Innovation Zones, Technological Upgrading, and Firm Productivity*

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Abstract

We examine the effects of place-based innovation policies on firm performance by leveraging Türkiye's staggered rollout of innovation zones (technoparks). Combining rich administrative data on all non-financial Turkish firms (2009–2023) with a matched difference-in-differences design, we document three key findings: incumbent firms in districts with newly established technoparks increase automation by 8.2%; they significantly increase their engagement in technology-intensive trade (both domestically and internationally); and they display substantial medium-term gains in total factor productivity. Our findings demonstrate how local innovation zones can accelerate technological upgrading and generate productivity gains that benefit the broader regional economy.

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1 Introduction

Low- and middle-income countries around the world are increasingly turning to spatially targeted initiatives (such as special economic zones, innovation hubs, and technoparks) to accelerate structural transformation and boost local economic growth (UNCTAD, 2019). Although intuitively appealing, the effectiveness of these policies remains heavily debated. Skeptics argue, for example, that local interventions simply reallocate economic activity across regions, producing limited net gains at the national level (Glaeser and Gottlieb, 2008). Empirical evidence on these interventions remains mixed, and the effectiveness of place-based policies in delivering development impact continues to be a central question in both academic and policy debates.

This paper contributes to these debates by focusing on a distinctive and increasingly prevalent intervention: Technology Development Zones (TDZs), commonly known as technoparks. Unlike programs aimed directly at employment or poverty alleviation, technoparks target technological upgrading and structural transformation through the spatial clustering of innovative firms. We focus on Türkiye's technopark policy, which launched in 2001 and expanded to over 90 parks nationwide by the early 2020s. Technoparks are typically located near research universities and offer tenant firms generous tax breaks, Research & Development (R&D) support, and facilitated access to academic knowledge and infrastructure. The rationale is that co-locating technology-oriented businesses in dedicated parks will generate knowledge spillovers, spur innovation, and ultimately enhance firm performance in the wider economy. Technoparks are therefore a form of place-based industrial policy designed to raise the technological intensity of economic activity.

Technoparks have proliferated globally in recent decades, with numerous countries—including Brazil, China, India, Russia, and South Korea—establishing parks to promote technological development.[1] The Turkish model closely approximates this global trend,

[1] Approximately three-quarters of these technoparks were established over a decade ago, primarily during the 2000s and 2010s. As of 2024, there are 338 science and technology parks operating across 78 countries (IASP, 2024).

both in terms of timing and in how its technoparks are typically structured: strategically located near or adjacent to universities to facilitate knowledge spillovers between academia and industry.[2] Türkiye's initiative thus exemplifies a policy approach adopted by a range of emerging economies to foster technological upgrading.

Despite their widespread adoption, rigorous evidence on technopark effectiveness remains scarce. We examine the Turkish case to test whether technoparks accelerate firm-level technology adoption and productivity growth—a key question for policymakers designing similar spatial interventions. Our analysis exploits the staggered rollout of technoparks across Turkish districts to estimate their causal impact on nearby firms located within the same district but outside the technopark itself.

Our analysis draws on rich administrative data on all non-financial firms in Türkiye from 2009 to 2023. In addition to detailed financial information, we have access to exhaustive records of domestic inter-firm transactions from an invoice database maintained by the Tax Authority. This allows us to reconstruct the full domestic supply chain and to identify whether firms are buying or selling technology-intensive goods and services—and whether their trading partners are located inside or outside technopark districts. We further merge in customs data from the Ministry of Trade, containing the universe of Turkish firms' export and import transactions at the 6-digit Harmonized System (HS) level. This enables us to build granular measures of firms' participation in international technology-intensive trade and to track the adoption of automation-related technologies.

To analyze these rich data, we employ a spatial, matched difference-in-differences estimation strategy. We first identify treated districts that opened a technopark during the sample period and match each one to a similar control district without a technopark. This matching strategy, based on pre-treatment economic trends and characteristics, mitigates potential endogeneity concerns regarding technopark placement by ensuring that treated districts and their selected counterparts exhibit parallel pre-trends. In a second step, we compare the evolution of firm outcomes in treated districts versus matched controls, while leveraging variation in the timing of technopark openings (staggered adoption). Our em-

[2] 75% of technoparks worldwide are situated within five kilometers of a university campus (IASP, 2024).

pirical strategy thus differences out any time-invariant district attributes and common regional shocks, isolating the impact of the technopark introductions.

Our findings indicate that technoparks can generate substantial positive impacts on both technological adoption and firm performance. In the years following the opening of a technopark, nearby firms become substantially more likely to participate in technology-intensive trade. In particular, we find increased entry into exporting and importing of research-intensive and high-tech products, as well as a shift in firms' export baskets towards more sophisticated, higher-value-added goods. These changes in trade composition suggest that technoparks help firms upgrade the technological content of their operations and access foreign markets. This upgrading is also accompanied by medium-term productivity gains: total factor productivity (TFP) of firms in treated districts increases significantly faster relative to the control group. These productivity effects materialize with a lag of approximately three to five years after the zone's establishment, consistent with the idea that building local innovative capacity and reaping benefits takes time. The magnitudes imply economically relevant improvements. For example, our estimates indicate that the TFP of incumbent firms is on average about 2.9% higher than it would have been absent the technopark. We find no evidence that these gains come at the expense of neighboring areas; if anything, some benefits appear to diffuse regionally, hinting at some positive spillovers beyond the immediate district.

Our results are consistent with technoparks facilitating technology transfer through knowledge sharing, specialized talent pools, and academic collaborations. Importantly, we observe shifts toward more sophisticated products rather than merely output increases, indicating that technoparks upgrade firms' technological capabilities beyond scaling existing operations. These findings thus demonstrate that well-designed technoparks can effectively promote industrial upgrading at the local level.

Literature review and contribution. Our paper connects to several strands of the literature. First, we contribute to the growing body of work evaluating place-based industrial policies. A large literature has examined the effects of spatially targeted programs—

such as enterprise zones, regional subsidies, and special economic zones—on local economic outcomes (employment, wages, firm activity, investment, productivity, consumption, and poverty). Most research has focused on high-income countries. Early studies cast doubt on the impact of place-based policies, especially on net employment gains at the local level, with no or only modest net gains observed in many contexts (Glaeser and Gottlieb, 2008; Neumark and Kolko, 2010; Gobillon et al., 2012; Neumark and Simpson, 2015). Although some studies show positive long-term effects of place-based policies on economic activity, these often reflect displacement from non-targeted areas. For example, Von Ehrlich and Seidel (2018) study the long-term effect of a temporary place-based policy in West Germany. They find increased income per square kilometer in policy-affected areas, but emphasize that this represents spatial redistribution rather than new economic activity, as firms merely relocated from within a 20-30 km radius of targeted regions.

A recent literature has yielded more encouraging evidence on place-based policies across diverse contexts. Several studies from high-income economies show positive impacts: employment and wage gains from U.S. Empowerment Zones (Busso et al., 2013); persistent output growth from the Tennessee Valley Authority (albeit with some offsetting losses elsewhere) (Kline and Moretti, 2014); small-firm employment increases from UK investment subsidies (Criscuolo et al., 2019); job creation for younger and less-educated workers from German regional investment subsidies (with substantial spatial spillovers through commuting (Grunau et al., 2025)); and sustained manufacturing and service growth from Italian industrial clusters (Incoronato and Lattanzio, 2024). The emerging market evidence, though limited and focused exclusively on Special Economic Zones (SEZs), reveals similar patterns: Chinese SEZs increased investment, employment, and productivity (Wang, 2013; Alder et al., 2016; Lu et al., 2019, 2023), albeit creating non-competitive price behavior among firms (Brooks et al., 2021); Turkish place-based subsidies boosted economic activity with positive spillovers to connected businesses (Atalay et al., 2023); Indian localized tax incentives increased employment, total output, and the number of firms (Chaurey, 2017); and Vietnamese SEZs improved manufacturing employment and formalized labor contracts (Tafese et al., 2025). Gallé et al. (2024) shows

that SEZs established in India between 2005 and 2013 increased local manufacturing and service employment, with positive spillovers up to 10 km from the SEZ area, suggesting that SEZ may have served local structural change. A paper close to ours is Görg and Mulyukova (2024), which uses firm-level data from India to estimate the impact of the establishment of an SEZ on the productivity growth of firms. They report null results on the impact of SEZs on firm's productivity, masking significant heterogeneity by the ownership type of the SEZ: while public-owned SEZs have a negative impact on firm's growth, privately-owned ones foster firm's productivity, suggesting the possibility of distortions induced by rent-seeking behavior of firm managers.

We contribute novel causal evidence on an increasingly prevalent yet understudied place-based intervention: technoparks that aim to stimulate technological upgrading by firms. Unlike generic investment subsidies or employment programs, these parks explicitly target technologically advanced firms and seek to foster knowledge spillovers. We therefore move the focus from asking *"does a place get more jobs?"* to *"does a place upgrade technologically?"*. By analyzing firm-level automation, export sophistication, and total factor productivity, we offer new evidence on the effectiveness of these innovation-oriented place-based policies, showing how technoparks can lift productivity without the spatial displacement that plagues many subsidy programs. Unlike earlier studies that primarily focus on aggregate outcomes such as employment or firm entry, we provide novel evidence on the qualitative transformation of incumbent firms' operations, documenting how technoparks induce shifts toward more sophisticated export and import portfolios and increased automation adoption. This granular analysis of within-firm technological upgrading furthers our understanding of the mechanisms through which place-based innovation policies generate productivity gains.

Second, our paper brings complimentary evidence on agglomeration effects and local spillovers (Ellison et al., 2010; Greenstone et al., 2010; Bloom et al., 2013). Previous work demonstrates that firms benefit from colocation through labor pooling, input-output linkages, and information sharing, with meta-analyses showing that doubling employment density generates productivity gains of 3 to 8% (Rosenthal and Strange, 2004; Combes

et al., 2012). Although agglomeration effects justify spatial policies, evidence on policy-induced spillovers to incumbent firms remains scarce, particularly in emerging markets. We find that technopark establishment increases total factor productivity among local firms outside the parks. These spillovers are strongest in technology-intensive sectors, consistent with technoparks generating local "innovation multipliers" similar to the employment multipliers identified by Moretti (2010).

Third, we advance research on the geography of innovation and knowledge spillovers. Studies using patent citation data show that inventors build on the work of nearby peers (Jaffe et al., 1993) and that innovation concentrates geographically in R&D-intensive sectors (Audretsch and Feldman, 1996). Although many governments have established science parks to replicate successful innovation clusters like Silicon Valley, very little is known about their efficacy in emerging economies.[3] Our study evaluates formally designated innovation clusters in such a context, finding technoparks help firms shift toward more sophisticated exports and higher productivity. Using HS-6 product data and firm-to-firm invoices, we show firms begin pivoting toward more R&D-intensive product lines upon technopark establishment, with these effects strengthening over time. Productivity gains build more gradually, consistent with models where the full benefits of localized knowledge spillovers and innovation capacity take time to materialize.

Fourth, our results align well with insights from modern theories of endogenous technological change (Romer, 1990). This literature emphasizes that to avoid the middle-income trap—where countries cease converging to the global technology frontier (Aghion and Howitt, 1992; Rodrik, 2016)—economies must eventually transition from investment-based to innovation-based growth (Acemoglu et al., 2006; Aghion and Howitt, 2006). This transition may require addressing potential market failures in innovation and firm-level technological upgrading. In this light, Akcigit et al. (2016) demonstrate how firms' decisions to develop or abandon ideas shape aggregate growth, highlighting the role of efficient idea markets for technological upgrading. Akcigit et al. (2021) emphasize that sus-

[3] Schweiger et al. (2022) examine the long-run effects of historical place-based R&D policies, namely Soviet Russia's Science Cities. The authors find that former Science Cities at present still demonstrate greater innovation, higher productivity, more highly skilled workers, and higher salaries.

tained growth likewise requires improving R&D systems, particularly through policies that stimulate interaction between public research and the private sector. Our findings provide new micro-level evidence supporting these theoretical frameworks by showing how place-based innovation policies can facilitate firm-level technological upgrading and, in doing so, serve as an effective policy lever to spur structural transformation. Our results are also consistent with broader arguments for targeted industrial policy in middle-income settings, where market failures tend to be pervasive (Rodrik, 2007).

We proceed as follows. Section 2 provides institutional background and describes the staggered roll-out of technoparks across Türkiye. Sections 3 and 4 then present our data and empirical strategy, respectively. Section 5 reports our main results on automation, technology-intensive trade, and firm productivity. Section 6 discusses spatial spillovers and Section 7 concludes.

2 Institutional Background

2.1 Technoparks in Türkiye

Technology Development Zones (TDZs), commonly known as technoparks, are specialized sites that encourage collaboration between firms, startups, and research institutions to drive innovation and corporate technological upgrading. They often also provide incentives to maximize knowledge spillovers, aiming to improve firms' operational efficiency and the quality and innovativeness of their products and services. As a targeted form of place-based industrial policy, technoparks have been widely adopted, especially in low- and middle-income economies that seek to accelerate the development of high-tech industries and regional growth.

Türkiye initiated its technopark program with the Technology Development Zones Law (Law No. 4691) of July 2001. This legislation established the governance framework for technoparks and outlined the incentives available to firms located inside the parks, including corporate tax exemptions on income generated from software and R&D activities, exemptions from VAT and customs duties, and reduced income tax for R&D personnel. These incentives, combined with the close proximity to universities and other

innovative firms, aim to boost private R&D investment and increase innovative output. Typically, firms choosing to locate within technoparks operate in technology-intensive sectors, including software development, information and communication technologies (ICT), advanced engineering, biotechnology, and e-commerce.

Most Turkish technoparks are developed in close collaboration with leading regional universities or research institutes. Universities contribute land or facilities and ensure that tenant firms have access to academic expertise, laboratories, and a steady flow of skilled graduates. Technopark management companies also offer support services such as patent assistance, business incubation, and networking events.

2.2 The Staggered Rollout of Technoparks

Türkiye's technopark initiative has expanded gradually over the past two decades. In the early 2000s, only a few technoparks were operational, mainly in major cities such as Ankara, Istanbul, and İzmir. By 2024, the number of technoparks exceeded 100, covering various provinces across the country. Figure 1 illustrates the evolution of technopark openings. The red bars reflect the number of new technopark openings each year, while the blue line represents the cumulative count over time. Although the number of new openings fluctuates from year to year, the overall trend is upward, reflecting sustained policy support for the technopark program. The staggered establishment of technoparks—where parks were launched at different times across different districts—is central to our identification strategy.[4]

All technoparks operate under a unified legal framework with common overarching goals, although there is some variation in terms of size and sectoral specialization. Despite these differences, the uniform policy environment allows us to treat technopark establishment as a comparable treatment group across different regions.

Appendix Table A1 provides a breakdown of firms located in treated districts by main

[4]Türkiye's administrative structure consists of 12 regions (NUTS-1), 26 subregions (NUTS-2), 81 provinces (NUTS-3), and 973 districts (LAU-1). The Nomenclature of Territorial Units for Statistics (NUTS) is the European Union's system to standardize territorial divisions into three levels, with Local Administrative Units (LAUs) below these levels. A Turkish district (ilçe) functions similarly to a U.S. county but has significantly less local autonomy and typically is smaller in terms of geographic and population size.

sector of activity. Although manufacturing (C), wholesale and retail trade (G), and construction (F) account for a large share of firms, there is also substantial representation from sectors closely aligned with the innovation mandate of technoparks. For example, over 10,000 firms operate in professional, scientific, and technical activities (M), and more than 4,000 in information and communication (J). This confirms that the treated districts—not just the technoparks themselves—host a diverse mix of firms, including a meaningful share from high-tech and knowledge-intensive industries.

3 Data

We assemble a comprehensive panel of Turkish firms and regions (2009–2023) by combining multiple administrative data sources. Our primary data come from the Central Bank of the Republic of Türkiye (CBRT) and various government agencies, accessed under secure protocols. All datasets are linked using anonymized firm identifiers (tax identification numbers), allowing us to track the same firm across different data sources and over time.

3.1 Sample Selection Criteria

We restrict our sample to pre-existing firms—those observed at least once before a technopark opens in their district. This restriction applies symmetrically: firms in treated districts must appear before the technopark's opening year, while firms in control districts must appear before the corresponding year. This ensures a comparable firm composition across the treated and control areas. This restriction serves three purposes. First, it enables us to observe pre-treatment firm characteristics, essential for testing parallel trends and estimating dynamic effects. Second, it prevents selection bias from new firm entry after technopark establishment, isolating the policy's impact on incumbent firms. Third, since these pre-existing firms cannot be initial technopark tenants, we capture spillover effects on the broader local economy rather than direct effects on park occupants. Our estimates thus reflect how technoparks generate productivity and technological upgrading externalities among surrounding non-tenant firms.

