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ESTONIAN FIRMS' GREEN TRANSITION AND ITS EFFECTS ON FIRM PERFORMANCE

Master's Thesis

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I have written this Master's Thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

Abstract

As decarbonization pressures intensify, firms are increasingly required to adjust their production strategies in response to the green transition. Understanding whether such adjustment improves firm productivity, and how its effects propagate through production networks, has become increasingly important. This thesis develops a framework in which green transition affects firm performance through technology upgrading and learning, while also generating temporary adjustment frictions along buyer-supplier linkages. Using Estonian administrative data for 2015-2023, this thesis measures firm-level green transition through imports of environmental goods and estimates its effects using the Callaway and Sant'Anna (2021) difference-in-differences estimator together with network-based exposure measures. The results show that green imports raise firm productivity, with the gains strengthening over time. By contrast, upstream green transition reduces downstream productivity in the short run, while this negative spillover attenuates as firms adjust. Changes in labor costs and capital intensity account for a limited share of the overall effect. The findings indicate that green transition is a broader process of technological and organizational adjustment, with gains emerging over time and adjustment costs extending to connected firms. This underscores the need for both researchers and policymakers to move beyond firm-level analysis and consider the broader network of companies involved in the green transition.

Keywords: green transition; firm productivity; value chain spillovers; green imports; dynamic effects.

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1. Introduction

Increasingly stringent environmental constraints are forcing firms to adjust their strategies in response to the green transition. In practice, this involves a series of consequential operational decisions, including whether to invest in cleaner technologies, when to replace energy-intensive equipment, and how to meet tighter environmental standards without sacrificing productive efficiency. Understanding the productivity consequences of these decisions is important. It not only helps assess whether the green transition yields net benefits for firms, but also shapes how policymakers balance environmental goals with economic competitiveness.

A substantial body of empirical research has examined the relationship between firms' green transition and performance, while the productivity consequences of green transition remain debated (Ghisetti & Rennings, 2014; Zhang & Kong, 2022; Cobbinah et al., 2026). The literature remains limited in three respects. In terms of measurement, most studies rely on survey indicators, patent data, or composite indices, which often suffer from limited coverage and may not reflect actual adoption behavior (Demirel et al., 2025; Yuan et al., 2021). In terms of transmission mechanisms, although the literature on supply chain shock propagation is well established (Acemoglu et al., 2012), it has rarely been applied to examine how firms' green transition affects connected firms through value chain linkages. In terms of causal identification, standard OLS or fixed effects specifications are less well suited to capturing the dynamic adjustment process associated with green transition (Corrocher & Ozman, 2020; Aastvedt et al., 2021).

To fill these gaps, this study uses Estonian administrative data covering the period 2015 to 2023. Estonia provides a useful setting for this analysis for two reasons. First, as a small open economy with limited domestic capacity to produce green capital goods, Estonia relies heavily on imports for the adoption of green technologies. This makes customs transaction data especially informative for identifying firms' green transition, which we measure using the OECD Combined List of Environmental Goods. Second, although Estonia's production network is relatively sparse, it is highly concentrated around a small number of hub firms (Criscuolo et al., 2024). This structure provides a useful setting for tracing how green shocks propagate through value chain linkages. Thus, we combine customs data with VAT records on inter-firm transactions and business registry data. Methodologically, we use the Callaway and Sant’Anna (2021) difference-in-differences estimator to account for staggered treatment timing and estimate dynamic treatment effects. We then incorporate firm-level network centrality to examine how these effects spread through the production network.

Our main findings can be summarized as follows: (i) green imports have a positive causal effect on productivity, and this effect appears immediately after treatment and grows over time, consistent with learning-by-doing and technology accumulation mechanisms; (ii) spillovers along the value chain are asymmetric. Upstream suppliers’ green transition reduces downstream firms’ productivity in the short run, but the magnitude of this negative spillover declines over subsequent lags, suggesting gradual adjustment within production networks. By contrast, downstream firms’ green transition has no significant effect on upstream firms. This asymmetry is related to the broader production-network literature and to FDI spillover studies showing that firm-to-firm linkages can transmit shocks and technologies across connected firms (Acemoglu et al., 2016; Alfaro-Ureña et al., 2022; Masso & Vahter, 2023); (iii) green imports improve productivity partly through changes in labor costs and capital intensity, although these channels explain only a limited share of the overall effect. This indicates that direct technology transfer and learning play a more important role; (iv) the productivity effects are heterogeneous across firms. The gains are concentrated in manufacturing and services, especially in higher-technology manufacturing and less knowledge-intensive services, and are more significant among small and mature firms.

This study contributes to the literature in three respects. First, at the measurement level, we show that product-level import data can serve as a comprehensive and objective measure of firm-level green transition adoption. Second, at the mechanism level, we analyze how green transition generates negative short-run productivity externalities through production networks and trace how these upstream shocks decline over time, thereby extending the literature on green innovation spillovers. Third, at the methodological level, we apply the CSDID estimator using a preferred first-adoption treatment definition, while also comparing spike-based and CIS-based alternative treatment specifications.

The remainder of this thesis is organized as follows. Section 2 presents theoretical background. Section 3 reviews the relevant literature and develops the hypotheses. Section 4 describes the data and empirical strategy. Section 5 reports the empirical results, including the baseline regressions, dynamic effects, and network spillover analysis. Section 6 discusses the findings and concludes.

2. Theoretical Background

2.1. Green imports and productivity gains

When firms import intermediate products and capital equipment, they gain access to technologies embedded in these goods that may not be available domestically (Blalock & Veloso, 2007). Green products, such as energy-efficient machinery, pollution abatement equipment, and clean production technologies, are no exception. Their distinctive feature lies in their ability to enhance both production efficiency and environmental performance. This section develops the theoretical rationale for why green imports are expected to enhance firm productivity, drawing on three mechanisms.

First, green imports serve as a direct channel for technology transfer. The technologies embedded in imported capital goods and intermediate inputs can be incorporated directly into the production process (Savvides & Zachariadis, 2005), enabling firms to upgrade their production methods without bearing the full cost of research and development. This mechanism is particularly relevant for small open economies such as Estonia, where domestic technological capabilities in green industries remain limited and firms rely heavily on imported technology to close the gap with the technological frontier (Burinskas et al., 2021).

Second, the process of integrating imported green products generates learning-by-doing effects. Green technologies often embody knowledge and standards that differ from those underlying a firm's existing production system, and cannot simply be deployed without adaptation. Their effective adoption typically requires complementary activities, including worker training, process reorganization, adjustments to existing production routines, and the development of organizational learning capabilities (Bhatia, 2021). Through these complementary adjustments, firms accumulate experience that can generate efficiency gains beyond the direct contribution of the imported inputs themselves (Foster & Rosenzweig, 1995). Importantly, learning effects are cumulative and self-reinforcing: the more experience a firm accumulates in applying green technologies, the more efficiently it learns thereafter, and the more pronounced the resulting productivity improvements become.

Third, green imports intensify competitive pressure in the domestic market. The adoption of imported green products confers a technological advantage on adopting firms while simultaneously raising the prevailing technological threshold and environmental standards within the industry (Zhang et al., 2022). Firms that fail to keep pace face disadvantages in terms of cost, product quality, or regulatory compliance, and risk losing market share. This competitive pressure compels firms to streamline their production processes and eliminate inefficiencies, thereby contributing to aggregate productivity growth (Olper et al., 2017).

2.2. Value chain transmission and adjustment frictions

In modern economies, firms are interconnected through value chain networks. As Acemoglu et al. (2012) show, when production networks are asymmetric and contain highly connected firms or sectors, firm- or sector-specific shocks may not average out in the aggregate but can propagate through input-output linkages. When upstream firms undergo green transitions, they alter the characteristics and usage requirements of the intermediate inputs they supply. While such changes may improve input quality over the longer term, in the short run, they are more likely to impose adjustment frictions on downstream production processes.

On one hand, input adjustment frictions arise from changes in the physical attributes and technical specifications of intermediate inputs brought about by the green transition, including alterations in material composition and design parameters (Schillebeeckx et al., 2022). Downstream firms that have optimized their production processes around existing input specifications must recalibrate equipment, retrain workers, and modify production workflows to accommodate the new inputs (Hashemi-Petroodi et al., 2021). In the short term, these frictions reduce operational efficiency and depress measured productivity.

On the other hand, search and matching costs further amplify the frictions associated with this adjustment process. When upstream inputs change, downstream firms may need to identify, evaluate, and integrate new suppliers or substitute inputs. Establishing new supply relationships typically entails transaction costs, quality verification procedures, and contract negotiations, all of which consume managerial resources and introduce uncertainty (Wu et al., 2019). During the transitional period, supply instability and fluctuations in input quality further impair firm performance.

It is important to note that the propagation of shocks along the value chain is asymmetric in direction. Due to input specificity and the limited short-run substitutability of intermediate products, downstream firms find it difficult to offset upstream supply shocks quickly (Kashiwagi et al., 2021). By contrast, upstream firms can buffer demand-side shocks by adjusting output volumes or redirecting sales to alternative buyers. Consequently, when green transition occurs upstream, the resulting changes in intermediate inputs can create adjustment frictions for downstream firms and weaken their productivity in the short run (Kharazi et al., 2025).

2.3. Transmission channels: labor skill upgrading and capital deepening

Green imports affect productivity not only through the technology they embody but also through the changes they induce in the structure of factor inputs within the firm. This section examines how green imports reshape the production structure and promote productivity growth through two channels: labor skill upgrading and capital deepening.

