entry period, consistent with the ATT results. In contrast, outcomes related to applied innovation and commercialization respond immediately following entry. Completed projects, developed products, and sold products increase at event time $k = 0$, with positive effects persisting into the subsequent period.

The strongest responses are observed for turnover. Both domestic and international turnover exhibit sharp increases in the first full year after TDA entry, indicating rapid commercialization gains. While confidence intervals widen in later periods – reflecting reduced effective sample size and greater heterogeneity – point estimates remain positive for most outcomes.

Overall, the event-study evidence complements the average ATT estimates by showing that the effects of TDA participation materialize quickly and primarily along applied innovation and commercialization dimensions, while short-run effects on patenting remain limited.

6. Discussion

A central motivation for this study is the disconnect between Türkiye's improving macro-level innovation indicators and the slower accumulation of underlying innovation capacity. While R&D expenditure and patenting activity have converged more rapidly toward OECD benchmarks, the expansion of R&D human capital has lagged behind, potentially constraining longer-run inventive capacity and raising questions about the microeconomic mechanisms through which innovation policies operate. The firm-level evidence presented in this paper helps reconcile this pattern.

Our results show that entry into Technology Development Areas (TDAs) primarily affects downstream innovation and commercialization outcomes – such as project completion, product development, and sales – while having limited short-run impact on patenting. This pattern suggests that TDAs may improve the efficiency with which existing capabilities are translated into market outcomes, rather than immediately expanding the stock of inventive capacity.

In this sense, the micro-level treatment effects documented here provide a plausible micro-foundation for the macro-level asymmetries observed in Türkiye's innovation convergence. Across both two-way fixed effects and cohort-specific Difference-in-Differences estimates, TDA entry is associated with substantial increases in developed products, sold products, and both domestic and international turnover, while effects on patent counts remain small and statistically indistinguishable from zero.

An additional insight emerges from specifications that include time-varying firm characteristics. TWFE estimates indicate that within-firm increases in R&D expenditure are positively associated with innovation and commercialization outcomes, whereas changes in R&D personnel are not. This pattern suggests that short-run post-entry responses may be more closely linked to financial intensity than to adjustments in research headcount. These associations should not be interpreted causally, as R&D inputs are potentially endogenous and may respond to anticipated performance. Nonetheless, the contrast between expenditure and personnel is consistent with the broader findings: TDAs appear to facilitate scaling and commercialization through cost relief, financing, and applied R&D support, rather than inducing immediate expansions in firms' underlying research capacity. These patterns align with the institutional objectives and operating logic of TDAs. Rather than functioning primarily as generators of formal intellectual property, TDAs are designed to support applied R&D, firm–university interaction, access to shared infrastructure, and proximity to complementary firms and markets.

These results are also informative about the mechanisms through which TDAs operate. The evidence is consistent with two complementary channels. First, TDAs provide direct cost relief through tax exemptions and financial incentives, which lower the marginal cost of applied R&D and commercialization activities. Second, they offer ecosystem-level benefits – such as access to shared infrastructure, managerial and technical support services, proximity to universities, and interaction with other innovative firms – that may enhance coordination and reduce frictions in bringing products to market. The dominance of commercialization effects over patenting suggests that these ecosystem and cost channels operate primarily by accelerating the deployment of existing knowledge rather than by generating new codified inventions in the short run.

The absence of a detectable patent response does not necessarily imply an absence of innovative activity. Patenting is only one channel of knowledge appropriation and is highly sensitive to firm strategy, sectoral norms, and the expected commercial value of inventions. Firms may prioritize speed to market, product iteration, or trade secrecy over patenting – especially if TDAs reduce fixed costs of development and facilitate rapid commercialization. From a policy perspective, this distinction is important: if the objective is to stimulate patenting specifically, complementary instruments – such as targeted intellectual property support or patent advisory services – may be required alongside TDAs.