3.2 Firm-Level Data

We use five main data sources at the firm level. First, we obtain balance sheet and income statement data from administrative records. These financial statements are collected by the Tax Authority and processed by the Turkish Statistical Institute and the CBRT. They provide annual information on the assets, liabilities, sales, value added, and other accounting variables of firms, as well their industry classification.[5] Using these financial data, we follow Olley and Pakes (1996) to create a TFP proxy for all Turkish firms. These estimations are performed iteratively at the 2-digit NACE sector level and are based on financial statement inputs including gross sales (value added), long-term tangible fixed assets (capital), inventories, and the number of employees.

Second, we incorporate firm location data from the Tax Authority, which indicates the district (LAU-1 level) of each firm's headquarters. This georeferenced information is crucial for defining treatment versus control firms in our study.

Third, we use granular data on domestic inter-firm transactions from an invoice database maintained by the Tax Authority. This dataset records all business-to-business sales in Türkiye above a certain invoice value (TL 5,000), essentially capturing the entire domestic supply chain network. From these records, we can observe whether a firm is selling or purchasing technology-intensive goods and services, as well as whether those transactions involve firms located inside or outside technopark districts.

Fourth, we incorporate foreign trade data from the Ministry of Trade, which covers the universe of export and import transactions by Turkish firms. For each firm-year, we observe the total value of exports and imports, and we have product-level details at the 6-digit Harmonized System (HS) level. This allows us to construct highly granular measures of a firm's engagement in international technology-intensive trade—for instance, whether the firm exports high-tech products or imports advanced machinery. With regard to the latter, we follow the methodology outlined by Acemoglu and Restrepo (2022) to detect imports of capital goods connected to firm-level automation, such as industrial robots, computer numerical control machines, and automated guided vehicles.

[5] We exclude financial sector firms, as our focus is on non-financial corporations.

Fifth, to analyze firm-level employment dynamics, we use administrative employment records obtained from Türkiye's Social Security Institution (SGK), which we access via the Central Bank of the Republic of Türkiye (CBRT). These records provide annual information on the number of registered employees per firm, allowing us to construct consistent panel data on employment levels. In addition to total employment, we observe total wage bills, which we use to compute average wages per employee. These variables enable us to assess whether technopark establishment affects firms' labor demand, and whether observed productivity gains are accompanied by shifts in employment or changes in compensation patterns. As with our other firm-level variables, we link employment data to our core sample using anonymized firm identifiers.

Our analysis focuses on the period 2009–2023. We start in 2009 because most of our data (especially the financial and transaction records) are consistently available from that year onward. By 2009, some technoparks already existed; however, our empirical strategy (described below) will only utilize the post-2009 openings for identification.

We apply three sample restrictions to ensure data quality. First, we drop firm-year observations where total assets or gross sales are zero or missing, as such firms are likely economically inactive. Second, we drop firms that lack location identifiers (province/district), since location is critical for our study. Third, because our difference-in-differences design compares firms in treated versus control districts, we restrict the sample to firms located in either a treated or a matched control district (we define these districts in Section 4.2). We thus focus on the subset of districts that established a technopark after 2009 (the treatment group) or were selected as an adequate control. This ensures a like-for-like comparison and avoids extrapolating to areas that are very different.

Finally, we impose that firms must appear in the data for a minimum of four years, including at least one year before the technopark is established in their district. This guarantees that we observe pre-treatment outcomes (to establish trends) and that we track the firm for some time post-treatment.[6] After applying these filters, our final panel consists of approximately 245,000 unique firms, yielding roughly 2.37 million firm-year observations

[6]When we instead not impose this restriction, all our results remain very similar in terms of both statistical significance and magnitude.

over 15 years. This large sample provides ample statistical power and covers a wide range of firms and industries.

3.3 Measuring the Technology Content of Trade

To assess the technological sophistication of firms' domestic trade, we use firm-to-firm invoice data from the Turkish Tax Authority, in combination with Eurostat's high-technology industry classification. We define a firm as engaging in *High-Tech Domestic Purchases* if it purchases raw materials, intermediate goods, or finished products from suppliers in 2-digit NACE sectors classified by Eurostat as high-technology or medium-high-technology industries.[7] Similarly, we define *High-Tech Domestic Sales* as transactions in which a firm sells goods or services to customers operating in these high-tech sectors.

Next, we construct indicators of the technological intensity of firms' international trade using product-level customs data from the Turkish Ministry of Trade. Our first measure, *High-R&D Exports*, follows the R&D intensity taxonomy proposed by Galindo-Rueda and Verger (2016), which classifies economic activities by their R&D intensity according to the International Standard Industrial Classification (ISIC). As the Turkish customs data report export products using 6-digit HS codes, we employ correspondence tables developed by the United Nations Statistics Division (UNSD), using the Central Product Classification (CPC) system to link ISIC sectors to HS codes. We begin by identifying 2-digit ISIC codes with high or medium-high R&D intensity, along with their associated 4-digit subcategories.[8] These are then mapped to CPC codes, which we subsequently match to HS product codes to construct a firm-level, time-varying indicator of *High-R&D Exports*.

In an alternative approach, we use the same customs data to evaluate export technol-

[7] These sectors include the manufacture of chemicals and chemical products (NACE 20); basic pharmaceutical products and pharmaceutical preparations (NACE 21); computer, electronic, and optical products (NACE 26); electrical equipment (NACE 27); machinery and equipment not elsewhere classified (NACE 28); motor vehicles, trailers and semi-trailers (NACE 29); and other transport equipment (NACE 30). More details are available at https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries.

[8] Following Galindo-Rueda and Verger (2016), these include pharmaceuticals (ISIC 21); computer, electronic, and optical products (ISIC 26); other transport equipment (ISIC 30); motor vehicles, trailers, and semi-trailers (ISIC 29); machinery and equipment not elsewhere classified (ISIC 28); chemicals and chemical products (ISIC 20); and electrical equipment (ISIC 27).

ogy intensity based on TurkStat's own classification, which maps each 6-digit HS code to a predefined level of technology intensity. We define *High-Tech Exports* as exports of goods falling within the medium-high and high-tech categories.

Finally, we construct a *High-Skill Exports* indicator based on Aksoy et al. (2024), who identify high-skill-intensive products using the 3-digit Standard International Trade Classification (SITC). We map these SITC codes to CPC, and then to HS codes, enabling us to track firms that export goods requiring a higher intensity of labor skills.

3.4 Regional Data

We compile a rich set of district covariates for our matching and regression analyses. We first obtain official records from the Ministry of Industry and Technology showing the exact year each technopark became operational and which district (LAU-1 level) it is located in. We focus only on technoparks that opened after 2009, excluding earlier ones.[9]

We then gather (from TurkStat) baseline (2009) demographic characteristics of each district to help create a comparable control group of districts: population density; population growth; average household size; the gender ratio (male-to-female) of the population; and the youth ratio (share of the population that is of young working age).

We also create district-level measures of economic activity by aggregating our more granular firm-level data. For each district, we compute the number of active firms in 2009 (a proxy for firm density, labeled *Firm Intensity*), the total sales of firms in that district (*Sales Intensity*), and total employment in the district (*Employment Intensity*). The latter is obtained by summing employment across firms using social security records.

To proxy for local financial development, we use the CBRT's credit registry and count how many bank branches were active in the district as of 2009 (*Bank Presence*), reasoning that a higher branch presence indicates better local access to finance. Next, as a political variable, we include *Political Preferences*, the margin of victory of the ruling party in the 2009 municipal elections (data from the Electoral Board). This captures political alignment and may correlate with both the likelihood of receiving a technopark and the quality of

[9] In three cases, multiple technoparks were opened in the same district after 2009. We then retained only the earliest opening.

local governance. Lastly, we incorporate data on nighttime light intensity at the district level (sourced from satellite imagery via the IMF) as an overall proxy for economic activity.

All monetary variables (such as sales) are appropriately scaled or logged to reduce skewness, and we fix these covariates at their pre-treatment values.[10] We will use these district variables to match technopark districts with similar non-technopark districts and to subsequently check for balance between both groups. Appendix Table A2 lists these variables along with their definitions and data sources.

4 Identification Strategy

Evaluating the causal impact of technoparks is challenging due to their non-random allocation across districts. Comparing firms in technopark districts to others could be misleading if these districts were systematically more developed or on different trajectories. Our empirical strategy addresses this by combining propensity score matching with a difference-in-differences (DiD) design—first selecting comparable control districts and then implementing DiD analysis on this matched sample.

4.1 Matching

After compiling the district-level variables that capture macroeconomic, demographic, financial, and political conditions in 2009 (cf. Section 3.4), we implement replacement-free nearest-neighbor propensity score matching. For each treated district, we select a control district from the same NUTS-2 sub-region that has the closest propensity score, based on 2009 covariates. This ensures exact geographic matching and helps mitigate unobserved regional confounders. The final matched sample consists of 40 treated districts (those with a technopark opening after 2009) paired with 40 control districts. Figure 2 displays the geographic distribution of the matched sample. Treated (control) districts are shown in red (blue). The map confirms broad spatial coverage across Türkiye, with treated and control pairs well distributed within their respective sub-regions.

[10] The variables *Population Density*, *Firm Intensity*, *Sales Intensity*, *Employment Intensity*, and *Bank Presence* are log-transformed, with a small constant added where needed to handle zero values.

Table 1 compares treated and control districts before and after matching. Before matching, treated districts were significantly more urbanized and economically active, with higher population density, population growth, firm intensity, and nighttime light emissions. After matching, observable differences between treated and control districts are substantially reduced. Normalized differences across all covariates fall well below conventional balance thresholds, indicating that the matching procedure achieves a high degree of covariate balance.

In addition to district-level balance, we assess whether firms in treated and control districts are comparable in their baseline characteristics. Table 2 reports the results of an OLS regression of a technopark indicator on observables at the firm level using data from 2009. The dependent variable is an indicator of whether a firm is located in a district that later receives a technopark. The coefficients on firm-level controls, including firm size, equity ratio, sales, liquidity, and employment, are all economically negligible and statistically insignificant. These results confirm that, conditional on matched districts, firms in treated and control areas were similar prior to the introduction of technoparks.

Although matching ensures baseline similarity between treated and control districts, the key identification assumption for our difference-in-differences approach is parallel trends—that outcomes in treated and control districts would have evolved similarly absent technoparks. Matching on covariate levels increases this assumption's plausibility since districts with similar initial conditions tend to respond similarly to common shocks. As our event study analyses will demonstrate, pre-treatment trends across multiple outcome variables are indeed parallel between matched treated and control districts, making it plausible that any post-treatment divergence can be attributed to technoparks rather than pre-existing differences.

Matching on pre-treatment levels also offers additional methodological advantages. It reduces model dependence by limiting comparisons to truly comparable districts, preventing extrapolation to dissimilar units and decreasing sensitivity to functional form assumptions. Furthermore, even with parallel pre-trends, selection into treatment might correlate with time-varying factors or heterogeneous treatment effects. Matching on ob-

servables addresses this potential confounding by ensuring balance on characteristics that could drive both selection and future outcomes.

4.2 Estimation Strategy

4.2.1 Firm Entry and Exit

Before analyzing technoparks' effects on existing firms, we investigate their impact on district-level firm dynamics. Using data from the Turkish Revenue Administration, we track new firm creation and exit patterns. We construct $FirmEntry_{dt}$ by counting all firms that became operational for the first time in district d in year t. We also monitor the entry of firms engaging in technologically sophisticated activities from inception, using the high-technology indicators defined in Section 3.3: *High-Tech Domestic Purchases*, *High-Tech Domestic Sales*, *High-R&D Exports*, *High-Tech Exports*, and *High-Skill Exports*. Additionally, we examine whether technopark establishment affects firm exit rates.

We leverage the staggered rollout of technoparks across districts after 2009, comparing firm dynamics in treated districts to those in matched control districts over time, by estimating the following specification:

$$FirmEntry_{dt} = \gamma \cdot Technopark_{dt} + \delta_d + \delta_{rt} + \varepsilon_{dt} \tag{1}$$

where $Technopark_{dt}$ is 'one' after the opening of a technopark in district d in year t; 'zero' otherwise. The model includes district fixed effects (δ_d) and sub-region × year fixed effects (δ_{rt}), which control for time-varying shocks common to all districts within the same NUTS-2 region. Standard errors are heteroskedasticity robust.

4.2.2 Technological Upgrading and Productivity

After estimating the impact of technopark openings on district-level firm dynamics, we turn to their effect on individual incumbent firms. Here our baseline specification is:

$$Y_{idt} = \beta \cdot Technopark_{dt} + \delta_i + \delta_{rt} + \varepsilon_{idt} \tag{2}$$

where Y_{idt} denotes the outcome of interest for firm i in district d and year t. The treatment variable, $Technopark_{dt}$, is a binary indicator equal to 'one' if a technopark has been established in district d by year t; 'zero' otherwise. The coefficient of interest, β, captures the effect of technopark openings on incumbent firms in treated relative to control districts.

The specification includes firm fixed effects (δ_i), which absorb all time-invariant firm characteristics, and sub-region × year fixed effects (δ_{rt}). This structure allows us to compare treated and control firms within the same broader region, netting out regional economic trends and common shocks. Standard errors are clustered at the district-by-year level to account for spatial and serial correlation in treatment assignment.

These estimations compare within-firm changes before and after technopark openings, relative to changes in firms in control districts over the same period. As discussed before, identification relies on the standard parallel trends assumption: in the absence of technopark openings, firms in treated and control districts would have experienced similar trends in outcomes. We assess the plausibility of this assumption using pre-treatment event study plots and robustness checks, which we present in the results section.

Our outcomes focus on three key dimensions of technological upgrading. First, we examine firms' engagement in technology-intensive trade, exploring both domestic transactions and international export patterns. Second, we assess firms' capital imports related to automation and advanced production technologies. Third, we analyze changes in firm-level total factor productivity (TFP), a direct measure of efficiency gains that might result from technological upgrading. In addition, we investigate employment outcomes at the firm level, including changes in total employment and wage levels, to assess whether technological upgrading is accompanied by shifts in labor demand.

5 Empirical Results

5.1 District-level Firm Entry and Exit

Table 3 presents findings on firm entry and exit at the district level based on Equation 1. Column (1) shows that technopark establishment leads to a statistically significant in-

crease in firm creation, with treated districts experiencing an average of 43.93 additional new firms annually relative to matched control districts. Columns (2) and (3) reveal that this entrepreneurial response is particularly pronounced among firms engaged in high-tech domestic transactions. In contrast, columns (4)–(6) show no significant effects on the entry of firms engaged in technology-intensive international trade—whether measured by R&D intensity, high-tech product classifications, or skill content of exports. This pattern suggests that technoparks primarily catalyze domestic technology networks rather than immediately fostering globally oriented high-tech ventures. Finally, column (7) addresses potential displacement effects by examining firm exit rates. The statistically insignificant coefficient indicates that technoparks neither crowd out existing firms nor accelerate market reallocation through Schumpeterian creative destruction. The net effect is thus unambiguously positive for local firm demographics, though the absence of increased exit rates may suggest limited competitive pressures on incumbent firms.

5.2 Technology Upgrading in Domestic Trade

Table 4 presents firm-level estimates of technopark effects on domestic technology linkages. The results reveal a consistent pattern of technological upgrading across both input sourcing and output markets. Input side effects (purchases, columns 1–4) show that technoparks significantly alter firms' procurement patterns. The extensive margin results indicate that firms in treated districts are 0.97 percentage points more likely to purchase high-tech inputs while being 0.90 percentage points less likely to rely exclusively on low-tech suppliers. These effects represent economically meaningful changes—a 3.4% increase and 1.5% decrease relative to control group means of 28.8% and 58.8%, respectively. The intensive margin results in columns (3) and (4) corroborate this technological shift: high-tech procurement values increase by 3.5% while low-tech inputs decline by 1.5%.

The output side effects (sales, columns 5–8) mirror this upgrading pattern. Firms in technopark districts show a 1.04 percentage point higher propensity to engage in high-tech sales—a 4.0% increase relative to the control mean of 26.1%. In contrast, exclusive participation in low-tech markets declines by 1.06 percentage points (1.8% relative to the

control mean). Interestingly, while the extensive margin effects are symmetric across purchases and sales, the intensive margin results differ: high-tech sales values show no significant increase despite the positive extensive margin effect, whereas low-tech sales values decline significantly.

The event study evidence in Figures 3 and 4 validates our identification strategy. Both extensive and intensive margin coefficients remain flat prior to technopark establishment, with marked shifts emerging only after treatment. This absence of pre-trends supports a causal interpretation of our findings. Collectively, these results demonstrate that technoparks catalyze a reorientation of local firms toward technology-intensive domestic value chains, with particularly strong effects on input procurement patterns. The asymmetry between extensive and intensive sales margins suggests that, while more firms participate in high-tech markets, building substantial market share in these segments may require longer-term capacity development.