2.3.1. Labor costs and skill upgrading

The adoption of green technologies typically requires corresponding investments in human capital. The new production processes associated with green inputs demand workers with higher technical skills, environmental management expertise, and the ability to operate advanced equipment (Akyazi et al., 2022). Accordingly, firms that adopt green imports must invest in employee training, recruit more skilled personnel, or upgrade the competencies of their existing workforce in order to effectively integrate the new technologies into their operations.

This skill upgrading process manifests empirically as an increase in unit labor costs, reflecting the wage premium associated with a more skilled workforce as well as higher training expenditures. Although these outlays raise short-run operating costs, they also enhance labor productivity by improving the quality of the workforce and enabling more effective utilization of green technologies (Liu et al., 2025).

2.3.2. Capital deepening

The green transition is typically accompanied by complementary investments in physical capital. Introducing new green inputs often requires firms to upgrade or replace existing equipment, install new production lines, or invest in pollution control and energy management infrastructure (Gallo et al., 2025). These capital expenditures raise the capital intensity of the firm, reflecting a process of capital deepening directly triggered by the green transition.

From the perspective of the production function, capital deepening raises the capital-labor ratio and, holding other factors constant, increases labor productivity through the factor accumulation channel. Moreover, the new capital investments associated with the green transition typically embody more advanced technologies, so that capital accumulation represents not merely a quantitative increase but also a qualitative improvement, further contributing to productivity growth.

It is worth noting that labor upgrading and capital deepening are complementary rather than competing mechanisms. This is consistent with the capital-skill complementarity hypothesis, under which new capital equipment and skilled labor are mutually reinforcing inputs (Krusell et al., 2000). The adoption of green transition requires both higher-quality labor and additional capital investment, and the interaction between these two factors may yield further productivity gains through factor complementarity (Xiao and You, 2021). However, these two channels are expected to play a supporting rather than dominant role in the productivity gains associated with green imports. The remaining gains are attributable primarily to the direct technology transfer, learning-by-doing effects, and competitive pressure discussed in Section 2.1.

2.4. Dynamic effects: learning accumulation and adjustment recovery

The productivity effects of green imports do not emerge immediately. Rather, they exhibit a significant dynamic pattern over time: the direct effects tend to strengthen progressively, while the negative spillover effects transmitted through the value chain gradually dissipate.

2.4.1. Progressive strengthening of direct effects

The positive impact of green imports on firm productivity tends to be lagged and to intensify over time. In the initial phase, production efficiency typically falls short of its potential level because firms are unfamiliar with the new inputs, production processes have not yet been fully adjusted, and organizational adjustment frictions remain high (Di Luozzo et al., 2021). As firms accumulate experience through actual production, operational efficiency improves and unit costs decline, and the learning effects gradually materialize (Thompson, 2012). At the same time, firms progressively develop management routines, coordination mechanisms, and decision-making practices that are compatible with green production. The accumulation of these organizational capabilities enables firms to utilize the new inputs more effectively, thereby unlocking greater scope for productivity improvement.

Furthermore, the green transition typically involves a range of complementary investments. The human capital investments and capital deepening discussed in Section 2.3 constitute key components of this complementary set. As these complementary elements are gradually put in place, the productivity returns to the initial investment are amplified in subsequent periods (Milgrom & Roberts, 1990).

2.4.2. Gradual dissipation of value chain spillover effects

In contrast to the strengthening direct effects, the negative productivity spillovers arising from upstream green transitions are expected to diminish over time and eventually dissipate.

On one hand, adjustment frictions are inherently temporary. The productivity losses experienced by downstream firms, as analyzed in Section 2.2, originate from one-time costs of adapting to changes in input characteristics. These costs diminish as firms complete the adjustment process. Once downstream firms have recalibrated their production processes, retrained their workers, and stabilized their supplier relationships, the productivity losses attributable to friction disappear. The speed of this adjustment depends on the organizational flexibility of the firm and the magnitude of the initial change in input characteristics, but the direction of the dynamic is unambiguous: adjustment costs decline monotonically over time (Gelber et al., 2020).

On the other hand, repeated interactions facilitate relational adaptation. As upstream and downstream firms continue to transact following the green transition, they accumulate shared knowledge about new input specifications, build mutual trust, and develop relationship-specific assets that reduce future coordination costs (Fan et al., 2024). This process of relational adaptation further accelerates the dissipation of negative spillover effects.

The strengthening of direct effects and the weakening of spillover effects operate in tandem, producing a distinctive temporal pattern in the aggregate impact of the green transition on the production network. In the short run, negative spillover effects may partially offset the direct productivity gains. Over time, however, the spillover frictions gradually dissipate and the direct effects come to dominate. Figure 1 summarizes the theoretical framework, hypotheses, and overall research design of this study.

3. Literature Review and Hypotheses

3.1. Green transition and firm productivity

A large body of empirical work has examined the relationship between green transition and firm productivity. Several studies find positive effects, consistent with the view that environmental investments can stimulate process innovation and improve resource efficiency (Porter & Van der Linde, 1995; Martínez-Ferrero & Frias-Aceituno, 2015; Gangi et al., 2020). However, the gains depend on institutional context, regulatory design[1], and the type of innovation undertaken (Ambec et al., 2013; Ghisetti & Rennings, 2014).[2] Moreover, these benefits tend to materialize with a lag (Hart & Ahuja, 1996).

Other studies emphasize the cost burden of environmental compliance, documenting short-term productivity declines following the introduction of stricter regulations (Palmer et al., 1995; Commins et al., 2011; Dewaelheyns et al., 2023). Compliance-driven innovations in particular may generate limited or even negative returns (Ghisetti & Rennings, 2014). The relationship may also be nonlinear, with moderate investment enhancing productivity but excessive investment crowding out other productive inputs (D'Angelo et al., 2023).

Existing studies have also investigated the channels through which green transition affects firm performance. One well-documented channel operates through resource efficiency. Green technologies can reduce energy consumption, raw material waste, and pollution-related expenditures, thereby lowering operating costs (Al Barazanchi & Rasheed, 2024; Piprani et al., 2025). Özbuğday et al. (2020), studying European SMEs, find that allocating more than 1% of annual turnover to resource efficiency improvements increases the probability of sales growth by 13% to 18%. Another channel involves factor reallocation, as green adoption may reshape firms' labor and capital input structures (Bello-Pintado et al., 2019; Zhang & Ke, 2022; Wang et al., 2023). These findings suggest that the productivity effects of green transition depend not only on adoption itself, but also on the organizational and input adjustments that accompany it.

The productivity effects of green transition vary significantly across firms and industries. Firm size is one source of heterogeneity: large enterprises benefit from resource advantages, specialized management systems, and established technology networks, making it easier to adopt and integrate green technologies (Marakova et al., 2021; Klausmann et al.,

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[1] Following Ambec et al. (2013), regulatory design refers here to whether environmental rules provide flexibility and incentives for innovation rather than merely imposing prescriptive compliance requirements.

[2] Ghisetti and Rennings (2014) distinguish between energy and resource efficiency innovations (e.g., reducing energy or material use per unit of output) and externality reducing innovations (e.g., reducing air, water, or soil pollution), finding that only the former positively affects firm profitability.

2025). At the same time, SMEs, despite facing stricter resource constraints and institutional barriers, may achieve larger marginal gains from green investment due to greater room for efficiency improvement and higher organizational flexibility (Cuerva et al., 2014; Chien et al., 2021; Muangmee et al., 2021).

Firm age and life cycle stage also shape the effects of green transition. Younger firms in the growth phase are typically better positioned to integrate green technologies into expanding operations, leading to more pronounced productivity gains (Karpenko et al., 2021). Mature firms, by contrast, face path dependence and tend to prioritize incremental improvements over radical innovations.

Industry characteristics also play a critical role. In energy-intensive and high-pollution industries, firms face stricter regulatory pressure but also have greater room for resource efficiency gains (Li et al., 2014). In services and digital sectors, green transition tends to operate through process optimization, resource efficiency, and intangible channels such as reputation, rather than through capital-intensive technology adoption (Ström, 2020; Aithal & Jeevan, 2016). This suggests that the productivity effects of green transition differ not only in magnitude but also in their underlying mechanisms across industries.

However, a notable limitation of this literature is its reliance on survey-based indicators (e.g., Demirel et al., 2025; Ghisetti & Montresor, 2019), patent data (e.g., Yuan et al., 2021), or composite indices (e.g., Fang, 2024; Peng et al., 2022), which may not capture actual adoption behavior. Moreover, most studies employ static estimators (e.g., OLS, fixed effects, or Poisson regressions) that cannot trace the dynamic adjustment process following adoption (Corrocher & Ozman, 2020; Aastvedt et al., 2021; Vasileiou et al., 2022).

3.2. Production networks and technology spillovers

Upstream suppliers' trade integration and export participation can raise downstream productivity via quality upgrading of intermediate inputs, cost reduction, and knowledge diffusion (Newman et al., 2023). In U.S. manufacturing, a 10.5% increase in supplier IT capital can raise downstream industry output by 0.22% to 0.24% (Cheng & Nault, 2007). Upstream foreign direct investment and R&D also play positive roles: domestic firms that procure directly from foreign-owned suppliers experience significant productivity gains

(Newman et al., 2015), and supply chain R&D spillover effects on labor productivity have been found to exceed within-industry spillover effects (Foreman-Peck & Zhou, 2023).