Event-time estimates further suggest that these effects emerge quickly after entry. Statistically insignificant effects on patenting may reflect timing rather than a true null effect, as patenting responses may materialize only with longer lags between project initiation, invention, and application or grant outcomes. With a longer post-entry horizon, future work could estimate extended event-study profiles to assess whether innovation responses intensify after an initial settlement period and whether effects persist or attenuate over time. The widening confidence intervals observed in later periods (Figure 5.2; k=1) further underscore heterogeneity in firm responses and reinforce the importance of cohort-specific methods when evaluating place-based policies with staggered adoption.

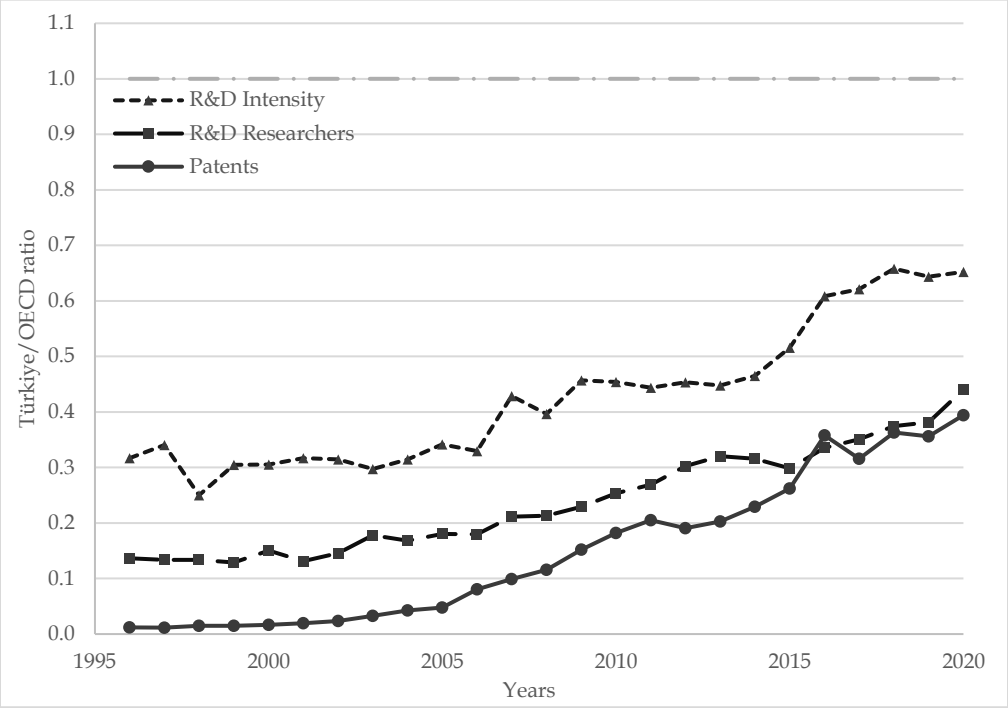
The results also highlight the value of strengthening future data collection practices for TDAs. Evaluation would benefit from a standardized longitudinal framework in which firms are observed consistently before and after entry, with annual measures of innovation inputs (e.g., R&D personnel, expenditures, external funding, and collaboration) and outputs (e.g., patents, projects, developed and commercialized products, and domestic and international sales). Recording collaboration structures – particularly university–industry linkages – and firms' engagement with specific TDA services would help identify the mechanisms driving commercialization effects and distinguish transitional adjustments from longer-run impacts.

Finally, it is important to clarify the scope of interpretation. The estimated effects capture average treatment effects for firms that make the decision to enter TDAs and should not be interpreted as the effect of offering TDA access to all firms. Moreover, the analysis focuses on short-run outcomes, given the available observation window. Within these bounds, the results suggest that TDAs are effective instruments for supporting applied innovation and

commercialization, even if their immediate impact on patenting is limited. Future research could extend this analysis to longer horizons and explore heterogeneous effects across sectors, firm size, ownership structure, and collaboration intensity as richer post-entry data become available.