5.3 Technology Upgrading in Foreign Trade

We now examine how technoparks affect firms' participation in technology-intensive international trade across three dimensions: R&D intensity, technological sophistication, and skill content. Table 5 reports the impact on R&D-intensive exports. The extensive margin results (columns 1–3) reveal that technoparks increase firms' propensity to export high-R&D products by 0.33 percentage points—a 4.5% increase relative to the control while the exclusive participation in low-R&D export markets unchanged. The intensive margin estimates (columns 4–6) show a corresponding 5.3% increase in high-R&D export values, with no effect on low-R&D export volumes. This pattern suggests that technoparks specifically promote innovation-intensive rather than traditional export activities.

Table 6 presents analogous results using technology-intensity classifications. Firms in technopark districts are 0.30 percentage points more likely to export high-tech products (a 4.3% increase relative to controls), with high-tech export values rising by 4.1%. As with R&D intensity, we find no displacement of low-tech exports, indicating that technological upgrading represents a net expansion of firms' export capabilities rather than substitution

between product categories.

Table 7 completes the analysis by examining skill-intensive exports. The results maintain the established pattern: technoparks increase high-skill export propensity by 0.29 percentage points (4.7% relative to the control mean) and high-skill export values by 3.4%, while leaving low-skill export activities unaffected. The event study evidence across Figures 5–7 consistently validates our identification strategy. Pre-treatment coefficients remain statistically indistinguishable from zero, followed by gradual increases post-treatment. This temporal pattern suggests that export upgrading requires time to materialize, likely reflecting the period needed for firms to develop new capabilities and establish international market connections.

Taken together, these results demonstrate that technoparks fundamentally alter the composition of local firms' export portfolios. The consistency across multiple measures of technological sophistication—whether defined by R&D intensity, technology classification, or skill requirements—provides robust evidence that technoparks facilitate firms' transition toward higher value-added segments of global value chains. The absence of negative effects on low-sophistication exports further suggests that this upgrading generates additional trade rather than simply redirecting existing export capacity.

5.4 Productivity Effects

We next examine whether technoparks generate firm-level efficiency gains by analyzing their impact on total factor productivity (TFP). We employ the semiparametric approach of Olley and Pakes (1996), as implemented by Yasar et al. (2008), which addresses the well-known simultaneity between input choices and unobserved productivity shocks, as well as selection bias from endogenous exit. This method leverages firms' investment and exit decisions to identify consistent production function parameters. We estimate TFP separately for each 2-digit NACE sector to allow for heterogeneous production technologies across industries.[11] Table 8 reports the impact of technopark establishment on firm pro-

[11]Our TFP estimation uses gross sales as the output measure and includes long-term tangible fixed assets (capital), inventories (materials), and number of employees (labor) as inputs. All monetary values are deflated using Türkiye's Producer Price Index. The resulting TFP measures are winsorized at the 2nd and

ductivity. The coefficient of 0.0286 indicates that firms in treated districts experience a 2.9% increase in TFP relative to their counterparts in control districts. This magnitude is economically substantial—comparable to the productivity gains from exporting documented in the international trade literature—and suggests that technoparks generate genuine efficiency improvements rather than mere reallocation of resources.

Figure 8 traces the dynamic evolution of these productivity gains. The pre-treatment coefficients hover near zero and remain statistically insignificant, confirming parallel pre-trends between treated and control firms. Post-treatment, TFP rises gradually over the first three years before stabilizing. The apparent decline at t+3 reflects sample attrition rather than dissipating treatment effects, as the number of firms observed for the full post-treatment window decreases due to natural exit. This gradual materialization of productivity gains aligns with theories of technology diffusion and organizational learning, suggesting that firms require time to absorb knowledge spillovers and implement new production practices. The persistence of these TFP improvements distinguishes technoparks from policies that generate only temporary boosts to measured productivity through capacity utilization or demand shocks. Instead, our results point to lasting efficiency gains consistent with technology transfer and knowledge spillovers from innovation clusters.

5.5 Robustness

Before examining additional results on firm-level automation, employment effects, and spatial spillovers, we first present a series of robustness checks to validate our main findings. These address potential concerns related to sample selection, unobserved heterogeneity, and our identification strategy. We implement seven robustness strategies across all key outcomes: (i) using a stricter sample inclusion rule where firms must be observed for at least six years (instead of four); (ii) adding one-digit sector-by-year fixed effects to control for broad sectoral dynamics; (iii) replacing sub-region (NUTS-2) by year fixed effects with province (NUTS-3) by year fixed effects to capture variation in local input and output markets at a more granular level; (iv) using only "never treated" firms as the

98th percentiles.

control group to eliminate potential contamination from future treatment; (v) using the imputation-based DiD estimator proposed by Borusyak et al. (2024) instead of a conventional Two-Way Fixed Effects (TWFE) estimator, (vi) dropping sole proprietorship firms, (vii) exploiting an alternative proxy for treatment allocation through firm location; and (viii) simulatenously controlling for a district-level indicator of the rollout of organized industrial zones (OIZs). In terms of treatment allocation, the baseline model employs the official and standardized firm location information provided by administrative records. Despite its advantages of reliability and standardization, this particular data source only equips us with time-invariant characterization of firms' location in respective districts.[12] Moreover, for the main outcomes, we perform sensitivity analyses based on district coverage. To ensure that the matching process of districts in our empirical design does not entirely drive the findings, we repeat the estimations by excluding a matched pair of districts at a time and obtain iterative "leave-one-out" estimates of the treatment effects. In Figure A1 of the Appendix, we see that the estimates derived from sensitivity analyses are vastly in line with the baseline results.

Domestic Technology Upgrading. Appendix Table A3 confirms that our core finding—technopark openings increase firms' propensity to engage in high-tech domestic purchases—is robust across all specifications. The coefficients remain positive and statistically significant, with only small changes in magnitude.[13] Similarly, the Appendix Table A4 shows that the intensive margin effect on high-tech domestic purchases (measured by purchase amounts) also holds under main robustness checks. Comparable results are found for high-tech domestic sales at both the extensive and intensive margins (Appendix

[12] Although firm relocation is rare in our sample, we construct an indirect proxy for firm location using employment records from the Social Security Institution, to ensure that this limitation does not systematically bias our findings. Specifically, we first calculate the number of employees of each sample firm in every LAU-1 district over the sample period. We then identify, for each year, the district where each firm has the largest share of its workforce, and use this as the input for a revised treatment allocation with time-varying firm location. Finally, we re-estimate the main extensive-margin specifications—albeit on a smaller sample due to missing data—and show that, under this alternative definition of firm location, adoption of the technopark programme continues to improve technological sophistication and productivity

[13] The imputation-based DiD estimator by Borusyak et al. (2024) yields larger coefficients than traditional TWFE, a difference that likely arises because our treatment effects increase over time, causing TWFE's negative weighting to bias the estimates downward.

Tables A5 and A6).

Export Sophistication. Appendix Tables A7 and A8 document robust effects on the likelihood and amount of high-R&D exports, supporting the interpretation that technoparks stimulate technological upgrading. The results remain consistent across different robustness tests. Likewise, Appendix Tables A9 and A10 confirm impacts on high-tech exports, both in terms of firm participation and export value. Similar patterns emerge for high-skill exports in Appendix Tables A11 and A12: technopark presence increases both the propensity and value of skill-intensive exports, and several robustness strategies yield significant results, confirming the consistency of these findings.

Productivity Gains. Finally, Appendix Table A13 verifies that the estimated increase in total factor productivity (TFP) among firms in technopark districts remains statistically significant across different robustness specifications. This strengthens the conclusion that technoparks generate meaningful and robust efficiency gains, not driven by compositional shifts or model specification choices. Taken together, across all outcome dimensions—domestic upgrading, export sophistication, and productivity—technopark openings consistently improve firm performance in the medium term.

5.6 Firm-level Automation

As a next step, we analyze the effect of technopark openings on another key facet of firms' technological advancement: firm automation. Following the existing literature, we measure the degree of automation by examining firms' import patterns of specific capital goods. Specifically, we use granular foreign trade data for Türkiye and apply the taxonomy developed by Acemoglu and Restrepo (2022) to identify whether sample firms import capital goods associated with the automation of business processes. We identify 6-digit HS codes corresponding to industrial robots, dedicated machinery, and other automated capital goods. [14] Based on this classification, we construct a binary variable (*Firm Automa-*

[14]The full list of HS codes includes: industrial robots (847950); dedicated machinery (847989); numerically controlled machines (845600–846699, 846820–846899, 851511–851519); automatic welding machines

tion) that takes the value of one if a firm initiates imports of automation-related capital goods, and zero otherwise.

The column (2) of Table 8 shows a positive and statistically significant effect of the opening of a technopark on subsequent automation by nearby firms in the same district. The positive coefficient on the likelihood of firms engaging in automation-related imports (0.0013) is economically meaningful, corresponding to an 8.18% increase relative to the control group mean (0.0159).

5.7 Employment Composition and Skill Upgrading

We next examine whether technopark establishment induces changes in firms' workforce composition toward more technology-intensive occupations. This analysis addresses a key mechanism through which innovation zones may generate productivity spillovers: by incentivizing firms to upgrade their human capital and adopt more skill-intensive production processes.

To measure the technological intensity of employment, we classify occupations following the European Centre for the Development of Vocational Training (CEDEFOP) taxonomy. We identify four categories of technology-intensive occupations at the 2-digit ISCO level: science and engineering professionals (ISCO 21), ICT professionals (ISCO 25), science and engineering associate professionals (ISCO 31), and ICT technicians (ISCO 35). These classifications capture workers directly engaged in R&D, technology implementation, and technical support functions.

We match this occupational taxonomy to firm-level employee registry data from Turkey's Social Security Institution (SGK), which provides annual snapshots of workforce composition for all registered firms. Due to data availability constraints, occupational information is only available from 2012 onward, restricting this analysis to the 2012–2023 period. Using these data, we then construct two measures of technology-intensive employment. First, we define a binary indicator, *High-Tech Employment Propensity*, equal to

(851521, 851531, 851580, 85190); weaving and knitting machines (844600–844699, 844700–844799); other textile-dedicated machinery (844400–844590); automatic conveyors (842831–842839); automatic regulating instruments (903200–903299); and 3-D printers (847780). In line with Domini et al. (2022), we extend the original list from Acemoglu and Restrepo (2022) to include 3-D printers.

one if a firm employs at least one worker in the technology-intensive occupations defined above. Second, we calculate *High-Tech Employment Share* as the percentage of a firm's workforce in these occupations.

Table 9 presents the results. Column (1) shows that technopark establishment increases firms' propensity to employ high-tech workers by 0.84 percentage points—a 3.1% increase relative to the control mean of 27.2%. Column (2) reveals a more pronounced intensive margin effect: the share of high-tech employment rises by 0.29 percentage points (3.8% relative to the control mean). These effects persist across multiple robustness checks, including the exclusion of single-employee firms, alternative sample selection criteria, and sector-adjusted thresholds for defining high-tech employment intensity.

These employment composition effects reinforce our main findings. The shift toward skilled workers coincides with increased automation and high-tech trade, indicating that technoparks drive broad organizational change beyond simple technology adoption.

5.8 Firm Network

In the next phase, we investigate how the establishment of technoparks influences the centrality of a firm in its value chain. In other words, we attempt to understand whether the technological improvement caused by technoparks has also helped firms expanding their business network. To test this empirically, we first revisit the micro-data on firm-to-firm trade. Then, we synthesize the indicators to monitor how many unique companies a sample firm interacts with in a given period in terms of customer and supplier relationships. In this context, we also identify the locational distribution of firm network in case any potential impact on network is driven by other firms located in the same district of a specific sample firm, or by other firms from different districts. In the last step, we modify our baseline specifications to run the firm-level regressions predicting the shifts in firm network.

In column (1) of Table 10, we find that the adoption of the technopark program leads to a significant and positive impact on *Firm Relationships*, which measures the total number of customers and suppliers. While the findings in column (2) displays an inconclusive

effect on customer count, results in column (3) suggests an improvement in terms of customers within the same districts of sample firms. On the other hand, columns (5) to (7) show that the establishment of technoparks is associated with an expansion of upstream part of supply chain, regardless of the locational restrictions. Overall, our findings are in line with the notion that technological and productivity-related improvements in firm profile co-exist with an expansion of firm network.

5.9 Heterogeneous Impact by Firm Size

We now examine heterogeneity in technopark impacts by firm size to assess whether effects are driven primarily by smaller or larger firms. Although some aspects of technopark policy (e.g., access to university laboratories and other research infrastructure, venture capital connections, and patent assistance services) mainly target large firms with substantial R&D operations, others (such as VAT exemptions) are also relevant to smaller firms. The agglomeration of technology-intensive firms within technopark districts may also create opportunities for smaller firms to benefit from knowledge spillovers and potential supply chain linkages with larger, more sophisticated enterprises. Moreover, the proximity to skilled graduates from partner universities offers access to talent that might otherwise be prohibitively expensive for small firms to recruit independently.

In Table 11, we define large firms as those with 10 or more employees, corresponding to the 75th percentile of the employment distribution in the year prior to technopark establishment. The reported coefficients reflect the interaction between the Technopark indicator and a dummy for larger firms, capturing whether these firms respond differently to the introduction of a technopark in their district. Panel A shows that while larger firms experience more pronounced increases in technology-intensive trade activities, the baseline effects remain positive and significant for the full sample, indicating that smaller firms also benefit, albeit to a lesser degree.

Panel B reveals that productivity gains, wage increases, and automation adoption are particularly concentrated among larger firms, consistent with their greater ability to exploit the knowledge spillovers and infrastructure access that technoparks provide. This

size-dependent response aligns with organizational learning theories and suggests that while technopark policies generate broad-based benefits, the magnitude of technological upgrading also depends on firm-level capabilities and resources. In other words, these findings highlight the importance of absorptive capacity: larger companies are better able to harness knowledge spillovers and resource links facilitated by technoparks, consistent with evidence that larger firms generally achieve higher productivity through better technology adoption and organizational capabilities (Idson and Oi, 1999).

6 Spatial Spillovers and Aggregate Dynamics

There are several reasons to expect that establishing a technopark in one district may generate spillovers in neighboring districts that do not host technoparks. Spillovers may go in either direction. On the one hand, technoparks may draw firms and employees away from nearby areas, producing negative spillovers. On the other hand, the presence of an innovation hub could make it profitable for firms to locate in adjacent districts, leading to positive spillovers.

To test whether technopark openings merely reallocate firms or stimulate additional entry, we employ the difference-in-differences estimator developed by Gardner (2022) and adapted by Butts (2021). The procedure has two stages. We first identify every district that shares a border with a treated district—defined as a district that hosts a technopark in year t. Figure 11 maps treated districts (dark blue) and their contiguous neighbors (light blue) across Türkiye. Let $S_{it} = 1$ for districts that are never treated themselves but border a treated district in year t. Using only districts that never host a technopark and do not border one ("far-away" districts), we estimate:

$$Y_{irt} = \delta_i + \delta_{rt} + u_{it} \tag{3}$$

where Y_{it} is the outcome of interest (e.g., the number of new firms), δ_i are district fixed effects and δ_{rt} NUTS-2-by-year fixed effects. The residuals $\tilde{Y}_{it}$ provide counterfactual outcomes.

In a second step, we then estimate:

$$\tilde{Y}_{it} = \tau D_{it} + \gamma(1 - D_{it})S_{it} + \varepsilon_{it} \tag{4}$$

where $D_{it} = 1$ if a technopark opens in district i in year t and 0 otherwise. The coefficient $\hat{\tau}$ captures the total local impact of a technopark, while $\hat{\gamma}$ measures the average spillover in neighboring districts.

Figure 12 presents the results for six district-level outcomes: total firm entry and five categories of high-technology firm entry defined in Section 5.1. Two findings stand out. First, neighboring districts experience a small rise in additional firm formation relative to never-treated, far-away districts (a spillover effect that is statistically significant over a three-year treatment horizon). Second, the direct treatment effect $\hat{\tau}$ is positive and significant—as in our baseline estimation approach—but pre-trend diagnostics reveal anticipatory dynamics, underscoring the advantage of our baseline matched DiD estimator.

7 Conclusions

This paper evaluates the impact of place-based innovation policy on firm-level outcomes by studying the staggered rollout of technology development zones (technoparks) in Türkiye. Using rich administrative microdata covering all non-financial firms from 2009 to 2023 and a matched difference-in-differences design, we find that firms located in technopark districts exhibit increased engagement in technology-intensive trade and experience significant gains in total factor productivity over the medium term. These effects suggest that targeted regional innovation policies can enhance firms' technological capabilities and efficiency.