In contrast, the evidence on downstream-to-upstream spillover effects is more limited. On the one hand, downstream firms with stringent requirements can induce upstream suppliers to upgrade production processes and improve product quality by imposing higher standards for quality and delivery (Ueki, 2016). On the other hand, downstream firms may also pass competitive pressure upstream through lower procurement prices, stricter delivery requirements, or shorter contract horizons. These pressures can squeeze suppliers' profit margins and reduce their capacity to finance innovation or green upgrading (Dai et al., 2024). The role of demand information is also uncertain. If suppliers cannot clearly observe whether downstream green demand is stable and long term, they may either delay investment or allocate capacity inefficiently. Therefore, downstream exposure can generate both upgrading incentives and cost pressures, making its net effect on upstream productivity theoretically ambiguous.

Despite this evidence, the production network framework has rarely been applied to the green transition context. In particular, few studies distinguish whether green technology spillovers differ between upstream and downstream directions (Guo et al., 2024; Lin et al., 2025).

3.3. The Estonian context

Estonia's green transition is guided by the "Estonia 2035" strategy, with a strong emphasis on renewable energy and energy market integration (Khorishko et al., 2023). However, in contrast to many OECD countries, Estonia maintains a relatively neutral tax regime[3] and provides limited direct fiscal incentives for green innovation, implying that firm-level green transition is driven primarily by regulatory pressure and market forces

[3] A distinctive feature of the Estonian corporate income tax system is that undistributed profits are not taxed. As a consequence, the system does not readily allow activity-specific tax exemptions, such as those for R&D or green investment, which limits the scope for profit-tax-based targeted incentives.

(Bunn, 2021; Raudla et al., 2025). At the same time, Estonia's historical reliance on oil shale as its primary energy source implies higher adjustment costs for firms undertaking green transition compared to most other OECD economies (Kaaret et al., 2022). Moreover, recent geopolitical shocks and EU-level policy pressures have simultaneously accelerated decarbonization efforts while exposing vulnerabilities in energy supply chains, further increasing uncertainty for firms (Goldthau & Youngs, 2023).

The policy environment shapes how companies perceive and respond to the green transition. Survey evidence suggests that most firms view green transition as a source of cost pressure rather than a strategic opportunity, with only a small subset able to leverage it for competitive advantage (Kekkonen et al., 2023; Pesor et al., 2024). In traditional industrial regions, limited local resources and constrained investment further hinder green transition efforts. Nevertheless, Estonia's production network is sparse but highly skewed, with a small number of central firms occupying hub positions in the domestic buyer-supplier network.[4] This structure may amplify the transmission of shocks and practices through key value chain linkages (Criscuolo et al., 2024). This network structure offers a distinct advantage for studying how green import shocks propagate across firms through value chain linkages.

3.4. Hypothesis development

Drawing on the theoretical mechanisms developed in Section 2 and the empirical evidence reviewed above, we formulate the following hypotheses.

H1: Green imports have a positive effect on firm productivity.

H2: Upstream green transitions have a negative effect on downstream firm productivity in the short run.

H3a: Green imports increase firms' labor costs per employee, as green technology adoption often requires higher-skilled labor and labor input adjustment.

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[4] For comparison, in 2019 Estonia's network density was 0.008%, above the 0.003% reported for Belgium; the average firm had 7.9 domestic buyers and suppliers, with the 99th percentiles reaching 105 buyers and 94 suppliers (Criscuolo et al., 2024).

H3b: Green imports increase firms' capital intensity, as green technology adoption often requires complementary investment in equipment and production capacity.

H4a: The positive effect of green imports on firm productivity strengthens progressively over time.

H4b: The negative spillover effects of upstream green transitions on downstream firm productivity diminish progressively over time.

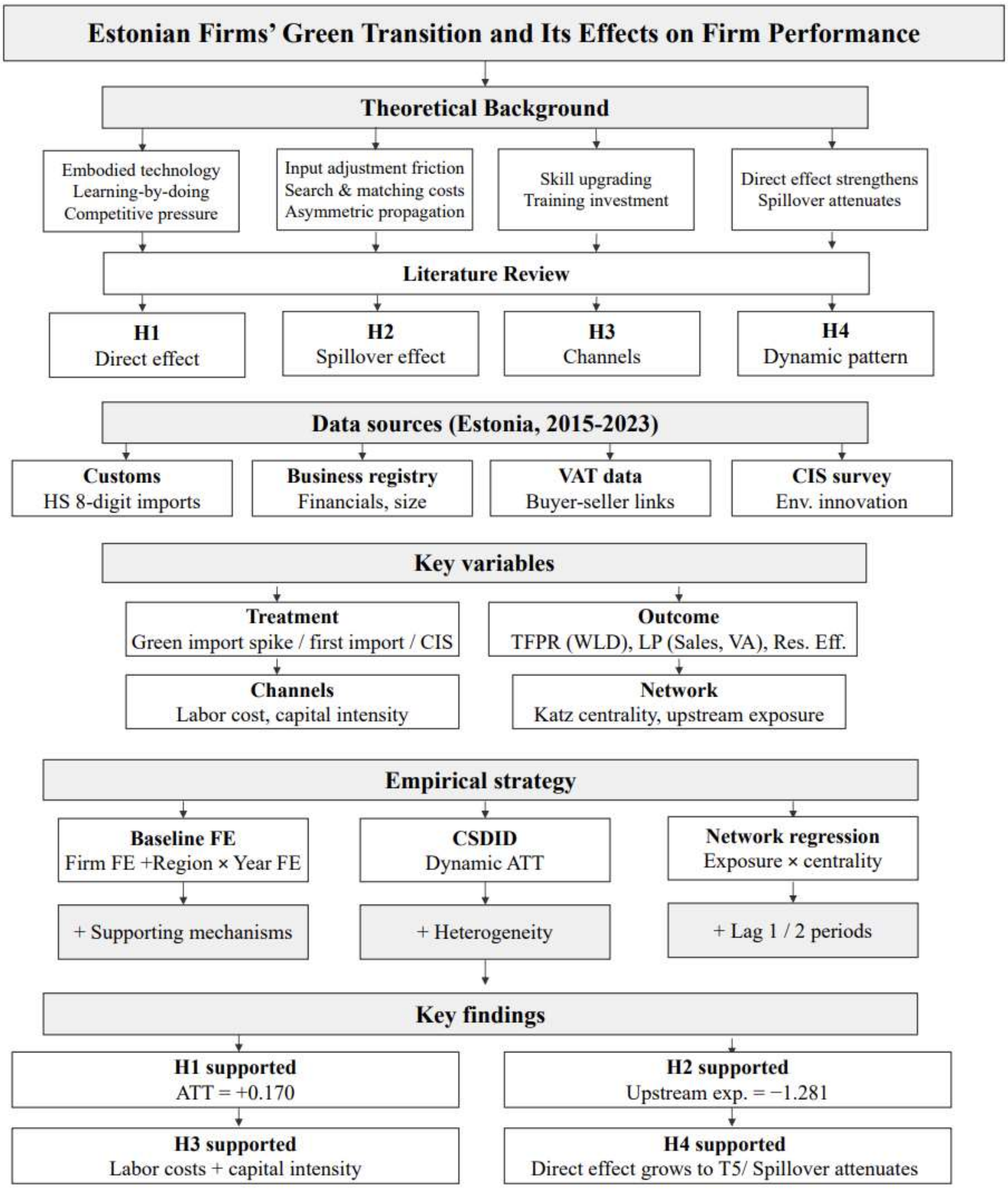

Figure 1. Research Framework and Methodology Overview

4. Empirical Strategy

4.1. Data

This study draws on multiple administrative and survey datasets provided by Statistics Estonia, covering the period 2015-2023. The data allow us to link firm-level green import behaviors, productivity outcomes, and production network structures.

The Estonian Business Registry (Äriregister) provides annual financial statements for the population of Estonian enterprises, including turnover, intermediate inputs, employment, fixed assets, and ownership structure. This serves as the primary source for constructing productivity measures and firm-level control variables.

Customs transaction data provides detailed product import records at the HS 8-digit level. Following the approach of using product-level import data to proxy technology adoption (Domini et al., 2022; Pavlenkova et al., 2024), we use these records to identify green product imports based on the OECD environmental goods classification (Moïsé & Tresa, 2025), which comprises 345 HS 6-digit product codes.

As Table 1 shows, the classification spans 11 categories. Renewable energy plant equipment constitutes the largest category with 91 product codes, followed by cleaner and renewable energy products (63 codes) and heat and energy management equipment (46 codes). These three categories together account for more than half of all classified products, reflecting the classification’s emphasis on energy-related environmental technologies. The remaining categories cover environmental monitoring, waste management, water treatment, air pollution control, and other environmental functions.

The VAT transaction data records annual domestic transactions between Estonian firms at the buyer-seller pair level. We use this data to construct the production network, following Masso and Vahter (2023), and compute network centrality measures following Criscuolo et al. (2024).

The Community Innovation Survey (CIS) is conducted biennially and covers approximately 1,500 firms per wave in Estonia (Masso & Vahter, 2008). We use CIS measures of environmental innovation to construct an alternative treatment indicator based on whether a firm reports environmental benefits from its innovation activities, such as reduced energy use, lower CO2 emissions, or the substitution of hazardous inputs (OECD/Eurostat, 2018).[5]

Table 1. *Summary of the OECD Combined List of Environmental Goods*

Category	Code	N	Example products
Renewable energy plant	REP	91	Solar panels, wind turbines, hydroelectric generators
Cleaner & renewable energy	CRE	63	Biomass stoves, hydrogen-fuelled equipment
Heat & energy management	HEM	46	Heat exchangers, insulation materials, thermostats
Environmental monitoring & analysis	MON	42	Gas/smoke analysers, UV/IR spectrometers
Solid & hazardous waste management	SWM	38	Waste incinerators, recycling machinery, crushers
Wastewater & potable water treatment	WAT	33	Water filtration systems, UV disinfection equipment
Air pollution control	APC	13	Catalytic converters, gas purifying machinery
Environmentally preferable products	EPP	9	Natural fibre products, biodegradable materials
Soil & water remediation	SWR	4	Soil remediation equipment
Natural resources protection	NRP	3	Erosion control equipment
Noise & vibration abatement	NVA	3	Silencers, acoustic panels
Total		345	

Notes: This table summarizes the OECD Combined List of Environmental Goods (CLEG) by medium-level category. "Code" refers to the OECD medium-level category code. "N" is the number of HS 6-digit product codes in each category.