Appendix

Figure 1.1: Türkiye's relative convergence in innovation outputs and inputs (OECD=1).



Source: World Bank

Notes: The figure plots Türkiye-to-OECD ratios for residential patent applications, R&D researchers per million people, and R&D expenditure as a share of GDP over the period 1996–2020. The horizontal dashed line denotes the OECD benchmark. While R&D intensity has converged rapidly toward the OECD frontier since the mid-2000s, growth in R&D researcher density has been more gradual. Innovation outputs, measured by patent applications, have increased substantially but remain more closely aligned with researcher density than with financial investment.

Table 3.1: Distribution of Firms by TDA Entry Year

Entry year	Firms	Share (%)
2010	203	19.5
2011	323	31.1
2012	409	39.3
2013	105	10.1
Total	**1,040**	**100**

Notes: The table reports the number and percentage of firms by Technology Development Area (TDA) entry cohort in the estimation sample.

Table 3.2: Variable Definitions and Construction

Variable	Definition	Unit / Scale	Transformation	Role
A. Treatment and Timing				
TDA entry	Indicator equal to 1 from the first full calendar year after entry into a Technology Development Area	Binary (0/1)	None	Treatment
Entry year	Calendar year in which the firm enters a TDA	Year	None	Timing
Event time	Years relative to TDA entry (0 = entry year)	Integer	None	Timing
Post	Indicator equal to 1 for years after TDA entry	Binary (0/1)	None	Timing
B. Firm Characteristics (Time-Invariant)				
Establishment year	Year in which the firm was established	Year	None	Control
Foreign ownership	Ownership status: local, foreign, or foreign-partnered	Categorical	None	Stratifier
Foreign share	Share of foreign ownership	Percent	None	Stratifier
Academician firm	Indicator equal to 1 if firm is owned by an academic	Binary (0/1)	None	Stratifier
Firm type	Firm classification: incubator, spin-off, or private firm	Categorical	None	Stratifier
C. Innovation Inputs				
R&D personnel	Number of employees engaged in R&D activities	Count	IHS	Control
R&D expenditure	Firm-level expenditure on R&D activities (real, 2010 TL)	Thousand TL	IHS	Control
D. Innovation Activities				
Projects	Number of completed innovation projects	Count	IHS	Outcome
E. Innovation Outputs				
Developed products	Number of newly developed products	Count	IHS	Outcome
Sold products	Number of developed products sold	Count	IHS	Outcome
National patents	Number of nationally registered patents	Count	IHS	Outcome
F. Commercialization Outcomes				
Domestic turnover	Turnover from domestic sales (real, 2010 TL)	Thousand TL	IHS	Outcome
International turnover	Turnover from international sales (USD converted to TL and deflated, real 2010 TL)	Thousand TL	IHS	Outcome

Notes: Monetary variables are expressed in constant 2010 Turkish lira. Variables originally reported in Turkish lira are deflated using the Turkish Consumer Price Index (CPI, 2010 = 100). International turnover, originally reported in U.S. dollars, is converted to Turkish lira using annual average USD/TRY exchange rates and subsequently deflated using the same CPI series. Variables with skewed distributions and a high prevalence of zero values are transformed using the inverse hyperbolic sine (IHS) transformation.

Table 3.3: Descriptive Statistics: Firm Characteristics

Continuous variables				
Variable	**Description**	**Mean**	**SD**	**N**
firm_age	Firm age	4.09	9.41	1,039
foreign_share	Foreign ownership share (%)	1.73	10.45	1,028
uni_industry_collab	University–industry collaboration index	0.97	1.12	1,038
Categorical variables				
Variable	**Description**	**Category**	**Percent (%)**	**N**
foreign	Foreign ownership	Local	95.57	993
		Foreign	1.35	14
		Foreign partnered	3.08	32
		Total	100	1,039
academician_firm	Academician-owned firm	No	76.03	790
		Yes	23.97	249
		Total	100	1,039
firm_type	Firm type	Incubator firm	21.47	187
		Spin-off firm	2.76	24
		Normal / private firm	75.77	660
		Total	100	871

Notes: For firm characteristics N refers to the number of firms. Differences in the number of observations across variables reflect missing information for some firm characteristics and the unbalanced structure of the panel. Firm characteristics are measured at baseline (event time $k = 0$).