Our findings contribute to ongoing policy debates about the effectiveness of place-based interventions. While much of the earlier literature has focused on labor market outcomes or investment responses to spatial subsidies, our results show that innovation-focused zones can also generate meaningful productivity spillovers. The observed increases in high-tech trade and firm-level productivity are consistent with mechanisms

such as knowledge diffusion, input sharing, and localised learning—core elements of agglomeration economies. The evidence, therefore, supports the view that place-based policies, when designed to foster firm-level technological upgrading, may have deeper and more persistent effects than some traditional industrial support measures.

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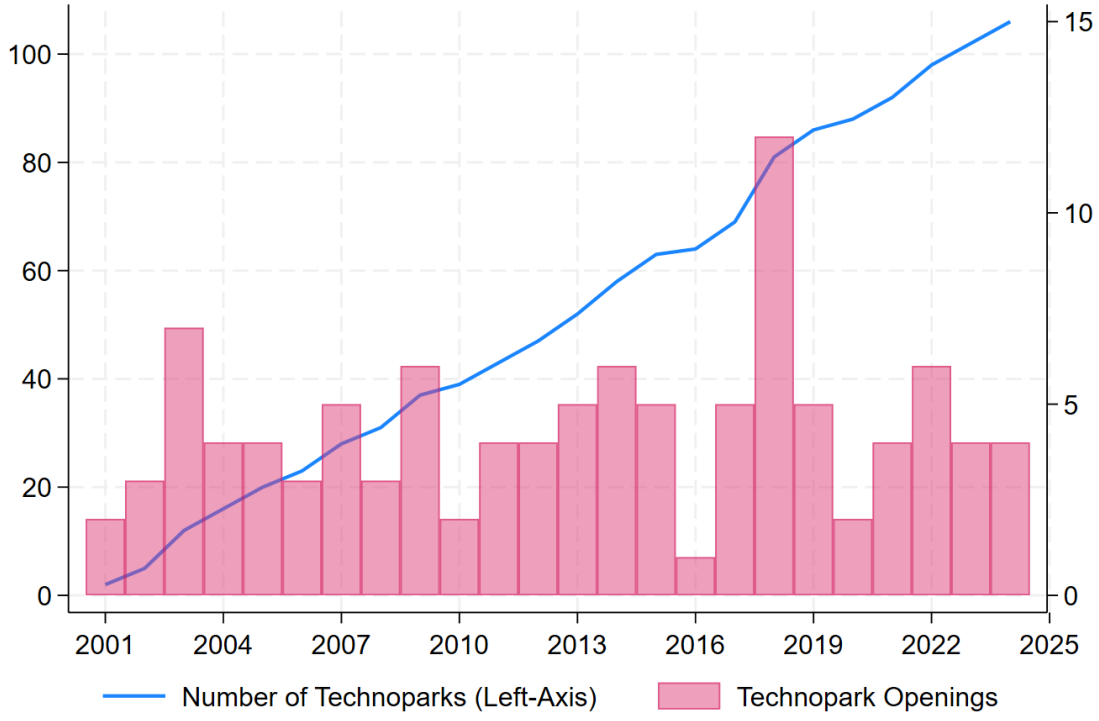
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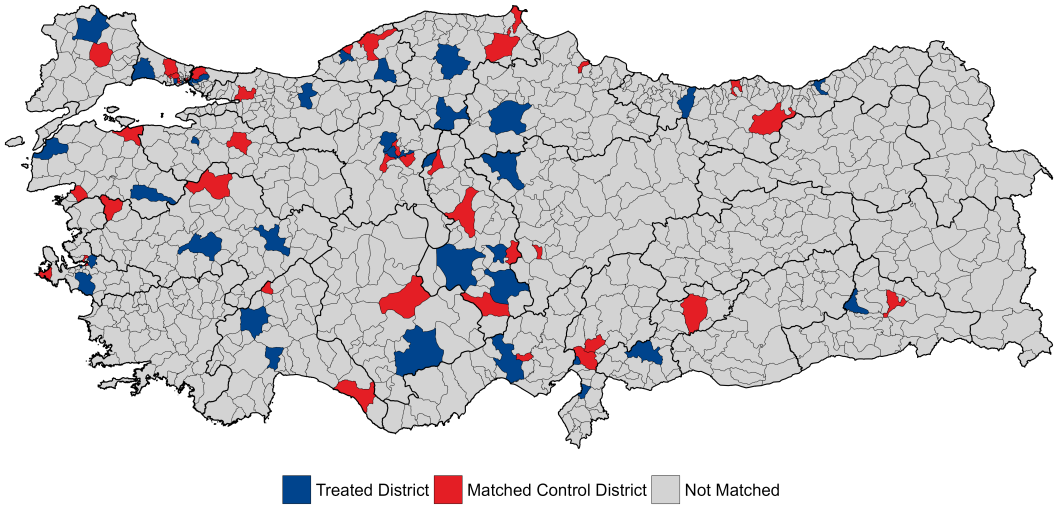
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Figure 1: Technopark Openings in Türkiye



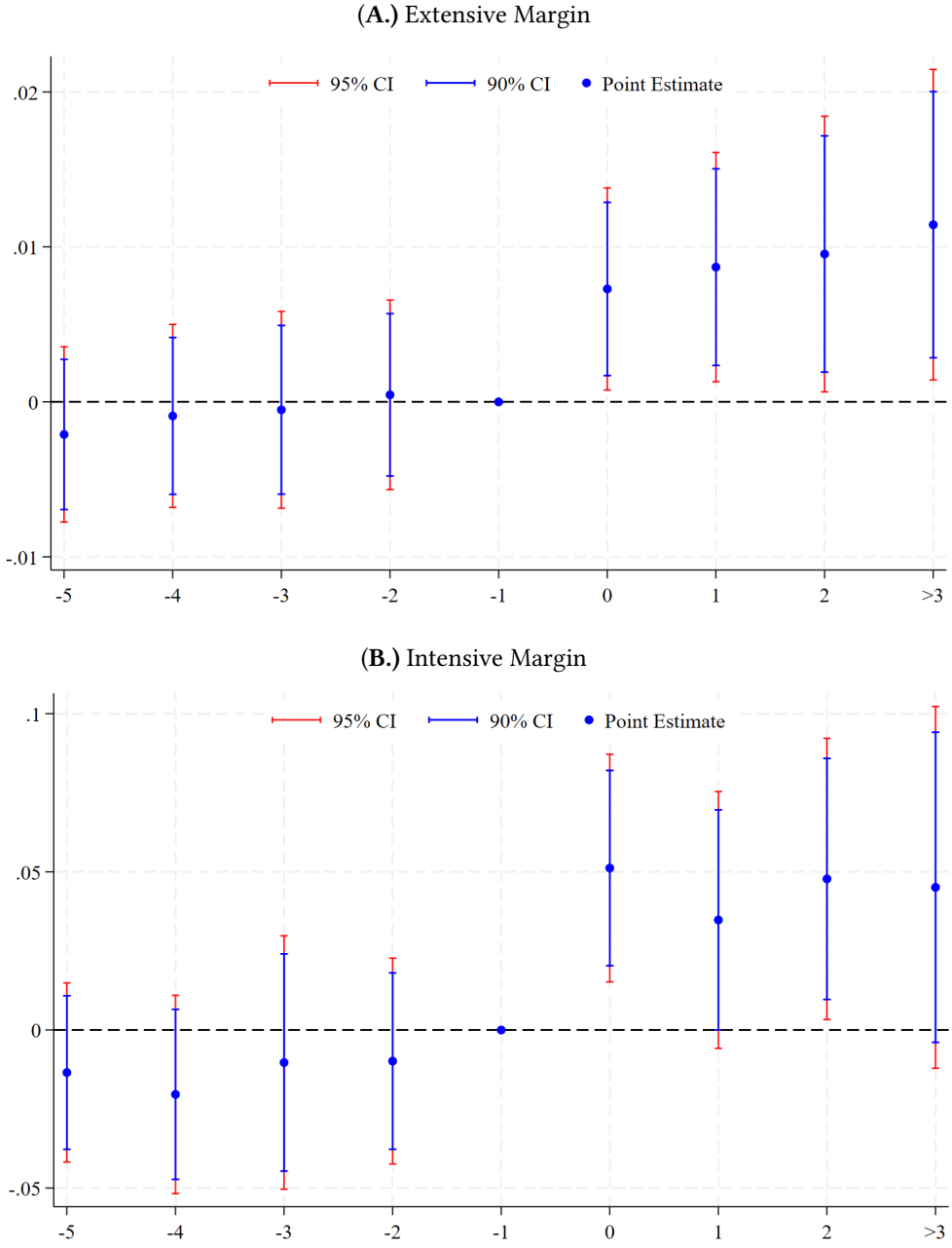
Notes: This chart shows the timeline of technopark openings in Türkiye. The blue solid line indicates the cumulative number of openings (left axis), while the red vertical bars represent the number of new openings each year (right axis). The data is sourced from the Ministry of Industry and Technology.

Figure 2: Geographic Distribution of Matched Treatment and Control Districts



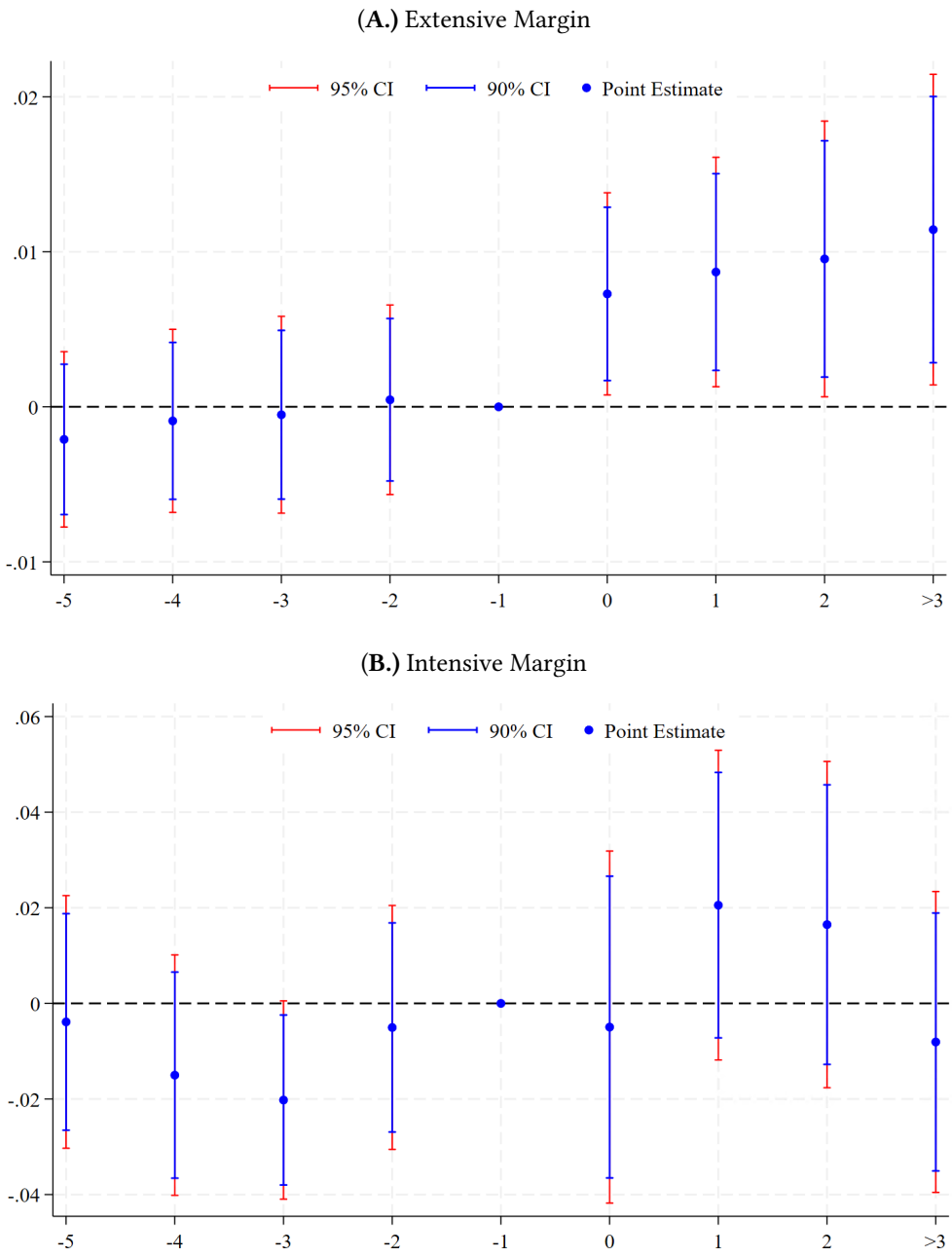
Notes: This map displays the spatial distribution of the 40 treated and control districts selected through the matching procedure described in Section 4.1. Thin borders represent districts, thick borders depict NUTS-2 sub-national regions. We implement one-to-one nearest neighbor propensity score matching based on 2009 values of key demographic, economic, and political characteristics, as detailed in Table 1. Exact matching is enforced within NUTS-2 sub-national regions, ensuring that each treated district–defined by a post-2009 technopark establishment–is paired with a control district that did not receive a technopark but shares the same sub-regional context.

Figure 3: Event Study — Technopark Impact on High-Tech Domestic Purchases



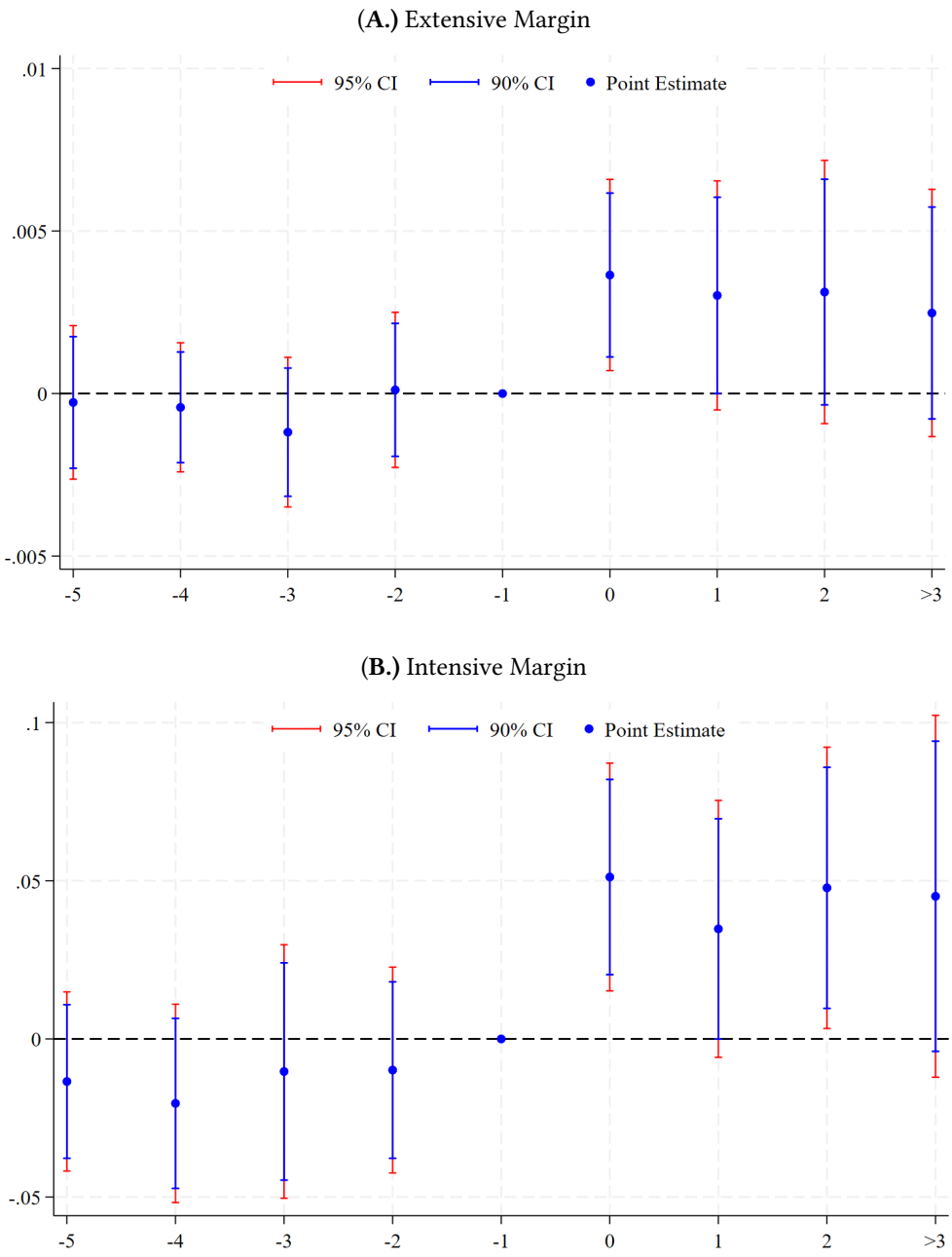
Notes: This figure shows event study estimates of the impact of technopark establishment on high-tech domestic purchases. The extensive margin (Panel A) captures the probability of firms engaging in high-tech domestic purchases, while the intensive margin (Panel B) captures the log amount of such purchases. Estimates are based on Equation 2. Vertical bars represent 90% and 95% confidence intervals, with standard errors clustered at the district-year level.