Source: Moïsé and Tresa (2025). The complete product-level list is available from the original publication.

4.2. Variables

4.2.1. Green import

We identify green imports using the updated OECD Combined List of Environmental Goods (Moïsé & Tresa, 2025), which classifies products with clear environmental functions

[5] Specifically, we rely on the environmental innovation items Q9.2 and Q9.3 in the CIS.

based on HS codes (Ben Zineb, 2019; Can et al., 2021). For each firm-year observation, we compute the total value of green imports by summing all import transactions corresponding to these products. In the baseline fixed-effects specifications, we use the natural logarithm of the monetary value of green imports as the main explanatory variable. In the CSDID analysis, treatment is defined using dummy indicators based on green import spikes and first-year adoption. To address the concern that the monetary value of green imports may partly reflect firm size, we also use the log of green imports per employee as a robustness check.

To examine whether the baseline HS-based measure is sensitive to the treatment of dual-use products, this thesis also constructs a stricter HS6 × NACE cross-referencing measure, which classifies an import as green only when both the product code and the importer's industry code jointly satisfy the green-technology taxonomy. This stricter measure is used as an additional robustness check in Section 5.5.

4.2.2. Treatment definition for CSDID

For the Callaway and Sant'Anna (2021) difference-in-differences estimation, the preferred treatment definition is the first year in which a firm imports green products. This first-adoption definition captures the timing at which a firm first becomes exposed to imported green technologies. Because green imports are lumpy, we also construct an alternative spike-based treatment definition, where treatment is assigned to the year in which a firm records its highest green import value, subject to the condition that the peak value exceeds three times the average of other years. This spike-based definition is used as an additional specification. Figure 2 illustrates the lumpy nature of green import activities: most importing firms engage in green imports in only one or two years, and the top-ranked year accounts for a disproportionately large share of a firm's total green imports. We apply the same analysis to automation imports and find a similarly lumpy pattern (Appendix Figure A1), suggesting that this pattern is not specific to green imports in Estonia, but reflects a common feature of capital goods adoption (Domini et al., 2022).

To reduce potential contamination from re-exporting activities, we exclude transactions in which a firm both imports and exports the same HS6 product in the same calendar year. This procedure removes 83,195 import transactions, corresponding to approximately 18% of imports involving green-candidate HS6 codes under the OECD environmental goods list. The remaining 3,107,414 transactions, retained for domestic use, form the basis for both our baseline identification and the robustness analyses. The spike-based definition and the CIS environmental innovation measure are used as alternative treatment specifications.

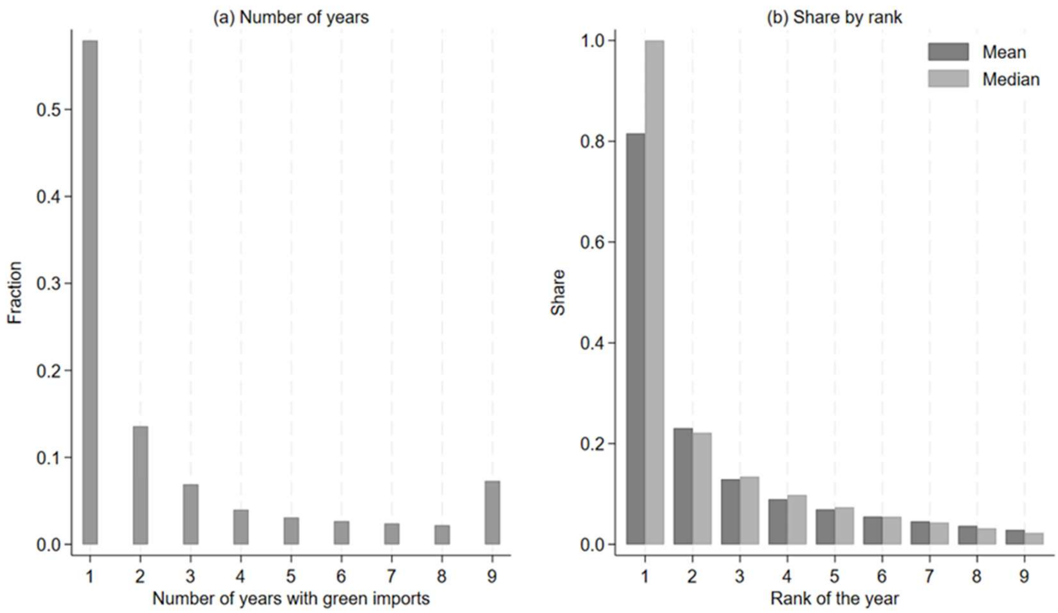

Figure 2. Distribution of Green Import Activities

Notes: Panel (a) shows the distribution of firms by the number of years with positive green imports during 2015-2023. Panel (b) shows the mean and median share of total green imports accounted for by each ranked year, where rank 1 corresponds to the year with the highest green import value for each firm. Green imports are classified using the OECD environmental goods list.

Source: Statistics Estonia, author’s calculations.

4.2.3. Outcome variables

We use three productivity measures as the main outcome variables. The preferred measure is revenue total factor productivity, denoted TFPR (WLD), estimated using the Wooldridge (2009) method. The production function is estimated at the 3-digit EMTAK industry level. Since output is measured using revenue rather than physical quantities, the estimated residual may reflect not only technical efficiency but also output-price variation under imperfect competition (Klette and Griliches, 1996; De Loecker, 2011). Following this logic, market share is included as an auxiliary control in the production-function estimation to account for differences in firms' demand position within narrowly defined industries. This helps reduce, but not fully remove, market-position differences in the productivity residual. Labor productivity is measured in two ways. The first is revenue-based labor productivity, defined as log (turnover / employees) and denoted Log LP (Sales). The second is value added per employee, defined as log ((turnover - intermediate inputs) / employees) and denoted Log LP (VA). In addition, we use log electricity consumption per employee to capture firms' energy use intensity.

Figure 3 compares the unconditional distributions of the main outcome variables for firms with and without green imports using kernel density estimates. Green importers tend to show higher productivity, particularly in terms of labor productivity (Panels B and C), while the distribution of electricity consumption per employee is less clearly shifted (Panel D). The Kolmogorov-Smirnov tests reported in Appendix Table A1 reject equality of distributions for all four variables. However, these differences likely reflect the tendency of more productive firms to adopt green transition, rather than causal effects.

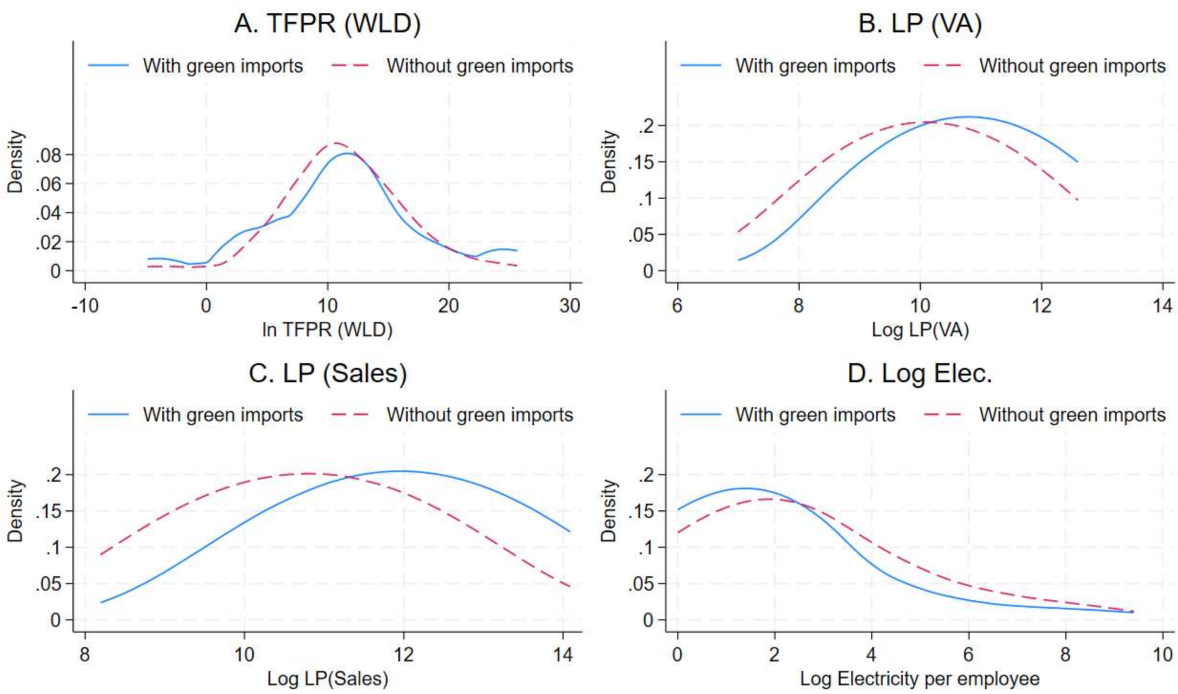

Figure 3. Kernel Density Productivity Distributions by Green Import Status

Source: Statistics Estonia, author's calculations.