Table 3.5: Distribution of firm-level outcomes before and after TDA entry

Panel A. Before Entry (event_time<=0)				
Variable	**Mean**	**SD**	**Min**	**Max**
ihs_rdpersonnel	1.25	1.01	0	5.92
ihs_rdexpenditure_real2010	6.55	5.18	0	17.61
ihs_project	0.52	0.61	0	5.73
ihs_dev_product	0.34	0.63	0	5.50
ihs_sold_product	0.28	0.88	0	9.90
ihs_patent_nat	0.04	0.19	0	2.35
ihs_turnover_nat_real2010	4.55	5.69	0	20.36
ihs_turnover_int_real2010	0.79	2.78	0	19.52
Panel B. After Entry (event_time>=1)				
Variable	**Mean**	**SD**	**Min**	**Max**
ihs_rdpersonnel	1.82	1.23	0	5.87
ihs_rdexpenditure_real2010	10.06	4.92	0	19.03
ihs_project	1.02	0.71	0	7.73
ihs_dev_product	0.64	0.90	0	5.99
ihs_sold_product	0.56	1.33	0	12.61
ihs_patent_nat	0.06	0.28	0	2.66
ihs_turnover_nat_real2010	6.32	6.24	0	19.51
ihs_turnover_int_real2010	0.95	3.23	0	24.95

Notes: This table reports descriptive statistics for firm-level outcomes before and after entry into a TDA. Entry year is treated as pre-treatment. All variables are inverse-hyperbolic-sine transformed. The purpose of the table is to document the absence of extreme values or distributional breaks around entry; these statistics are descriptive and do not have a causal interpretation.