Figure 4: Event Study — Technopark Impact on High-Tech Domestic Sales



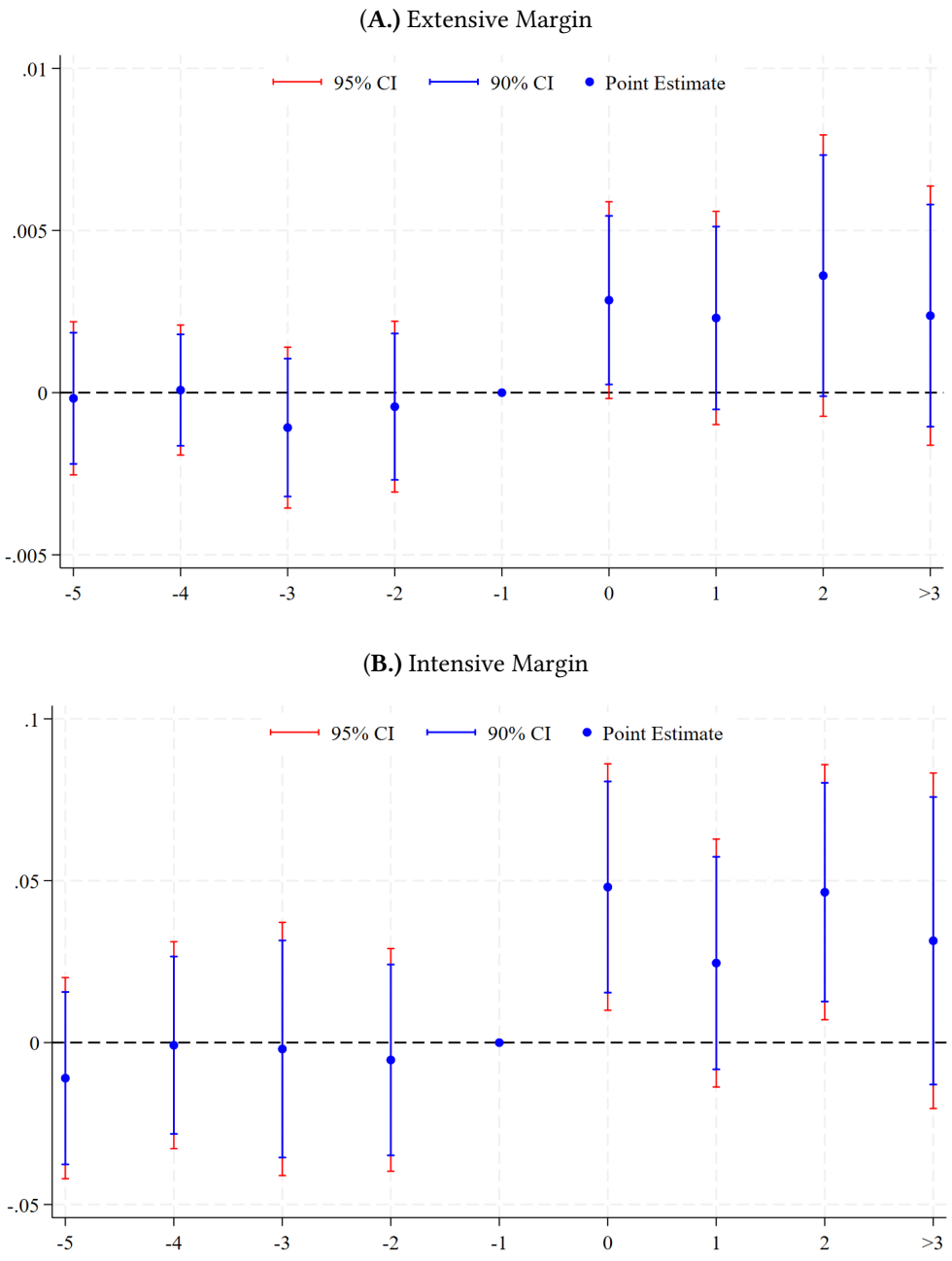
Notes: This figure shows event study estimates of the impact of technopark establishment on high-tech domestic sales. The extensive margin (Panel A) captures the probability of firms engaging in high-tech domestic sales, while the intensive margin (Panel B) captures the log amount of such sales. Estimates are based on Equation 2. Vertical bars represent 90% and 95% confidence intervals, with standard errors clustered at the district-year level.

Figure 5: Event Study — Technopark Impact on High-R&D Exports



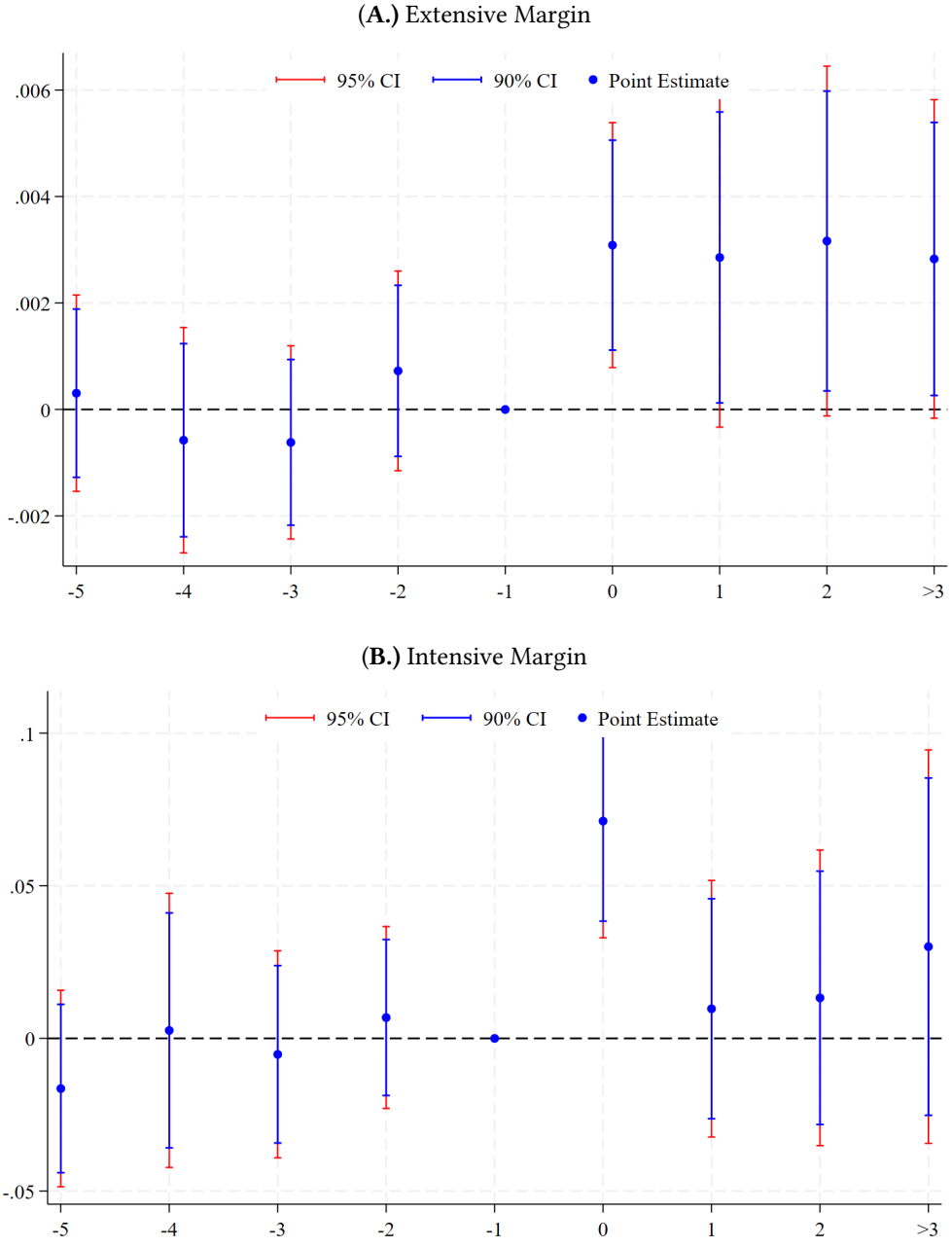
Notes: This figure presents event study estimates of the effect of technoparks on high-R&D exports. Panel A reports changes in the likelihood of a firm engaging in high-R&D exports, while Panel B reports the effect on the (log) value of such exports among exporting firms. Estimates are based on Equation 2. Vertical bars represent 90% and 95% confidence intervals, with standard errors clustered at the district-year level.

Figure 6: Event Study — Technopark Impact on High-Tech Exports



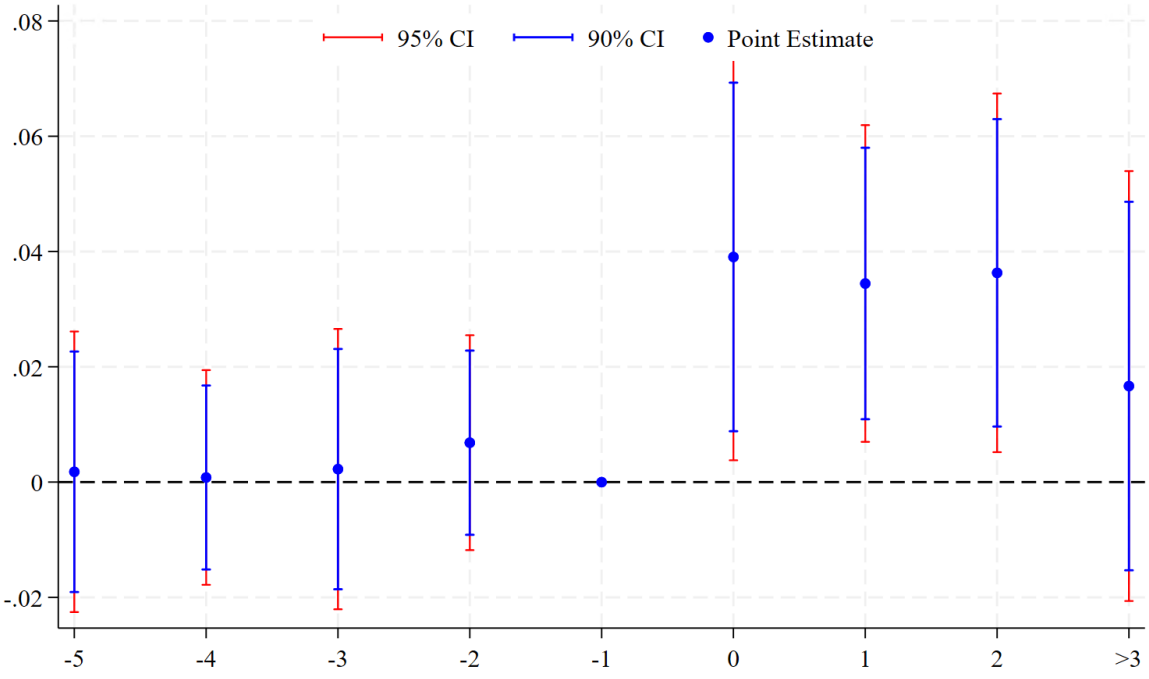
Notes: This figure shows event study estimates of the impact of technopark establishment on high-tech exports. The extensive margin (Panel A) captures the probability of firms engaging in high-tech exports, while the intensive margin (Panel B) captures the log amount of such exports. Estimates are based on Equation 2. Vertical bars represent 90% and 95% confidence intervals, with standard errors clustered at the district-year level.

Figure 7: Event Study — Technopark Impact on High-Skill Exports



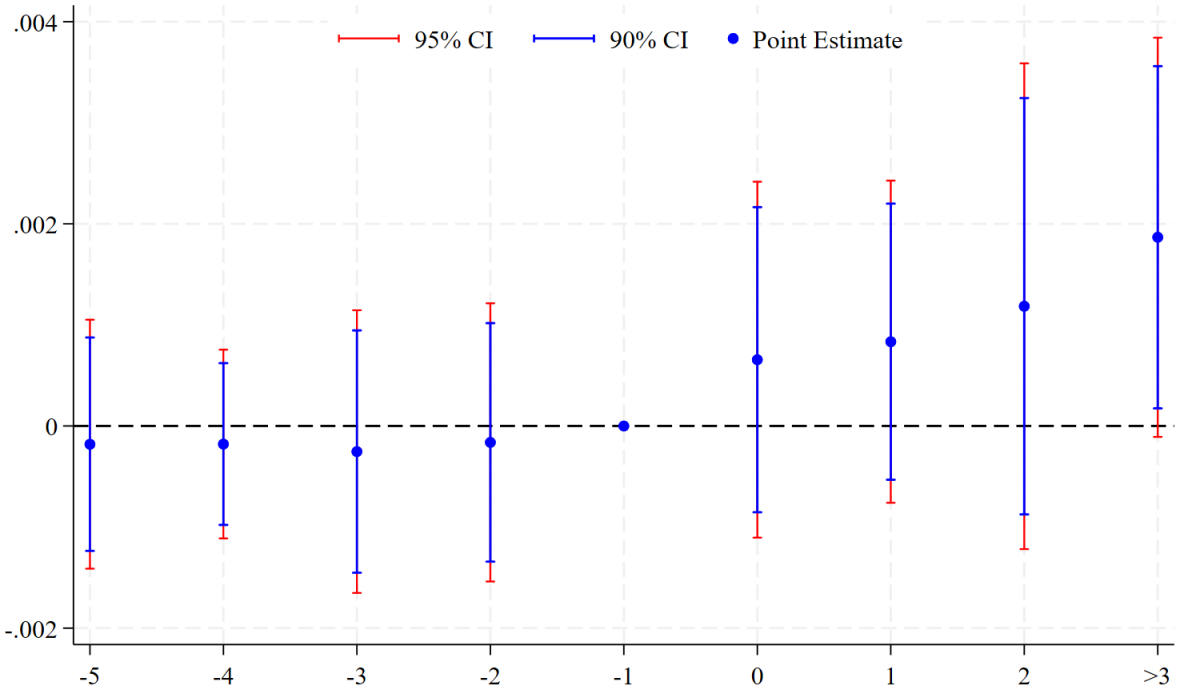
Notes: This figure presents event study estimates of the effect of technopark establishment on high-skill exports. The extensive margin (Panel A) shows changes in the likelihood of firms engaging in high-skill exports, while the intensive margin (Panel B) reports the log value of these exports. Estimates are based on Equation 2. Vertical bars represent 90% and 95% confidence intervals, with standard errors clustered at the district-year level.

Figure 8: Event Study — Technopark Impact on Total Factor Productivity



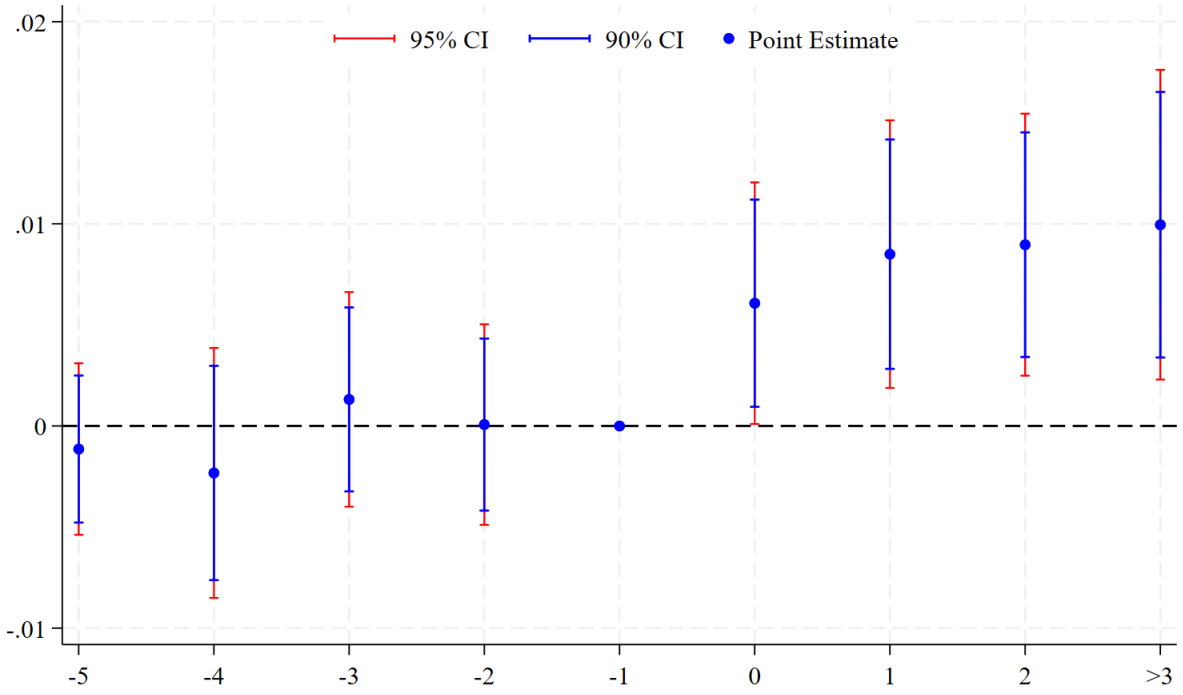
Notes: This figure shows event study estimates of the impact of technopark establishment on firm-level total factor productivity (TFP). Estimates are based on Equation 2. Vertical bars represent 90% and 95% confidence intervalss, with standard errors clustered at the district-year level.