4.2.4. Value chain network variables

Using the VAT transaction data, we construct the annual directed production network for Estonia, where firms are nodes and buyer-seller relationships define directed links. We compute Katz centrality for both buyer (k^{in}) and seller (k^{out}) positions in the network. The centrality vector k^{out} is defined as:

$$k^{out} = (I - \beta A)^{-1}\mathbf{1} \tag{1}$$

where

I – identity matrix

β – decay parameter, set below the inverse of the spectral radius

A – adjacency matrix of the production network

$\mathbf{1}$ – vector of ones

Table 2 reports summary statistics for Katz centrality by year, and Figure 4 illustrates the evolution of nodes and edges in the Estonian production network. The spectral radius increases over time, while both seller and buyer centrality measures exhibit a slight decline. Similar patterns are reported in Criscuolo et al. (2024), although their analysis relies on monthly transaction data, whereas this study is based on annual aggregates.

To capture indirect exposure through the production network, we construct trade-weighted measures based on firms' trading partners. Upstream exposure is defined as the weighted average of green imports of a firm's upstream suppliers. All exposure variables are lagged and expressed in logarithms.

$$Exposure_{i,t-1}^{up} = \sum_{j \in U(i,t-1)} w_{ij,t-1}^{up} GI_{j,t-1} \tag{2}$$

$$w_{ij,t-1}^{up} = \frac{Purchases_{ij,t-1}}{\sum_{k \in U(i,t-1)} Purchases_{ik,t-1}} \tag{3}$$

where

$U(i, t-1)$ – set of upstream suppliers of firm *i* at time *t* - 1

$w_{ij,t-1}^{up}$ – purchase share of supplier j in total purchases of firm i

$GI_{j,t-1}$ – green imports of firm j

$Purchases_{ij,t-1}$ – purchases from supplier j

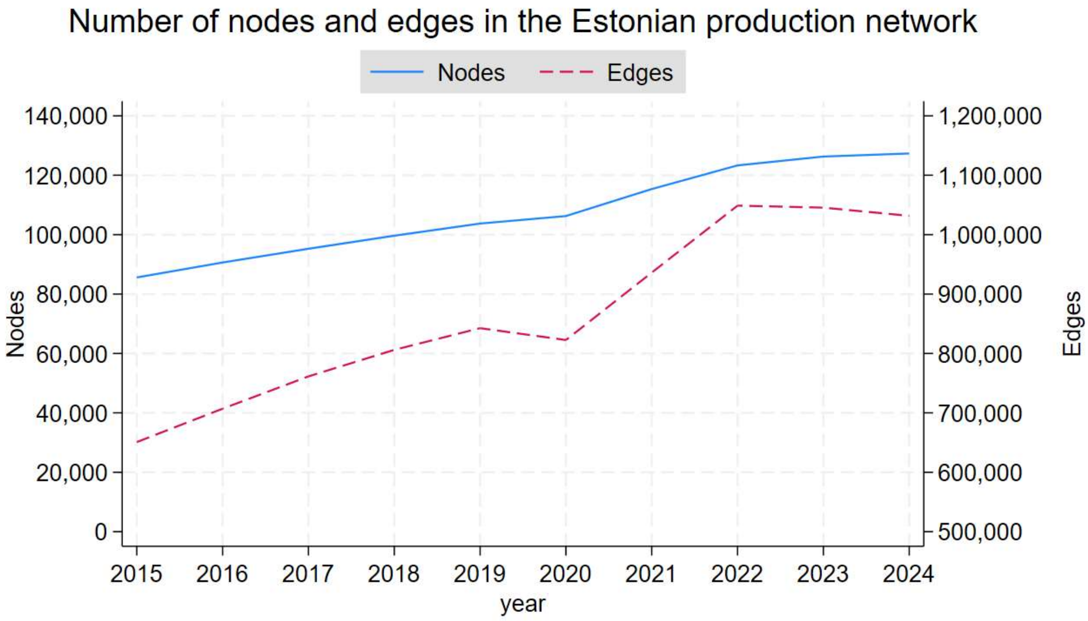

Figure 4. Number of Nodes and Edges in the Estonian Production Network

Source: Statistics Estonia, author's calculations.

Table 2. *Summary statistics of Katz centrality by year*

Year	Spectral Radius	Inverse (10^{-8})	Beta (10^{-8})	Seller Centrality (10^{-3})			Buyer Centrality (10^{-3})		
				Mean	SD	Med.	Mean	SD	Med.
2015	17,479,133	5.72	4.72	2.96	1.72	2.81	2.67	2.13	2.54
2016	24,324,913	4.11	3.11	3.15	1.05	3.07	3.13	1.12	3.05
2017	26,203,138	3.82	2.82	3.12	8.68	3.05	3.11	8.98	3.05
2018	29,144,449	3.43	2.43	3.09	6.85	3.04	3.09	6.91	3.04
2019	27,614,732	3.62	2.62	3.00	7.86	2.94	2.99	8.54	2.93
2020	27,411,099	3.65	2.65	3.00	6.53	2.94	2.95	8.55	2.90
2021	29,371,244	3.40	2.40	2.87	6.51	2.82	2.85	7.55	2.80
2022	32,353,514	3.09	2.09	2.77	6.39	2.73	2.77	6.43	2.73
2023	33,013,148	3.03	2.03	2.76	5.58	2.72	2.75	5.93	2.71

Note: Katz centrality is computed for seller and buyer positions in the annual directed production network. The parameter Beta is set below the inverse of the spectral radius each year to ensure convergence.

Source: Statistics Estonia, author’s calculations.

4.2.5 Control variables

We include a set of firm-level control variables in the FE and CSDID specifications. Firm size and age are measured as the logarithm of employment and years since registration, respectively, both entered with squared terms to allow for non-linear effects. Return on equity (ROE) is defined as net income over equity and captures firms’ financial performance. Capital intensity is measured as the logarithm of fixed assets per employee and reflects differences in production technology and input structure. Foreign ownership is a time-varying dummy equal to one if the majority owner is foreign, as foreign-owned firms may differ in access to technology, management practices, and international networks. Market share is calculated as the firm’s share of total turnover within its two-digit EMTAK industry-year and is included to control for differences in firms’ market position and competitive environment.

4.3. Descriptive statistics

We construct three analytical samples. Sample 1 (N = 405,791) includes all firms with non-missing control variables during 2015-2023 and serves as the initial regression panel. Sample 2 (N = 327,058) further excludes observations with missing productivity measures and serves as the main estimation sample for the FE and CSDID analyses. Sample 3 (N = 17,102) is restricted to CIS survey respondents and is used for robustness checks with an alternative treatment definition.

Table 3 reports summary statistics for the three samples. Comparing Sample 1 and Sample 2, the differences are modest. Sample 3 differs more substantially: CIS respondents are larger (size 3.182 vs 0.970), older (age 2.799 vs 2.238), more capital-intensive (9.364 vs 8.748), and more likely to be foreign-owned (20% vs 5%), consistent with the survey’s focus on medium and large enterprises.

Table 4 compares firms with and without a green import spike. Firms experiencing a spike exhibit higher productivity across all measures, including log labor productivity and total factor productivity. They also differ in observable characteristics, with a higher scale, greater capital intensity, and a higher share of foreign ownership. Most differences are statistically significant at the 1% level, except for ROE.

Table 5 documents the annual distribution of green importers and spikes. The share of firms importing green products ranges from 23% in 2015-2016 to approximately 37% from 2017 onward, with mean import values rising steadily from 92,882 euros to 236,971 euros by 2023. The share of firms experiencing a green import spike fluctuates between 6% and 10% annually.

The sectoral distribution of green imports is reported in Appendix Table A2. By import value, wholesale trade accounts for the largest share, at EUR 415.8 million or 21.5% of total green imports, followed by retail trade at 10.0% and motor vehicle trade at 6.5%. By number of firms, wholesale trade also ranks first, accounting for 2,027 firms or 23.4% of green importers, followed by retail trade, motor vehicle trade, specialized construction, and fabricated metals. Comparing 2015 and 2023, wholesale trade remains the leading sector, with its share broadly stable at 31.2% and 30.7%, respectively. Beneath this dominant category, the composition changes noticeably: civil engineering rises to second place in 2023, while motor vehicle trade increases from 4.9% to 12.2%. These shifts suggest that green import activity remains strongly concentrated in trade sectors, while becoming increasingly connected to infrastructure, transport, and selected manufacturing activities.

Figure 5 shows the dynamics of the five largest green import categories in Estonia. Renewable energy plant equipment (REP) is generally the largest category and rises sharply after 2021, reaching around EUR 370 million by the end of the period. Cleaner and renewable energy (CRE) shows a more volatile pattern, with an early spike around 2012-2013, a decline in the mid-2010s, and a renewed increase after 2021. Water treatment (WAT) and heat and energy management (HEM) display more gradual upward trends, while solid waste management (SWM) remains relatively stable with moderate fluctuations. At the firm level, Appendix Table A3 shows that REP has the highest prevalence, followed by WAT and HEM. Green importing is most common in construction, where nearly 19% of firms import green goods, with particularly high shares in REP, WAT, and HEM.