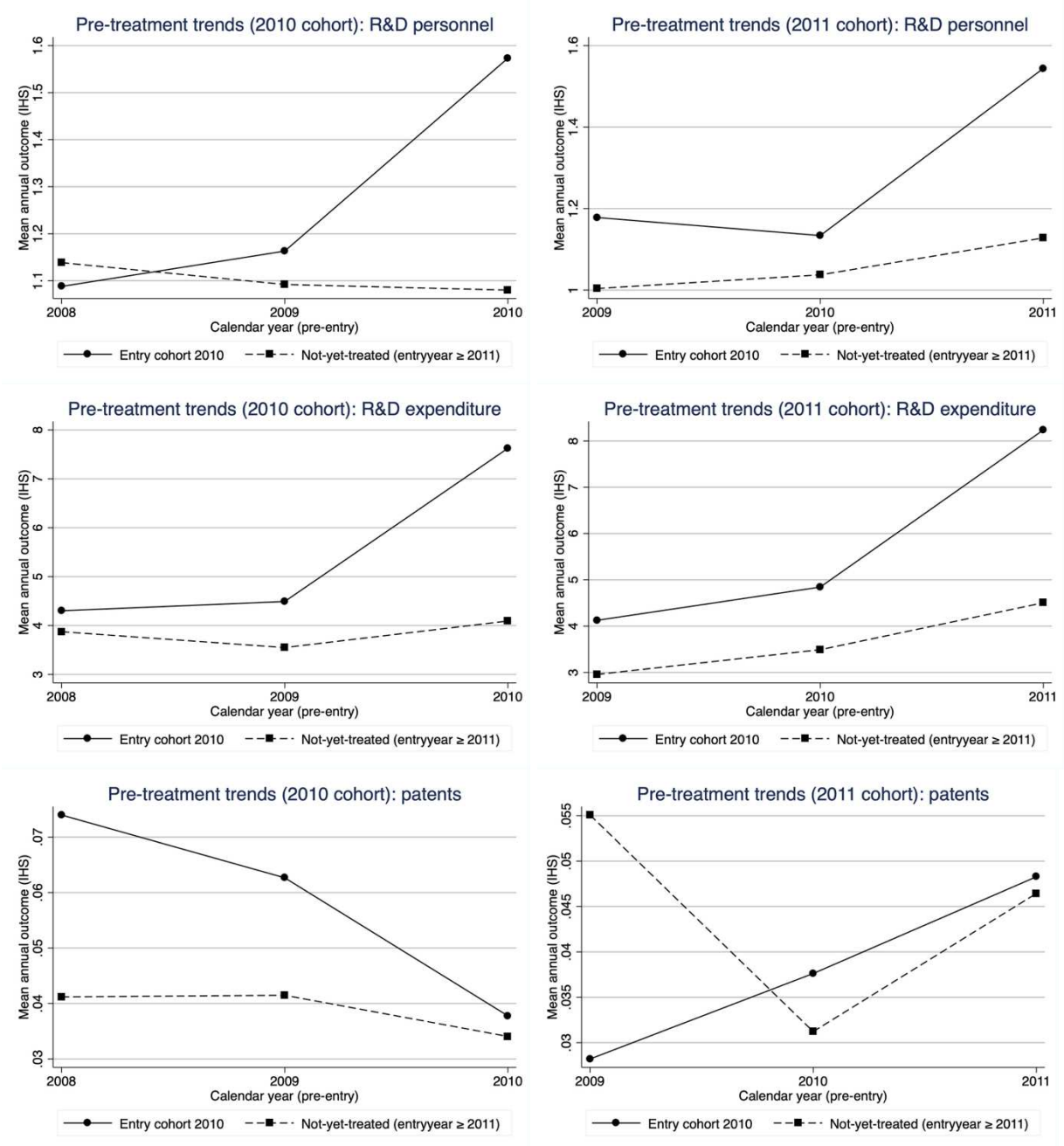
Table 5.4: Heterogeneous effects of TDA entry on patenting by university–industry collaboration

	(1) No collaboration	**(2) Collaboration**
ATT	-0.008	0.019
	(0.030)	(0.022)
Firm–year obs.	2,702	2,698

Notes: Cohort-specific DID estimates (Callaway and Sant'Anna, 2021). Firms grouped by pre-entry university–industry collaboration (none vs any). Not-yet-treated firms serve as controls. Outcomes are IHS-transformed. Standard errors clustered at the firm level.