Figure 9: Event Study — Technopark Impact on Firm Automation



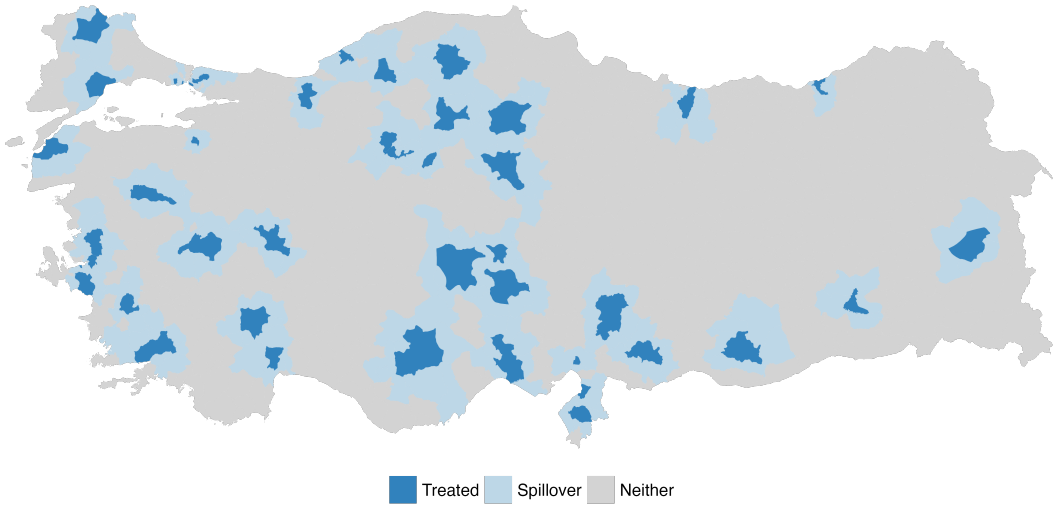
Notes: This figure shows event study estimates of the impact of technopark establishment on firm-level automation measure. Estimates are based on Equation 2. Vertical bars represent 90% and 95% confidence intervals, with standard errors clustered at the district-year level.

Figure 10: Event Study — Technopark Impact on High-Tech Employment



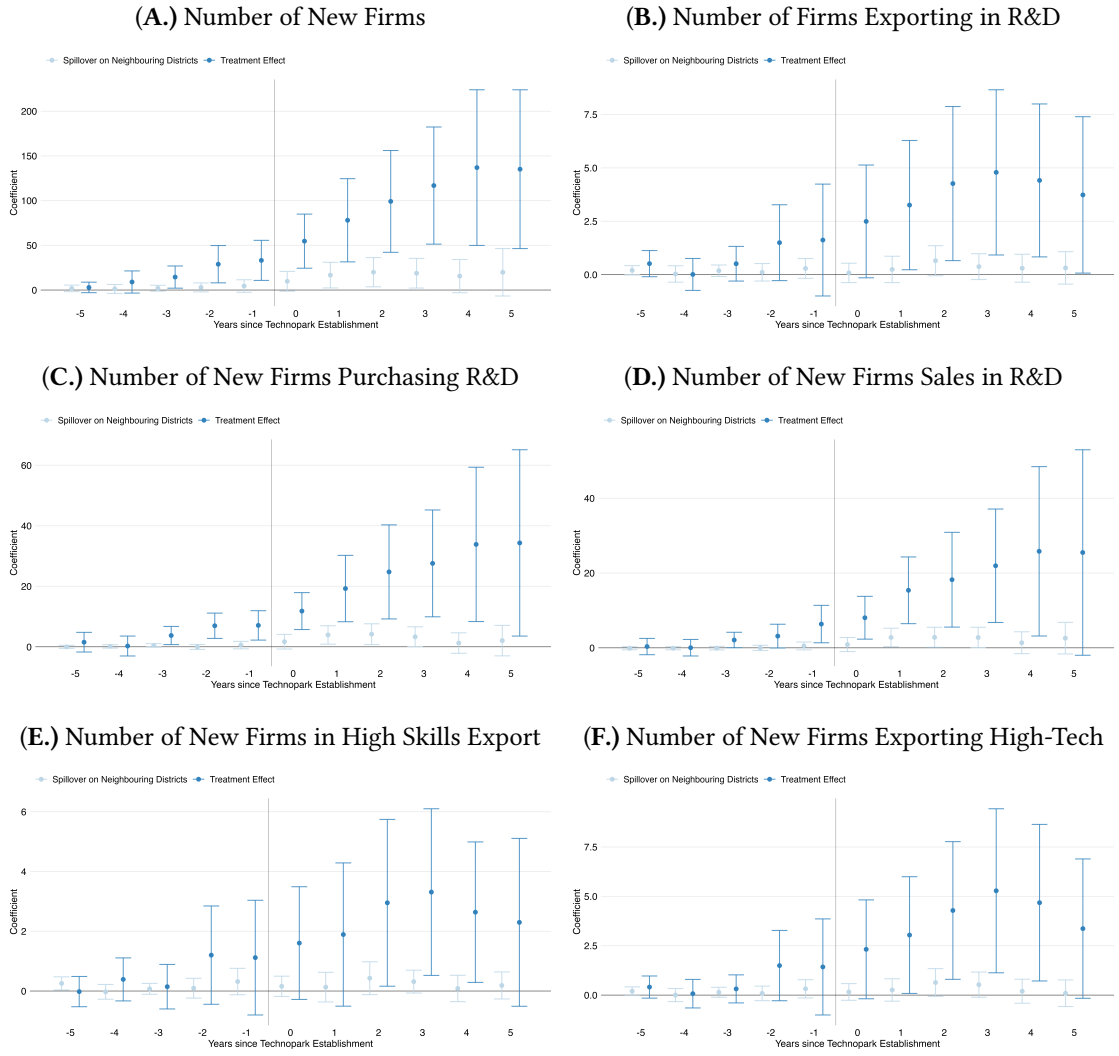
Notes: This figure shows event study estimates of the impact of technopark establishment on high-tech employment propensity. Estimates are based on Equation 2. Vertical bars represent 90% and 95% confidence intervals, with standard errors clustered at the district-year level.

Figure 11: Spillovers to Contiguous Districts



Notes: This map displays the spatial distribution of the 40 treated districts (in dark blue) and exposed spillover districts used in the procedure described in Section 6 (in light blue). Districts in gray are "far-away" districts used as the counterfactual control group.

Figure 12: Spillover Effects



Notes: This graph shows spillover effects using a method outlined in Section 6. Darker blue coefficient plots report treatment effects using contiguous districts as control group. Lighter blue coefficients report spillover effects on the contiguous districts. Spillover effects are studied in a period of [-5,5] years since the introduction of a technopark.

Table 1: Balance of District-Level Characteristics Before and After Matching

Variable	**Treated Mean** (Raw, $n = 40$)	**Control Mean** (Raw, $n = 880$)	**Diff.**	**Matched Treated** ($n = 40$)	**Matched Control** ($n = 40$)	**Diff.**	**Norm. diff.**
Pop. Density	5.92	3.97	1.95***	5.92	6.02	-0.10	-0.03
Pop. Growth (%)	2.64	-0.86	3.50***	2.64	2.71	-0.07	-0.01
Household Size	3.82	4.09	-0.27	3.82	3.76	0.06	0.06
Gender Ratio	100.99	100.62	0.37	100.99	101.10	-0.11	-0.02
Young Pop. Ratio	25.27	24.27	1.00	25.27	24.71	0.56	0.10
Firm Intensity	6.90	3.86	3.04***	6.90	6.50	0.40	0.20
Sales Intensity	21.63	17.47	4.16***	21.63	21.09	0.54	0.22
Empl. Intensity	9.57	5.75	3.82***	9.57	9.19	0.38	0.19
Bank Presence	2.96	1.25	1.71***	2.96	2.64	0.32	0.18
Political Pref. (%)	40.45	38.33	2.12	40.45	38.43	2.02	0.14
Nighttime Lights	8.75	7.31	1.44***	8.75	8.47	0.28	0.25

Notes: This table reports the balance of district-level covariates before and after propensity score matching. Columns (1)–(3) show means for the unmatched treated ($n = 40$) and control ($n = 880$) districts, along with their differences. Columns (4)–(6) report the same statistics for the matched treated and control districts ($n = 40$ each). Column (7) presents normalized differences, calculated as the mean difference divided by the square root of the pooled variances. *Population Density* is the log of population per square kilometer. *Population Growth* is the annual growth rate of the district's population (in %). *Household Size* denotes the average number of individuals per household. *Gender Ratio* is the male-to-female population ratio. *Young Population Ratio* is the share of individuals aged 0–24 in the total population (in %). *Firm Intensity*, *Sales Intensity*, and *Employment Intensity* refer to the log number of active firms, total sales, and employees, respectively, based on administrative firm-level records. *Bank Presence* is the log number of active bank branches. *Political Preferences* is the vote share gap between the ruling party and its closest competitor in the 2009 local elections (in %). *Nighttime Lights* captures the log intensity of satellite-detected nighttime light emissions. All variables refer to 2009 values. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2: Firm-Level Balance in Treated vs. Control Districts (Post-Matching)

Variable	**Technopark**
Firm Size	-0.00185
	(0.00639)
Equity	-0.00017
	(0.00031)
Sales	0.00000
	(0.00003)
Current Assets	-0.00019
	(0.00032)
Current Liabilities	-0.00015
	(0.00036)
Employees	0.00000
	(0.00001)
Observations	125,109
Method	OLS
Sector Fixed Effects	✓
Adj. R^2	0.013

Notes: This table reports OLS estimates of the association between firm characteristics and the likelihood of being located in a district with a technopark, using the 2009 sample of firms from matched treated and control districts. The dependent variable, *Technopark*, equals one if the firm is located in a district that eventually hosts a technopark, and zero otherwise. Control variables include: *Firm Size* (log of total assets), *Equity* (total equity over total assets), *Sales* (total sales over total assets), *Current Assets* (short-term assets over total assets), *Current Liabilities* (short-term liabilities over total assets), and *Employees* (number of employees). The reported number of observations is lower than the total number of sample firms due to the unbalanced nature of our panel. All variables except *Employees* are winsorized at the 2nd and 98th percentiles to reduce the influence of outliers. The model includes 2-digit NACE sector fixed effects. Standard errors clustered at the district level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: District-Level Results for Firm Entry and Exit

	(1) Entry	(2) Entry High-Tech Dom. Purchases	(3) Entry High-Tech Dom. Sales	(4) Entry High R&D Exports	(5) Entry High-Tech Exports	(6) Entry High-Tech (Skilled Exports)	(7) Exit
Technopark	43.93***	9.99**	9.87**	0.89	1.09	0.89	15.04
	(14.24)	(4.53)	(3.99)	(0.85)	(0.86)	(0.59)	(10.49)
Observations	1,200	1,200	1,200	1,200	1,200	1,200	1,200
Control mean	249.92	44.35	30.53	8.94	8.45	6.76	81.07
District FE	✓	✓	✓	✓	✓	✓	✓
NUTS-2 × Year FE	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.924	0.847	0.834	0.869	0.863	0.881	0.798

Notes: This table provides district-level estimation results for the effect of Technoparks on total and high-technology firm entry, based on Equation (2). The sample covers 2009–2023 and includes 80 PSM-matched districts in Türkiye. Column (1) uses the number of newly established firms. Columns (2)–(6) restrict the sample to firms with non-zero values in the specified high-tech indicators at the time of establishment. Column (7) reports firm exits. *Technopark* is a binary indicator equal to 1 if a technopark has been established in the district. All regressions include district and NUTS-2-by-year fixed effects. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Results on Domestic Purchases and Sales

	(1) High-Tech Purchases (Propensity)	(2) Low-Tech Purchases (Propensity)	(3) High-Tech Purchases (Amount)	(4) Low-Tech Purchases (Amount)	(5) High-Tech Sales (Propensity)	(6) Low-Tech Sales (Propensity)	(7) High-Tech Sales (Amount)	(8) Low-Tech Sales (Amount)
Technopark	0.0097***	-0.0090**	0.035***	-0.015*	0.0104***	-0.0106***	0.013	-0.019**
	(0.0025)	(0.0040)	(0.012)	(0.009)	(0.0024)	(0.0029)	(0.011)	(0.009)
Observations	2,377,439	2,377,439	1,518,853	2,137,901	2,377,439	2,377,439	1,367,056	2,122,333
Control mean	0.2880	0.5878	376	1,249	0.2608	0.5929	446	1,651
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
NUTS-2 × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.521	0.387			0.562	0.419		
Pseudo R^2			0.807	0.617			0.832	0.669

Notes: This table provides the firm-level estimation results for the effect of Technoparks on high-tech and "only" low-tech domestic purchases and sales from 2009 to 2023, based on 80 PSM-matched districts in Türkiye. Monetary outcomes are CPI-deflated and winsorized. Propensity columns use binary indicators; amount columns use Poisson regressions. The coefficients in columns (3), (4), (7) and (8) are semi-elasticities and the control means are expressed in TRY1000. Standard errors clustered at the district-year level. ***, ** and * indicate 1%, 5%, and 10% significance levels.

Table 5: Results on High- and Low-R&D Exports

	(1) Export Propensity	(2) High-R&D Export Propensity	(3) "Only" Low-R&D Export Propensity	(4) Export Amount	(5) High-R&D Export Amount	(6) "Only" Low-R&D Export Amount
Technopark	0.0041**	0.0033***	0.0007	0.027*	0.053***	-0.003
	(0.0016)	(0.0010)	(0.0007)	(0.016)	(0.014)	(0.018)
Observations	2,377,439	2,377,439	2,377,439	601,478	421,800	360,884
Control mean	0.1272	0.0731	0.0541	186	27	33
Firm FE	✓	✓	✓	✓	✓	✓
NUTS-2 × Year FE	✓	✓	✓	✓	✓	✓
Adj. R^2	0.647	0.588	0.491			
Pseudo R^2				0.757	0.646	0.554

Notes: This table provides the firm-level estimation results for the effect of Technoparks on high-R&D and "only" low-R&D exports in line with Equation (1). The estimation covers the interval 2009–2023 and is based on the set of 80 PSM-matched districts of Türkiye. The coefficients in columns (4), (5) and (6) are semi-elasticities and the control means are expressed in USD1000. *Technopark* is a binary indicator equal to one if a technopark has been established in a district. Sample firms are required to have at least four years of observations during the overall sample period. All columns include firm and sub-region-by-year fixed effects. Standard errors clustered at the district-year level are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Results on High- and Low-Tech Exports

	(1) Export Propensity	(2) High-Tech Export Propensity	(3) "Only" Low-Tech Export Propensity	(4) Export Amount	(5) High-Tech Export Amount	(6) "Only" Low-Tech Export Amount
Technopark	0.0041**	0.0030***	0.0010	0.027*	0.041***	-0.002
	(0.0016)	(0.0011)	(0.0008)	(0.016)	(0.014)	(0.016)
Observations	2,377,439	2,377,439	2,377,439	601,478	410,682	371,264
Control mean	0.1272	0.0701	0.0571	186	25	37
Firm FE	✓	✓	✓	✓	✓	✓
NUTS-2 × Year FE	✓	✓	✓	✓	✓	✓
Adj. R^2	0.647	0.589	0.495			
Pseudo R^2				0.757	0.651	0.559

Notes: This table provides the firm-level estimation results for the effect of Technoparks on high-tech and "only" low-tech exports in line with Equation (1). The estimation covers the interval 2009–2023 and is based on the set of 80 PSM-matched districts of Türkiye. The coefficients in columns (4), (5) and (6) are semi-elasticities and the control means are expressed in USD1000. The treatment variable, *Technopark*, is a binary indicator equal to one if a technopark has been established in a district, and zero otherwise. Sample firms are required to have at least four years of observations during the overall sample period. All columns include firm and sub-region-by-year fixed effects. Standard errors clustered at district-by-year level are provided in the parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 7: Results on High- and Low-Skill Exports