Table 3. *Descriptive statistics, 2015-2023.*

	Sample 1 (N = 405,791)		Sample 2 (N = 327,058)		Sample 3 (N = 17,102)	
Variables	Mean	SD	Mean	SD	Mean	SD
TFPR (WLD)	11.283	5.057	11.315	5.041	12.135	9.322
Log LP (Sales)	10.803	1.171	10.894	1.088	11.504	1.027
Log LP (VA)	10.120	0.995	10.128	0.982	10.563	0.751
Log Elec.	2.356	2.108	2.364	2.118	2.379	2.162
Firm size	0.970	1.150	1.005	1.127	3.182	1.062
Firm age	2.238	0.838	2.234	0.830	2.799	0.635
ROE	0.087	0.884	0.109	0.757	-0.115	0.534
Capital intensity	8.748	1.943	8.716	1.886	9.364	1.793
Foreign firm (dummy)	0.050	0.217	0.045	0.206	0.200	0.400
Market share	0.002	0.006	0.002	0.006	0.002	0.006
Katz In	-5.819	0.140	-5.837	0.123	-	-
Katz Out	-5.835	0.129	-5.820	0.131	-	-
Up. Exp.	8.574	4.094	8.483	4.076	-	-
Down. Exp.	7.476	5.172	7.366	5.145	-	-

Notes: All variables are defined in the main text. Continuous variables are winsorized at the 1% level. Firm size and capital intensity are measured in logs. Log Elec. = log electricity consumption, which is available for a subset of firms (N = 4,864 in Sample 1; N = 3,644 in Sample 2; N = 2,680 in Sample 3).

Source: Statistics Estonia, author's calculations.

Table 4. *Comparing firms with and without a green import spike, 2015-2023.*

	No Spike	Spike	Difference
Log LP (VA)	10.092	10.517	0.424***
Log LP (Sales)	10.759	11.447	0.688***
TFPR (WLD)	11.268	11.491	0.223***
Log Elec.	2.597	2.116	-0.481***
Firm size	0.921	1.699	0.778***
Firm age	2.223	2.462	0.238***
ROE	0.086	0.091	0.005
Capital intensity	8.714	9.253	0.539***
Foreign firm	0.046	0.099	0.053***
Market share	0.002	0.005	0.003***
Obs.	380,081	25,710	

Notes: The Difference column reports Spike minus No Spike. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.10. Log Elec. is available only for a subsample of firm-year observations.

Source: Statistics Estonia, author's calculations.

Table 5. *Green importers and spikes per year, 2015-2023.*

Year	Importers			Spikes			
	Importers Firms	Share (%)	Mean Import (€)	Spikes (base)	Share (%)	Spikes (strict)	Share (%)
2015	25,994	23.20	92,882	2,679	10.31	2,548	9.80
2016	26,541	22.92	90,643	2,488	9.37	2,368	8.92
2017	11,782	36.51	136,226	841	7.14	768	6.52
2018	11,828	37.66	147,534	879	7.43	815	6.89
2019	12,244	37.07	140,329	843	6.89	768	6.27
2020	11,963	37.76	147,113	806	6.74	745	6.23
2021	13,999	36.20	144,180	1,172	8.37	1,048	7.49
2022	13,418	34.48	219,073	1,125	8.38	999	7.45
2023	12,777	34.72	236,971	1,140	8.92	1,047	8.19

Notes: Green importers and spikes are defined using the OECD environmental goods classification. Importers denote firms with positive green imports in the year. Base spikes identify the year with the highest green import value. Strict spikes further require the peak-year value to exceed three times the average of other years.

Source: Statistics Estonia, author's calculations.

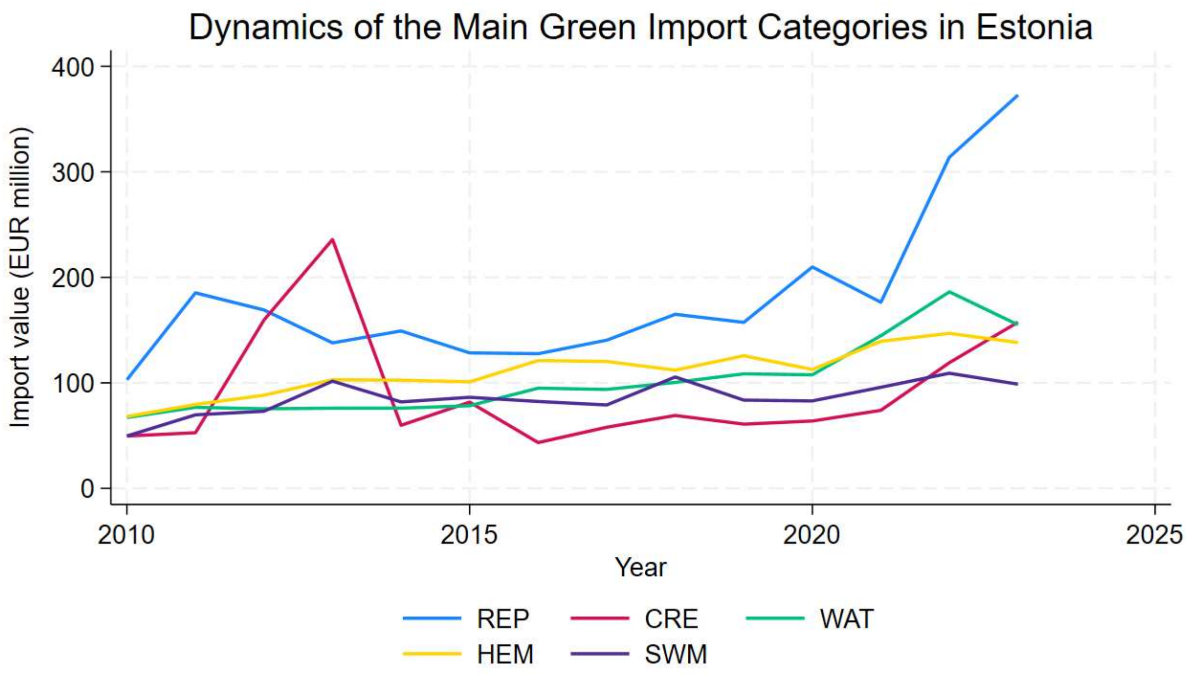

Figure 5. Dynamics of the Main Green Import Categories in Estonia

Notes: The figure plots annual import values for the five largest OECD green import categories in Estonia. Values are reported in EUR million. REP = renewable energy plant; CRE = cleaner and renewable energy; WAT = water supply and treatment; HEM = heat and energy management; SWM = solid waste management. Source: Statistics Estonia, author's calculations.

4.4. Econometric Framework

4.4.1. Baseline fixed effects

We first estimate a baseline fixed-effects model to examine the relationship between green imports and firm productivity. This specification controls for unobserved time-invariant firm heterogeneity. We include both firm fixed effects and region-by-year fixed effects. The latter absorb both common year shocks and region-specific shocks that vary over time, so separate year fixed effects are not included:

$$Y_{i,t} = \beta GI_{i,t} + \gamma X_{i,t} + \lambda_{r,t} + \mu_i + \varepsilon_{i,t} \tag{4}$$

where

$Y_{i,t}$ – firm productivity

μ_i – firm fixed effects

$\lambda_{r,t}$ – region-by-year fixed effects

$X_{i,t}$ – standard firm-level controls

4.4.2. Difference-in-differences

To identify the causal impact of green imports, we exploit variation in the timing of firms' first green-import adoption and estimate dynamic treatment effects following the Callaway and Sant'Anna (2021) estimator. This approach is well suited to our setting because firms adopt green imports at different points in time and treatment effects may be heterogeneous across cohorts and over time. Unlike conventional DID estimators, the CSDID framework avoids biases that may arise under staggered treatment timing with heterogeneous effects. The group-time average treatment effect on the treated is defined as:

$$ATT(g,t) = E\left[Y_{i,t}(1) - Y_{i,t}(0) \middle| G_i = g\right], \qquad t \geq g \tag{5}$$

where

G_i – the first treatment year of green importing of firm *i*.

$Y_{i,t}(1),\ Y_{i,t}(0)$ – treated and untreated outcome

$ATT(g,t)$ – the average treatment effect for firms first treated in period g and evaluated at time t.

The control group consists of firms that have not yet adopted green imports at time t, with never-treated firms used as a robustness check. We report both average treatment effects and event-study estimates to characterize the dynamic response to green imports.

4.4.3. Value chain network analysis

We next examine how green import shocks propagate through value chain linkages by incorporating partner exposure and firm centrality.

$$Y_{i,t} = \beta_1 GI_{i,t} + \beta_2 Exposure_{i,t-k} + \beta_3 Katz_{i,t} + \beta_4 (Exposure_{i,t-k} \times Katz_{i,t}) + \gamma X_{i,t} + \lambda_{r,t} + \mu_i + \varepsilon_{i,t} \tag{6}$$

where

$Exposure_{i,t-k}$ – exposure to green import activity from trading partners

$Katz_{i,t}$ – centrality in the production network

$Exposure_{i,t-k} \times Katz_{i,t}$ – interaction term capturing how network position shapes spillover effects

We estimate the specification separately for upstream and downstream linkages and consider lags of $k = 1, 2$ to capture the temporal dynamics of value chain spillovers.

5. Results

5.1. Baseline results

Table 6 presents the baseline fixed-effects estimates of the relationship between green imports and firm performance. The coefficients on green imports are positive and statistically significant across all specifications. For the three productivity outcomes, the estimates are significant at the 1% level, while the coefficient for electricity consumption per employee is positive and significant at the 5% level. These results indicate that green imports are associated with higher firm productivity, as well as higher energy use intensity.