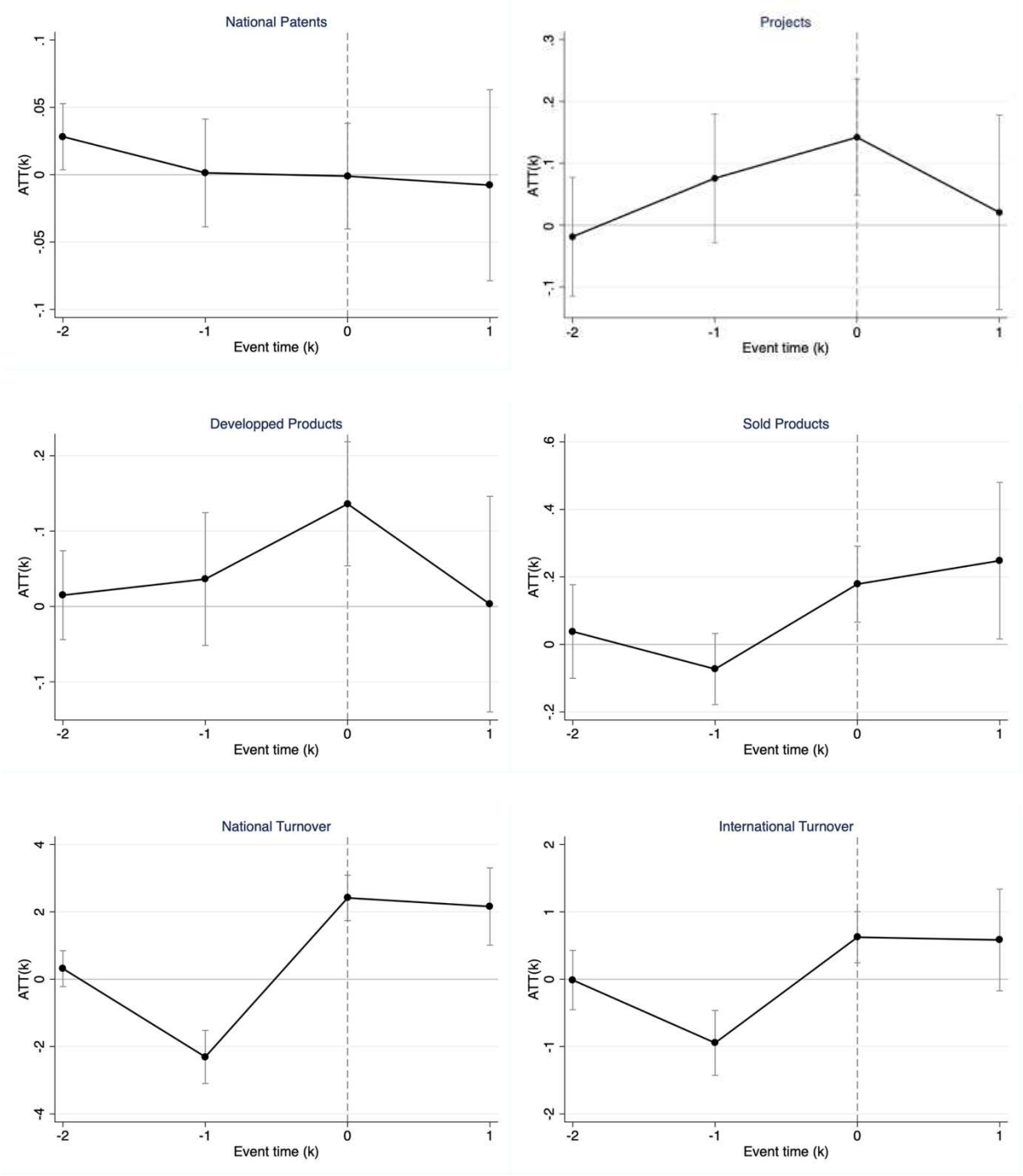
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 5.1: Pre-treatment trends by entry cohort and outcome



Notes: This figure plots mean values of inverse hyperbolic sine (IHS)–transformed outcomes for firms entering Technology Development Areas (TDAs) in 2010 or 2011 and for not-yet-treated firms in the same calendar years. For each treated cohort, outcomes are shown only for pre-entry calendar years. The control group consists of firms that have not yet entered a TDA by the corresponding year; firms already treated in a given year are excluded. The figures are intended as a diagnostic assessment of pre-treatment dynamics rather than formal tests of parallel trends.

Figure 5.2: Event-study estimates of dynamic treatment effects on innovation and commercialization outcomes



Notes: This figure presents event-study estimates of the dynamic effects of entry into a TDA on six firm-level outcomes: national patents, completed projects, developed products, sold products, domestic turnover, and international turnover. Estimates are obtained using the CSDID estimator proposed by Callaway and Sant'Anna (2021), with not-yet-treated firms serving as the control group in each period. Event time $k = 0$ denotes the first full year following entry into a TDA, while negative values correspond to pre-treatment periods. All outcome variables are transformed using the inverse hyperbolic sine function. Points represent cohort-aggregated average treatment effects on the treated, and vertical bars denote 95% confidence intervals based on standard errors clustered at the firm level.

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