	(1) Export Propensity	(2) High-Skill Export Propensity	(3) "Only" Low-Skill Export Propensity	(4) Export Amount	(5) High-Skill Export Amount	(6) "Only" Low-Skill Export Amount
Technopark	0.0041**	0.0029***	0.0011	0.027*	0.034**	0.003
	(0.0016)	(0.0009)	(0.0009)	(0.016)	(0.016)	(0.017)
Observations	2,377,439	2,377,439	2,377,439	601,478	368,901	467,433
Control mean	0.1272	0.0621	0.0651	186	6	35
Firm FE	✓	✓	✓	✓	✓	✓
NUTS-2 × Year FE	✓	✓	✓	✓	✓	✓
Adj. R^2	0.647	0.549	0.449			
Pseudo R^2				0.757	0.603	0.524

Notes: This table provides the firm-level estimation results for the effect of Technoparks on high-skill and "Only" low-skill exports in line with Equation (1). The estimation covers the interval 2009–2023 and is based on the set of 80 PSM-matched districts of Türkiye. The coefficients in columns (4), (5) and (6) are semi-elasticities and the control means are expressed in USD1000. The main treatment variable, *Technopark*, is a binary indicator equal to one if a technopark has been established in a district, and zero otherwise. Sample firms are required to have at least four years of observations during the overall sample period. All columns include firm and sub-region-by-year fixed effects. Standard errors clustered at district-by-year level are provided in the parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 8: Total Factor Productivity and Firm Automation

	(1) TFP	(2) Firm Automation
Technopark	0.0286***	0.0013**
	(0.0099)	(0.0005)
Observations	2,088,303	2,377,439
Control mean	5.4754	0.0159
Firm FE	✓	✓
NUTS-2 × Year FE	✓	✓
Adj. R^2	0.626	0.441

Notes: This table reports firm-level estimates of the effect of technopark establishment on total factor productivity (TFP) and firm automation propensity. The analysis covers the years 2009–2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. The treatment indicator equals one if a technopark has been established in the district by year t. The outcome variable in column (1) is the log-transformed TFP constructed using firm-level financial statements, while the outcome variable in column (2) is the binary indicator showing the likelihood of firm imports related to automation technologies. The regression includes firm and NUTS-2-by-year fixed effects. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Employment Composition

	(1) High-Tech Employment Propensity	(2) High-Tech Employment Share
Technopark	0.0084***	0.2865***
	(0.0021)	(0.0594)
Obs.	1,424,174	1,424,174
Control mean	0.2724	7.6039
Firm FE	✓	✓
NUTS-2 x Year FE	✓	✓
Adj. R^2	0.623	0.673

Notes: This table reports firm-level estimates of the effect of technopark establishment on high-tech employment. The analysis covers the years 2012–2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. The treatment indicator equals one if a technopark has been established in the district by year t. In column (1), the outcome variable is the binary indicator showing the likelihood of firms' engagement with high-tech employment, whereas in column (2), the outcome variable is the share of high-tech employment in total employment. The regression includes firm and NUTS-2-by-year fixed effects. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Firm Network

	(1) Firm Relationships	(2) Customer Count	(3) Within-Districts Customers	(4) Across-Districts Customer	(5) Supplier Count	(6) Within-Districts Suppliers	(7) Across-Districts Suppliers
Technopark	0.025**	0.016	0.017*	0.015	0.029***	0.032**	0.027***
	(0.011)	(0.010)	(0.010)	(0.009)	(0.011)	(0.014)	(0.010)
Observations	2,377,439	2,377,439	2,377,439	2,377,439	2,377,439	2,377,439	2,377,439
Control mean	2.695	1.979	0.922	1.751	2.091	0.915	1.897
Firm FE	✓	✓	✓	✓	✓	✓	✓
NUTS-2 × Year FE	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.773	0.773	0.710	0.869	0.752	0.723	0.754

Notes: This table provides firm-level estimation results for the effect of Technoparks on firm network. The sample covers 2009–2023 and includes 80 PSM-matched districts in Türkiye. Column (1) uses the total firm relationships count as the outcome variable. Columns (2)–(4) utilize the number of total customers, within-district customers and across-districts customers, while columns (5)–(7) employ similar measures for suppliers. The log(1+x) transformation is applied to all the variables representing firm relationships. *Technopark* is a binary indicator equal to 1 if a technopark has been established in the district. All regressions include firm and NUTS-2-by-year fixed effects. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

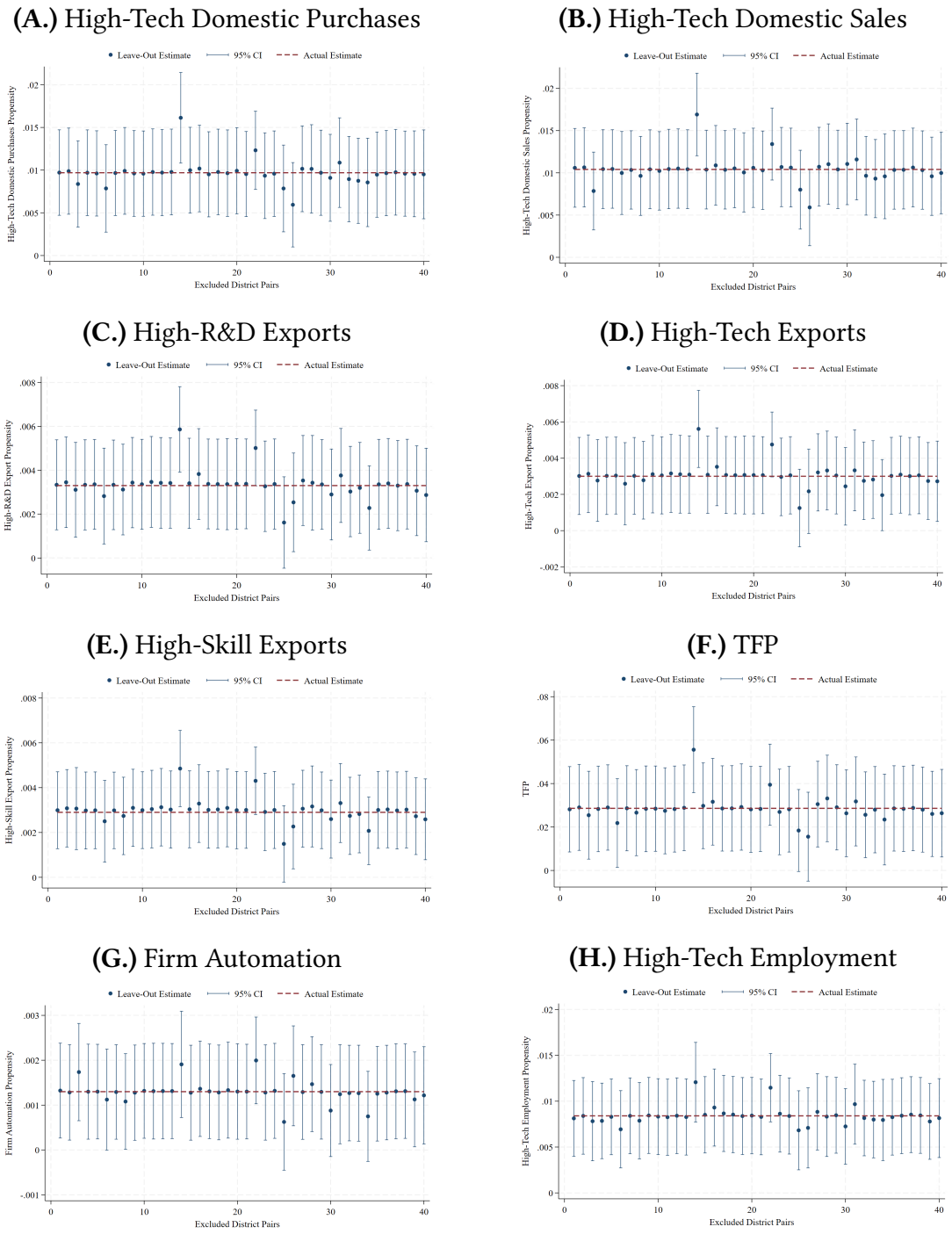
Table 11: Heterogeneous Effects of Technoparks by Firm Size

Panel A: Technology-Intensive Trade Outcomes	(1) High-Tech Domestic Purchases	(2) High-Tech Domestic Sales	(3) High R&D Exports	(4) High-Tech Exports	(5) High-Skill Exports
Technopark × Larger Firm	0.0209***	0.0228***	0.0057***	0.0059***	0.0049***
	(0.0025)	(0.0038)	(0.0011)	(0.0015)	(0.0013)
Firm Fixed Effects	✓	✓	✓	✓	✓
NUTS-2 × Year FE	✓	✓	✓	✓	✓
Panel B: Firm Performance Outcomes	(6) Employment	(7) Employee Pay	(8) TFP	(9) Firm Automation	
Technopark × Larger Firm	10.920***	44.477***	0.136***	0.0035***	
	(0.0925)	(2.4325)	(0.0028)	(0.0011)	
Firm Fixed Effects	✓	✓	✓	✓	
NUTS-2 × Year FE	✓	✓	✓	✓	

Notes: This table reports heterogeneous effects of technoparks on firm outcomes, estimated using an interaction term between the Technopark indicator and a dummy for larger firms (above the 75th percentile of the employment distribution, i.e., more than 10 employees). Panel A shows impacts on technology-intensive domestic and international trade indicators. Panel B presents effects on broader firm performance measures. All regressions include firm fixed effects and NUTS-2 region by year fixed effects. Standard errors, clustered at the district-year level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Figure A1: Sensitivity Analysis



Note: These charts display the results of sensitivity analysis. For all main outcomes, the estimations are repeated by excluding a pair of matched districts in an iterative way. The dots represent "leave-one-out" estimates, while vertical bars show 95% confidence intervals and dashed red lines stand for actual estimates.

Table A1: Sectoral Breakdown of Firms Located in Treated Districts

NACE	Sector	Firm Count
A	Agriculture, forestry and fishing	900
B	Mining and quarrying	745
C	Manufacturing	29,764
D	Electricity, gas, steam and air conditioning supply	636
E	Water supply; sewerage and waste management activities	425
F	Construction	18,672
G	Wholesale and retail trade	51,015
H	Transportation and storage	7,530
I	Accommodation and food service activities	6,121
J	Information and communication	4,079
L	Real estate activities	1,679
M	Professional, scientific and technical activities	10,525
N	Administrative and support service activities	5,181
P	Education	2,205
Q	Human health and social work activities	3,276
R	Arts, entertainment and recreation	785
S	Other service activities	1,634

Notes: This table presents the distribution of firms by main sector of activity in the treated districts, identified through the matching procedure described in Section 4.1. Column (1) lists NACE section codes based on the Eurostat classification; column (2) provides the corresponding sector names; and column (3) reports the number of firms in each sector. The sample includes firms located in treated districts, selected according to the criteria outlined in Section 4.2.

Table A2: District-Level Variables Used in Matching

Variable	Definition	Data Source
Population Density	Population per square kilometer based on census data	Turkish Statistical Institute (TSI)
Population Growth	Annual growth rate of census-based population (in %)	Turkish Statistical Institute (TSI)
Household Size	Average number of individuals per household	Turkish Statistical Institute (TSI)
Gender Ratio	Male-to-female population ratio (in %)	Turkish Statistical Institute (TSI)
Young Population Ratio	Share of population aged 0–24 in total population (in %)	Turkish Statistical Institute (TSI)
Firm Intensity	Total number of active firms in the district	Revenue Administration, CBRT
Sales Intensity	Total volume of firm sales	Revenue Administration, CBRT
Employment Intensity	Number of registered employees	Revenue Administration, CBRT
Bank Presence	Number of bank branches	Credit Registry, CBRT
Political Preferences	Vote share gap between ruling party and runner-up	Supreme Electoral Board
Nighttime Lights	Intensity of nighttime light emissions	IMF

Notes: This table describes the district-level variables used in the matching procedure to construct comparable treated and control groups, based on the geographic rollout of technopark establishments. It includes the variable definitions and associated data sources.

Table A3: Robustness Checks for High-Tech Domestic Purchases Propensity

	(1) 6 years obs.	(2) Sector-year FE	(3) Province-year FE	(4) Never treated controls	(5) Borusyak et al. DiD	(6) No sole proprietors	(7) Alt. firm location	(8) OIZ rollout
Technopark	0.0096***	0.0091***	0.0099***	0.0086***	0.0286***	0.0104***	0.0079***	0.0096***
	(0.0026)	(0.0024)	(0.0029)	(0.0027)	(0.0094)	(0.0025)	(0.0023)	(0.0025)
Observations	2,136,960	2,377,439	2,377,439	1,268,068	2,377,439	1,772,011	1,826,596	2,377,439
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
NUTS-2 x Year FE	✓	✓		✓	✓	✓	✓	✓
NUTS-3 x Year FE			✓					
Sector x Year FE		✓						
Adj. R^2	0.524	0.521	0.521	0.517		0.525	0.529	0.521

Notes: This table reports the robustness checks for the effect of technopark establishment on High-Tech Domestic Purchases propensity. These robustness checks are based on the baseline specification given in column (1) of Table 4. The analysis covers the years 2009-2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. In column (1), instead of requiring firms to have at least four years of observations throughout the whole sample, we require sample firms to have at least six years of observations. In column (2), we augment the specification with one-digit sector-by-year fixed effects. In column (3), we replace the sub-region-by-year fixed effects with more granular province (NUTS-3)-by-year fixed effects. In column (4), we restrict the sample by using only never treated firms as the control group. Column (5) implements the imputation-based DiD estimator proposed by Borusyak et al. (2024), instead of a conventional DiD estimator. Column (6) excludes sole proprietorship firms. Column (7) uses an alternative indicator of firm location generated from employment records. Column (8) controls for an additional variable representing the district-level rollout of organized industrial zones (OIZs). In all columns, the treatment indicator equals one if a technopark has been established in the district by year t. The estimation is performed with OLS. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A4: Robustness Checks for High-Tech Domestic Purchases Amount

	(1) 6 years obs.	(2) Sector-year FE	(3) Province-year FE	(4) Never treated controls
Technopark	0.034***	0.029***	0.028**	0.023**
	(0.012)	(0.011)	(0.014)	(0.009)
Observations	1,425,112	1,518,853	1,518,853	829,084
Firm FE	✓	✓	✓	✓
NUTS-2 x Year FE	✓	✓		✓
NUTS-3 x Year FE			✓	
Sector x Year FE		✓		
Pseudo R^2	0.808	0.808	0.807	0.147

Notes: This table reports the robustness checks for the effect of technopark establishment on High-Tech Domestic Purchases amount. These robustness checks are based on the baseline specification given in column (3) of Table 4. The analysis covers the years 2009-2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. In column (1), instead of requiring firms to have at least four years of observations throughout the whole sample, we require sample firms to have at least six years of observations. In column (2), we augment the specification with one-digit sector-by-year fixed effects. In column (3), we replace the sub-region-by-year fixed effects with more granular province (NUTS-3)-by-year fixed effects. In column (4), we restrict the sample by using only never treated firms as the control group. In all columns, the treatment indicator equals one if a technopark has been established in the district by year t. The estimation is performed with Poisson regression. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A5: Robustness Checks for High-Tech Domestic Sales Propensity

	(1) 6 years obs.	(2) Sector-year FE	(3) Province-year FE	(4) Never treated controls	(5) Borusyak et al. DiD	(6) No sole proprietors	(7) Alt. firm location	(8) OIZ rollout
Technopark	0.0099***	0.0104***	0.0106***	0.0112***	0.0281***	0.0101***	0.0091***	0.0104***
	(0.0024)	(0.0023)	(0.0028)	(0.0024)	(0.0089)	(0.0023)	(0.0021)	(0.0024)
Observations	2,136,960	2,377,439	2,377,439	1,268,068	2,377,439	1,772,011	1,826,596	2,377,439
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
NUTS-2 x Year FE	✓	✓		✓	✓	✓	✓	✓
NUTS-3 x Year FE			✓					
Sector x Year FE		✓						
Adj. R^2	0.564	0.562	0.562	0.554		0.578	0.577	0.562