The control variables generally display expected patterns. Firm age shows an inverted U-shaped relationship with the main productivity outcomes, while profitability is positively associated with productivity. Capital intensity is positively related to TFPR (WLD), Log LP(Sales), and Log LP(VA). The negative coefficients on firm size in Log LP(Sales) and Log LP(VA) may partly reflect variable construction, since the labor-productivity measures are defined per employee. Foreign ownership is mostly insignificant, except in the electricity-consumption specification. To address the concern that ROE may partly reflect firm productivity, we re-estimate all specifications excluding it. The results remain virtually unchanged (Appendix Table A4).

These results are consistent with H1, suggesting a positive association between green imports and firm productivity. However, they do not capture how the effects evolve over time. We therefore employ a CSDID approach in the next section to identify the causal effect of green transition on productivity.

Table 6. *Baseline Fixed Effects Estimates: Green Imports and Firm Productivity*

	TFPR (WLD)	*Log LP(Sales)*	*Log LP(VA)*	*Log Elec.*
	(1)	(2)	(3)	(4)
Green Imp.	0.014***	0.017***	0.011***	0.016**
	(0.005)	(0.001)	(0.001)	(0.007)
Size	0.242***	-0.355***	-0.256***	-0.139
	(0.037)	(0.009)	(0.010)	(0.197)
$Size^2$	0.003	0.003	-0.003	-0.017
	(0.014)	(0.003)	(0.004)	(0.034)
Age	0.329***	0.374***	0.381***	0.122
	(0.044)	(0.012)	(0.013)	(0.657)
Age^2	-0.049	-0.054***	-0.075***	0.147
	(0.032)	(0.007)	(0.008)	(0.246)
ROE	0.098***	0.102***	0.178***	-0.010
	(0.006)	(0.002)	(0.002)	(0.022)
Capital intensity	0.038***	0.074***	0.077***	0.037
	(0.007)	(0.002)	(0.002)	(0.040)
Foreign owned	0.008	0.023	0.011	0.222***
	(0.046)	(0.013)	(0.014)	(0.081)
Market share	0.375***	0.250***	0.206***	0.383***
	(0.070)	(0.007)	(0.006)	(0.070)
Firm FE	Yes	Yes	Yes	Yes

	TFPR (WLD)	*Log LP(Sales)*	*Log LP(VA)*	*Log Elec.*
	(1)	(2)	(3)	(4)
Region × Year FE	Yes	Yes	Yes	Yes
Obs.	327,058	327,058	327,058	3,644

Note: Green Imp. denotes the log of green product imports classified by the OECD environmental goods list. All regressions include firm fixed effects and region-by-year fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Source: Statistics Estonia, author's calculations.

5.2. Dynamic treatment effects

To further examine the causal effect of green transition on firm productivity, this section estimates dynamic treatment effects using the CSDID approach. Table 7 reports the results for TFPR (WLD) under four alternative specifications. All specifications satisfy the parallel trends test, with pre-trend p-values ranging from 0.140 to 0.421. Across specifications, the average post-treatment effects are positive and statistically significant, indicating that green transition increases firm productivity.

Column (1) uses the green import spike as the treatment definition. The estimated post-treatment effect is positive and statistically significant at the 10% level, but the dynamic pattern is less precisely estimated than in the alternative specifications. For this reason, the first-year adoption definition is used as the preferred CSDID specification. Column (2) defines treatment as the first year of green importing and shows a positive post-treatment ATT of 0.170, significant at the 5% level. Column (3) applies the same first-year adoption definition but uses never-treated firms as the control group, the estimate remains very similar, at 0.166, suggesting that the result is not sensitive to the choice of control group. Column (4), based on the CIS environmental innovation measure, also shows a positive and significant effect, with a post-treatment ATT of 0.363. This indicates that the positive productivity effect is not specific to the import-based treatment definition.

The dynamic estimates show that productivity gains emerge soon after treatment and remain positive over time. In Column (2), where treatment is defined as the first year of green importing, the effect appears in the treatment year (ATT = 0.099, $p < 0.10$), increases in year 1 (ATT = 0.149, $p < 0.05$), and remains positive in all subsequent post-treatment years. The largest estimate appears in year 5 (ATT = 0.338, $p < 0.05$), suggesting that the productivity gains become more pronounced over the longer run. Figure 6 further illustrates these dynamic effects across the four specifications. In all panels, the pre-treatment coefficients remain close to zero with no clear trend, while the post-treatment coefficients show a significant short-run increase following treatment, with an overall upward trend over time. This pattern indicates a short-term boost, medium-term adjustment, and long-term enhancement in productivity following the green transition, supporting H4a.

In addition, we implement the same CSDID method using alternative productivity measures, including Log LP (Sales), Log LP (VA), and Log electricity consumption. However, these specifications do not fully satisfy the parallel trends assumption and are therefore reported for completeness in Appendix Table A5.

Table 7. *Dynamic Treatment Effects*

Treatment	Spike-based	First-adoption	First-adoption	Env. Inno.
Control group	Not-yet-treated	Not-yet-treated	Never-treated	Not-yet-treated
	(1)	(2)	(3)	(4)
Pre avg.	0.003	-0.007	-0.015	0.002
	(0.034)	(0.038)	(0.039)	(0.135)
Post avg.	0.144*	0.170**	0.166**	0.363**
	(0.085)	(0.080)	(0.081)	(0.185)
year = 0	0.057	0.099*	0.090*	0.249**
	(0.048)	(0.053)	(0.053)	(0.122)
year = 1	0.105*	0.149**	0.144**	0.460***
	(0.062)	(0.067)	(0.067)	(0.177)
year = 2	0.093	0.136*	0.128	0.445**
	(0.085)	(0.080)	(0.081)	(0.218)
year = 3	0.120	0.129	0.119	0.395
	(0.116)	(0.103)	(0.105)	(0.249)
year = 4	0.160	0.169	0.173	0.298
	(0.141)	(0.124)	(0.125)	(0.312)
year = 5	0.331*	0.338**	0.342**	0.330
	(0.179)	(0.154)	(0.154)	(0.304)
Pre-trend joint test	0.385	0.151	0.140	0.421
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	308,893	291,754	291,518	15,007

Notes: The dependent variable is TFPR (WLD) across all specifications. Columns differ by treatment definition and control-group choice. Columns (1), (2), and (4) use not-yet-treated firms as the control group, while column (3) uses never-treated firms as the control group. Env. Inno. refers to the environmental innovation-based treatment definition. Pre avg. and Post avg. report the average pre-treatment and post-treatment ATT estimates. The pre-trend joint test reports the p-value for the null hypothesis that all pre-treatment coefficients are jointly equal to zero. All regressions include firm and year fixed effects and the full set of control variables. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Source: Statistics Estonia, author's calculations.

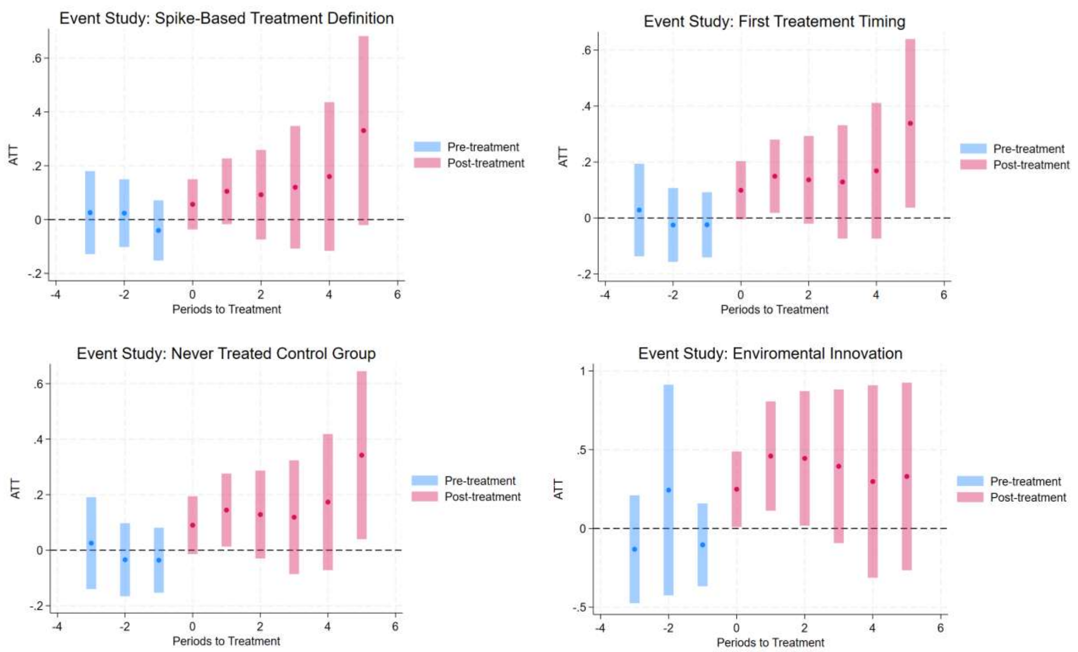

Figure 6. Dynamic Treatment Effects: Event Study Plots

Source: Statistics Estonia, author's calculations.

5.3. Mechanism: value chain network transmission

To understand how the effects of green transition propagate across firms, we examine its transmission through value chain networks, focusing on both upstream and downstream exposure as well as the moderating role of firm centrality.