Notes: This table reports the robustness checks for the effect of technopark establishment on High-Tech Domestic Sales propensity. These robustness checks are based on the baseline specification given in column (5) of Table 4. The analysis covers the years 2009-2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. In column (1), instead of requiring firms to have at least four years of observations throughout the whole sample, we require sample firms to have at least six years of observations. In column (2), we augment the specification with one-digit sector-by-year fixed effects. In column (3), we replace the sub-region-by-year fixed effects with more granular province (NUTS-3)-by-year fixed effects. In column (4), we restrict the sample by using only never treated firms as the control group. Column (5) implements the imputation-based DiD estimator proposed by Borusyak et al. (2024), instead of a conventional DiD estimator. Column (6) excludes sole proprietorship firms. Column (7) uses an alternative indicator of firm location generated from employment records. Column (8) controls for an additional variable representing the district-level rollout of organized industrial zones (OIZs). In all columns, the treatment indicator equals one if a technopark has been established in the district by year t. The estimation is performed with OLS. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A6: Robustness Checks for High-Tech Domestic Sales Amount

	(1) 6 years obs.	(2) Sector-year FE	(3) Province-year FE	(4) Never treated controls
Technopark	0.010	0.006	0.005	0.021*
	(0.010)	(0.009)	(0.011)	(0.011)
Observations	1,288,894	1,367,056	1,367,019	752,475
Firm FE	✓	✓	✓	✓
NUTS-2 x Year FE	✓	✓		✓
NUTS-3 x Year FE			✓	
Sector x Year FE		✓		
Pseudo R^2	0.833	0.832	0.832	0.826

Notes: This table reports the robustness checks for the effect of technopark establishment on High-Tech Domestic Sales amount. These robustness checks are based on the baseline specification given in column (1) of Table 4. The analysis covers the years 2009-2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. In column (1), instead of requiring firms to have at least four years of observations throughout the whole sample, we require sample firms to have at least six years of observations. In column (2), we augment the specification with one-digit sector-by-year fixed effects. In column (3), we replace the sub-region-by-year fixed effects with more granular province (NUTS-3)-by-year fixed effects. In column (4), we restrict the sample by using only never treated firms as the control group. In all columns, the treatment indicator equals one if a technopark has been established in the district by year t. The estimation is performed with Poisson regression. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A7: Robustness Checks for High-R&D Exports Propensity

	(1) 6 years obs.	(2) Sector-year FE	(3) Province-year FE	(4) Never treated controls	(5) Borusyak et al. DiD	(6) No sole proprietors	(7) Alt. firm location	(8) OIZ rollout
Technopark	0.0032***	0.0027***	0.0047***	0.0037***	0.0079**	0.0035***	0.0041***	0.0033***
	(0.0011)	(0.0009)	(0.0013)	(0.0011)	(0.0033)	(0.0012)	(0.0011)	(0.0010)
Observations	2,136,960	2,377,439	2,377,439	1,268,068	2,377,439	1,772,011	1,826,596	2,377,439
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
NUTS-2 x Year FE	✓	✓		✓	✓	✓	✓	✓
NUTS-3 x Year FE			✓					
Sector x Year FE		✓						
Adj. R^2	0.592	0.589	0.588	0.578		0.603	0.604	0.588

Notes: This table reports the robustness checks for the effect of technopark establishment on High-R&D Export propensity. These robustness checks are based on the baseline specification given in column (2) of Table 5. The analysis covers the years 2009-2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. In column (1), instead of requiring firms to have at least four years of observations throughout the whole sample, we require sample firms to have at least six years of observations. In column (2), we augment the specification with one-digit sector-by-year fixed effects. In column (3), we replace the sub-region-by-year fixed effects with more granular province (NUTS-3)-by-year fixed effects. In column (4), we restrict the sample by using only never treated firms as the control group. Column (5) implements the imputation-based DiD estimator proposed by Borusyak et al. (2024), instead of a conventional DiD estimator. Column (6) excludes sole proprietorship firms. Column (7) uses an alternative indicator of firm location generated from employment records. Column (8) controls for an additional variable representing the district-level rollout of organized industrial zones (OIZs). In all columns, the treatment indicator equals one if a technopark has been established in the district by year t. The estimation is performed with OLS. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A8: Robustness Checks for High-R&D Exports Amount

	(1) 6 years obs.	(2) Sector-year FE	(3) Province-year FE	(4) Never treated controls
Technopark	0.051***	0.050***	0.054***	0.060***
	(0.015)	(0.013)	(0.015)	(0.016)
Observations	399,305	421,800	421,738	228,546
Firm FE	✓	✓	✓	✓
NUTS-2 x Year FE	✓	✓		✓
NUTS-3 x Year FE			✓	
Sector x Year FE		✓		
Pseudo R^2	0.647	0.646	0.646	0.638

Notes: This table reports the robustness checks for the effect of technopark establishment on High-R&D Export amount. These robustness checks are based on the baseline specification given in column (5) of Table 5. The analysis covers the years 2009-2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. In column (1), instead of requiring firms to have at least four years of observations throughout the whole sample, we require sample firms to have at least six years of observations. In column (2), we augment the specification with one-digit sector-by-year fixed effects. In column (3), we replace the sub-region-by-year fixed effects with more granular province (NUTS-3)-by-year fixed effects. In column (4), we restrict the sample by using only never treated firms as the control group. In all columns, the treatment indicator equals one if a technopark has been established in the district by year t. The estimation is performed with Poisson regression. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A9: Robustness Checks for High-Tech Exports Propensity

	(1) 6 years obs.	(2) Sector-year FE	(3) Province-year FE	(4) Never treated controls	(5) Borusyak et al. DiD	(6) No sole proprietors	(7) Alt. firm location	(8) OIZ rollout
Technopark	0.0030***	0.0023**	0.0042***	0.0035***	0.0082**	0.0033**	0.0040***	0.0030***
	(0.0011)	(0.0009)	(0.0013)	(0.0012)	(0.0034)	(0.0013)	(0.0011)	(0.0011)
Observations	2,136,960	2,377,439	2,377,439	1,268,068	2,377,439	1,772,011	1,826,596	2,377,439
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
NUTS-2 x Year FE	✓	✓		✓	✓	✓	✓	✓
NUTS-3 x Year FE			✓					
Sector x Year FE		✓						
Adj. R^2	0.593	0.589	0.589	0.579		0.604	0.604	0.589

Notes: This table reports the robustness checks for the effect of technopark establishment on High-Tech Export propensity. These robustness checks are based on the baseline specification given in column (2) of Table 6. The analysis covers the years 2009-2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. In column (1), instead of requiring firms to have at least four years of observations throughout the whole sample, we require sample firms to have at least six years of observations. In column (2), we augment the specification with one-digit sector-by-year fixed effects. In column (3), we replace the sub-region-by-year fixed effects with more granular province (NUTS-3)-by-year fixed effects. In column (4), we restrict the sample by using only never treated firms as the control group. Column (5) implements the imputation-based DiD estimator proposed by Borusyak et al. (2024), instead of a conventional DiD estimator. Column (6) excludes sole proprietorship firms. Column (7) uses an alternative indicator of firm location generated from employment records. Column (8) controls for an additional variable representing the district-level rollout of organized industrial zones (OIZs). In all columns, the treatment indicator equals one if a technopark has been established in the district by year t. The estimation is performed with OLS. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A10: Robustness Checks for High-Tech Exports Amount

	(1) 6 years obs.	(2) Sector-year FE	(3) Province-year FE	(4) Never treated controls
Technopark	0.039***	0.037***	0.042***	0.048***
	(0.014)	(0.013)	(0.015)	(0.016)
Observations	389,041	410,682	410,602	223,612
Firm FE	✓	✓	✓	✓
NUTS-2 x Year FE	✓	✓		✓
NUTS-3 x Year FE			✓	
Sector x Year FE		✓		
Pseudo R^2	0.652	0.651	0.651	0.643

Notes: This table reports the robustness checks for the effect of technopark establishment on High-Tech Export amount. These robustness checks are based on the baseline specification given in column (5) of Table 6. The analysis covers the years 2009-2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. In column (1), instead of requiring firms to have at least four years of observations throughout the whole sample, we require sample firms to have at least six years of observations. In column (2), we augment the specification with one-digit sector-by-year fixed effects. In column (3), we replace the sub-region-by-year fixed effects with more granular province (NUTS-3)-by-year fixed effects. In column (4), we restrict the sample by using only never treated firms as the control group. In all columns, the treatment indicator equals one if a technopark has been established in the district by year t. The estimation is performed with Poisson regression. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A11: Robustness Checks for High-Skill Exports Propensity

	(1) 6 years obs.	(2) Sector-year FE	(3) Province-year FE	(4) Never treated controls	(5) Borusyak et al. DiD	(6) No sole proprietors	(7) Alt. firm location	(8) OIZ rollout
Technopark	0.0029***	0.0026***	0.0039***	0.0026***	0.0065***	0.0031***	0.0036***	0.0030***
	(0.0009)	(0.0008)	(0.0010)	(0.0009)	(0.0024)	(0.0010)	(0.0009)	(0.0009)
Observations	2,136,960	2,377,439	2,377,439	1,268,068	2,377,439	1,772,011	1,826,596	2,377,439
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
NUTS-2 x Year FE	✓	✓		✓	✓	✓	✓	✓
NUTS-3 x Year FE			✓					
Sector x Year FE		✓						
Adj. R^2	0.553	0.549	0.549	0.533		0.565	0.566	0.549

Notes: This table reports the robustness checks for the effect of technopark establishment on High-Skill Export propensity. These robustness checks are based on the baseline specification given in column (2) of Table 7. The analysis covers the years 2009-2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. In column (1), instead of requiring firms to have at least four years of observations throughout the whole sample, we require sample firms to have at least six years of observations. In column (2), we augment the specification with one-digit sector-by-year fixed effects. In column (3), we replace the sub-region-by-year fixed effects with more granular province (NUTS-3)-by-year fixed effects. In column (4), we restrict the sample by using only never treated firms as the control group. Column (5) implements the imputation-based DiD estimator proposed by Borusyak et al. (2024), instead of a conventional DiD estimator. Column (6) excludes sole proprietorship firms. Column (7) uses an alternative indicator of firm location generated from employment records. Column (8) controls for an additional variable representing the district-level rollout of organized industrial zones (OIZs). In all columns, the treatment indicator equals one if a technopark has been established in the district by year t. The estimation is performed with OLS. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A12: Robustness Checks for High-Skill Exports Amount

	(1) High-Skill Export Amount	(2) High-Skill Export Amount	(3) High-Skill Export Amount	(4) High-Skill Export Amount
Technopark	0.032**	0.032**	0.036**	0.048***
	(0.016)	(0.015)	(0.016)	(0.016)
Observations	349,058	368,901	368,845	191,404
Firm FE	✓	✓	✓	✓
(NUTS-2 x Year) FE	✓	✓		✓
NUTS-3 x Year FE			✓	
Sector x Year FE		✓		
Pseudo R^2	0.605	0.604	0.604	0.595

Notes: This table reports the robustness checks for the effect of technopark establishment on High-Skill Export amount. These robustness checks are based on the baseline specification given in column (5) of Table 7. The analysis covers the years 2009-2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. In column (1), instead of requiring firms to have at least four years of observations throughout the whole sample, we require sample firms to have at least six years of observations. In column (2), we augment the specification with one-digit sector-by-year fixed effects. In column (3), we replace the sub-region-by-year fixed effects with more granular province (NUTS-3)-by-year fixed effects. In column (4), we restrict the sample by using only never treated firms as the control group. In all columns, the treatment indicator equals one if a technopark has been established in the district by year t. The estimation is performed with Poisson regression. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A13: Robustness Checks for TFP

	(1) 6 years obs.	(2) Sector-year FE	(3) Province-year FE	(4) Never treated controls	(5) Borusyak et al. DiD	(6) No sole proprietors	(7) Alt. firm location	(8) OIZ rollout
Technopark	0.0260***	0.0232***	0.0309***	0.0214**	0.1062***	0.0286***	0.0229***	0.0284***
	(0.0099)	(0.0084)	(0.0119)	(0.0107)	(0.0323)	(0.0086)	(0.0067)	(0.0100)
Observations	1,911,488	2,088,303	2,088,303	1,120,223	2,077,877	1,629,252	1,671,238	2,088,303
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
NUTS-2 x Year FE	✓	✓		✓	✓	✓	✓	✓
NUTS-3 x Year FE			✓					
Sector x Year FE		✓						
Adj. R^2	0.630	0.629	0.627	0.620		0.685	0.685	0.441

Notes: This table reports the robustness checks for the effect of technopark establishment on firm-level TFP. These robustness checks are based on the baseline specification given in column (1) of Table 8. The analysis covers the years 2009-2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. In column (1), instead of requiring firms to have at least four years of observations throughout the whole sample, we require sample firms to have at least six years of observations. In column (2), we augment the specification with one-digit sector-by-year fixed effects. In column (3), we replace the sub-region-by-year fixed effects with more granular province (NUTS-3)-by-year fixed effects. In column (4), we restrict the sample by using only never treated firms as the control group. Column (5) implements the imputation-based DiD estimator proposed by Borusyak et al. (2024), instead of a conventional DiD estimator. Column (6) excludes sole proprietorship firms. Column (7) uses an alternative indicator of firm location generated from employment records. Column (8) controls for an additional variable representing the district-level rollout of organized industrial zones (OIZs). In all columns, the treatment indicator equals one if a technopark has been established in the district by year t. The estimation is performed with OLS. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A14: Robustness Checks for Firm Automation

	(1) 6 years obs.	(2) Sector-year FE	(3) Province-year FE	(4) Never treated controls	(5) Borusyak et al. DiD	(6) No sole proprietors	(7) Alt. firm location	(8) OIZ rollout
Technopark	0.0013**	0.0007	0.0015**	0.0009	0.0023**	0.0016**	0.0007	0.0013**
	(0.0005)	(0.0004)	(0.0006)	(0.0007)	(0.0009)	(0.0007)	(0.0006)	(0.0005)
Observations	2,136,960	2,377,439	2,377,439	1,268,068	2,377,439	1,772,011	1,826,596	2,377,439
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
NUTS-2 x Year FE	✓	✓		✓	✓	✓	✓	✓
NUTS-3 x Year FE			✓					
Sector x Year FE		✓						
Adj. R^2	0.447	0.441	0.441	0.439		0.446	0.445	0.441

Notes: This table reports the robustness checks for the effect of technopark establishment on firm automation propensity. These robustness checks are based on the baseline specification given in column (2) of Table 8. The analysis covers the years 2009-2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. In column (1), instead of requiring firms to have at least four years of observations throughout the whole sample, we require sample firms to have at least six years of observations. In column (2), we augment the specification with one-digit sector-by-year fixed effects. In column (3), we replace the sub-region-by-year fixed effects with more granular province (NUTS-3)-by-year fixed effects. In column (4), we restrict the sample by using only never treated firms as the control group. Column (5) implements the imputation-based DiD estimator proposed by Borusyak et al. (2024), instead of a conventional DiD estimator. Column (6) excludes sole proprietorship firms. Column (7) uses an alternative indicator of firm location generated from employment records. Column (8) controls for an additional variable representing the district-level rollout of organized industrial zones (OIZs). In all columns, the treatment indicator equals one if a technopark has been established in the district by year t. The estimation is performed with OLS. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A15: Robustness Checks for High-Tech Employment Propensity

	(1) 6 years obs.	(2) Sector-year FE	(3) Province-year FE	(4) Never treated controls	(5) Borusyak et al. DiD	(6) No sole proprietors	(7) Alt. firm location	(8) OIZ rollout
Technopark	0.0084***	0.0062***	0.0085***	0.0064***	0.2222***	0.0078***	-0.0007	0.0083***
	(0.0022)	(0.0017)	(0.0024)	(0.0021)	(0.0006)	(0.0021)	(0.0021)	(0.0021)
Observations	1,252,497	1,424,174	1,424,174	760,055	1,405,714	1,228,979	1,418,486	1,424,174
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
NUTS-2 x Year FE	✓	✓		✓	✓	✓	✓	✓
NUTS-3 x Year FE			✓					
Sector x Year FE		✓						
Adj. R^2	0.627	0.624	0.623	0.621		0.634	0.623	0.623

Notes: This table reports the robustness checks for the effect of technopark establishment on high-tech employment propensity. These robustness checks are based on the baseline specification given in column (1) of Table 9. The analysis covers the years 2009-2023 and is restricted to firms located in 80 PSM-matched districts in Türkiye. In column (1), instead of requiring firms to have at least four years of observations throughout the whole sample, we require sample firms to have at least six years of observations. In column (2), we augment the specification with one-digit sector-by-year fixed effects. In column (3), we replace the sub-region-by-year fixed effects with more granular province (NUTS-3)-by-year fixed effects. In column (4), we restrict the sample by using only never treated firms as the control group. Column (5) implements the imputation-based DiD estimator proposed by Borusyak et al. (2024), instead of a conventional DiD estimator. Column (6) excludes sole proprietorship firms. Column (7) uses an alternative indicator of firm location generated from employment records. Column (8) controls for an additional variable representing the district-level rollout of organized industrial zones (OIZs). In all columns, the treatment indicator equals one if a technopark has been established in the district by year t. The estimation is performed with OLS. Standard errors are clustered at the district-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.