Table 8 reports the value-chain transmission results using two exposure measures: transaction amount exposure and transaction share exposure. Panel A provides evidence for H2 by showing that upstream green exposure is associated with negative productivity effects for downstream firms, and that this effect is stronger among firms with higher Katz in-centrality. In the amount-based specification, the interaction between one-period lagged upstream exposure and Katz in-centrality is negative and significant (-0.954, $p < 0.01$), while the two-period lag interaction remains negative but becomes smaller in magnitude (-0.501, $p < 0.10$). The share-based specification shows the same pattern, with interaction coefficients of -0.221 ($p < 0.01$) for the one-period lag and -0.078 ($p < 0.10$) for the two-period lag. These findings indicate that firms occupying more central buyer positions are more strongly exposed to upstream green adoption shocks.

The decline in the magnitude of the interaction coefficients from the first to the second lag is consistent with H4b, which predicts that negative upstream spillover effects should weaken over time as downstream firms adjust to new input characteristics, supplier requirements, and production routines.

Panel B reports the results for downstream exposure. The coefficients on downstream exposure and its interactions with Katz out-centrality are statistically insignificant across both exposure measures. This suggests that value-chain transmission operates mainly through upstream supplier linkages rather than downstream customer linkages.

Table 8. *Value Chain Network Effects: Upstream and Downstream Green Exposure*

	TFPR (WLD)	*TFPR (WLD)*
	Amount exposure	*Share exposure*
	(1)	(2)
Panel A: Upstream exposure		
Green Imp.	0.008	0.008
	(0.006)	(0.006)
Up. Exp. L1	-5.571***	-1.281***
	(1.595)	(0.256)
Katz. in	1.452***	4.725***
	(0.334)	(1.049)
Up. Exp. L1 × Katz. in	-0.954***	-0.221***
	(0.273)	(0.044)
Up. Exp. L2	-2.915*	-0.452*
	(1.586)	(0.266)
Up. Exp. L2 × Katz. in	-0.501*	-0.078*
	(0.271)	(0.045)
Panel B: Downstream Exposure		

	TFPR (WLD)	*TFPR (WLD)*
	Amount exposure	*Share exposure*
	(1)	(2)
Down. Exp. L1	0.002	0.148
	(1.538)	(0.289)
Katz. out	1.229***	0.159
	(0.460)	(1.460)
Down. Exp. L1 × Katz. out	-0.002	0.024
	(0.264)	(0.050)
Down. Exp. L2	-0.823	0.270
	(1.245)	(0.366)
Down. Exp. L2 × Katz. out	-0.144	0.046
	(0.213)	(0.063)
Controls	Yes	Yes
Firm FE	Yes	Yes
Region × Year FE	Yes	Yes
Obs.	129,052	129,052

Notes: All regressions include firm and region-by-year fixed effects and the full set of control variables. Robust standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Source: Statistics Estonia, author's calculations.

5.4. Supporting mechanisms

We examine two standard channels: labor costs per employee and capital intensity. The results are reported in Table 9.

Panel A presents the labor cost channel. Green imports are positively associated with both productivity and labor costs per employee. When labor cost per employee is used as the dependent variable, the coefficient on green imports is positive and statistically significant (0.007, $p < 0.01$). In the productivity regression that additionally controls for labor costs, the coefficient on green imports decreases from 0.014 to 0.012, while labor cost per employee is positively associated with productivity. This pattern suggests that green importing firms experience labor input adjustment, possibly reflecting higher skill requirements or worker upgrading. However, the reduction in the green import coefficient is modest, indicating that this channel explains only a limited part of the productivity pattern.

A similar pattern emerges in Panel B for the capital intensity channel. Green imports are positively associated with capital intensity (0.017, $p < 0.01$), and capital intensity is positively related to productivity. After capital intensity is included in the productivity regression, the coefficient on green imports decreases slightly from 0.015 to 0.014. This suggests that green imports are accompanied by complementary capital investment, but this channel explains only a small part of the estimated productivity effect.

Although both channels are statistically significant, the small changes in the green import coefficients suggest that labor cost adjustment and capital deepening play a supporting rather than dominant role in explaining the productivity gains associated with green imports. These results provide support for H3a and H3b.

Table 9. *Supporting Mechanism Analysis: Labor Cost and Capital Intensity Channels*

Panel A: Labor Cost per Employee			
	TFPR (WLD)	Emp. Costs	*TFPR (WLD)*
	(1)	(2)	(3)
Green Imp.	0.014***	0.007***	0.012**
	(0.005)	(0.001)	(0.005)
Emp. costs			0.196***
			(0.008)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes
Obs.	327,058	325,027	325,027
Panel B: Capital intensity			
	TFPR (WLD)	Capital intensity	*TFPR (WLD)*
	(4)	(5)	(6)
Green Imp.	0.015***	0.017***	0.014***
	(0.005)	(0.002)	(0.005)
Capital intensity			0.038***
			(0.007)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes
Obs.	327,058	327,058	327,058

Notes: In Panel A, the dependent variable in Column (2) is the log of deflated labor costs per employee. In Panel B, the dependent variable in Column (5) is the log of capital intensity, measured as fixed assets per employee. All regressions include firm and region-by-year fixed effects and the full set of control variables. Robust standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Source: Statistics Estonia, author's calculations.

5.5. Robustness checks

5.5.1. Alternative import controls and scaling

To address the concern that our results may capture a general import effect rather than a green-specific channel, Table 10 reports estimates with automation imports included as an additional control (Acemoglu & Restrepo, 2022). The coefficient on green imports remains stable across all specifications. While automation imports are significant in some specifications, the green import coefficient is unaffected by their inclusion, demonstrating that the estimated effect is not driven by general capital goods imports.

Appendix Table A6 replaces the baseline green import measure with the log green imports per employee. The estimated coefficients remain positive and statistically significant across all productivity measures, confirming that the baseline results are not driven by firm scale.

Table 10. Green Imports and Automation Imports: Fixed Effects Estimates

	TFPR (WLD)	*Log LP (Sales)*	*Log LP (VA)*	*Log Elec.*
	(1)	(2)	(3)	(4)
Green Imp.	0.014***	0.016***	0.011***	0.015*
	(0.005)	(0.001)	(0.001)	(0.008)
Auto. Imp.	-0.004	0.006***	0.003**	0.008
	(0.009)	(0.001)	(0.001)	(0.006)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Obs.	327,058	327,058	327,058	3,644

Note: Robust standard errors clustered at the firm level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Source: Statistics Estonia, author's calculations.

5.5.2. A stricter HS6 × NACE identification rule

A further concern is that some HS6 product codes may capture dual-use goods that can be used in both green and non-green applications. To address this issue, we implement an additional robustness check based on a stricter HS6 × NACE cross-referencing rule. Under this definition, an import transaction is classified as green only when both the imported product's HS6 code and the importing firm's 4-digit NACE industry code jointly satisfy the green-technology taxonomy.

Table 11 reports the corresponding CSDID estimates. The results do not provide credible evidence of a robust productivity effect under the strict matching definition. Most post-treatment estimates are statistically insignificant. The only significant coefficient appears for Log LP(VA), with a post-treatment ATT of 0.895. However, this estimate cannot be interpreted causally because the joint pre-trend test strongly rejects parallel trends. More generally, the pre-trend tests reject the null of parallel trends for all four outcomes, with p-values of 0.036, 0.046, 0.000, and 0.000, respectively.

Diagnostic evidence reported in Appendix Tables A7-A9 suggests that this weak performance reflects a structural mismatch between the strict matching rule and the Estonian import structure. The HS6 × NACE rule is concentrated in manufacturing, utilities, and waste-management industries, while actual HS6 green-candidate imports in Estonia enter largely through wholesale and trading firms. Since customs data record the importer at the border rather than the final domestic user, the strict rule excludes many green-technology goods that may be resold to downstream users. This suggests that the strict HS6 × NACE measure under-covers relevant green-technology flows in Estonia. For this reason, the baseline HS-based measure remains more suitable for capturing product-level green import exposure in this setting.

Table 11. *Event-Study Estimates under HS6 × NACE Strict Matching*

	TFPR (WLD)	*Log LP(Sales)*	*Log LP(VA)*	*Log Elec.*
	(1)	(2)	(3)	(4)
Pre avg.	0.007	0.222	0.136	0.143
	(0.040)	(0.258)	(0.906)	(0.351)
Post avg.	0.013	0.121	0.895**	0.367
	(0.064)	(0.872)	(0.433)	(0.275)
Pre-trend joint test	0.036	0.046	0.000	0.000
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

	TFPR (WLD)	*Log LP(Sales)*	*Log LP(VA)*	*Log Elec.*
	(1)	(2)	(3)	(4)
Controls	Yes	Yes	Yes	Yes
Obs.	312,949	312,949	312,949	3,365

Notes: This table reports CSDID estimates using the HS6 × NACE strict-matching treatment definition. Pre avg. and Post avg. report average pre-treatment and post-treatment ATT estimates. The pre-trend joint test reports p-values for the null hypothesis of parallel pre-treatment trends. Robust standard errors are reported in parentheses. ** $p<0.05$.

Source: Statistics Estonia, author's calculations.

5.5.3. Placebo tests

We further assess the robustness of the CSDID results using placebo tests. Table 12 reports estimates based on artificially shifting the treatment timing by -2, -1, +1, and +2 years relative to the actual first-adoption year. Across all specifications, the parallel trends assumption is satisfied. When treatment timing is moved forward, the estimated effects are positive but statistically insignificant. When treatment is delayed, the coefficients become negative and remain insignificant.

Figure 7 presents the results from a randomization-based placebo test. Treatment status is randomly assigned across firms, and the model is re-estimated 200 times. The distribution of the estimated coefficients is centered around zero and roughly symmetric, suggesting no systematic effect under random assignment. These results indicate that our CSDID estimation is not driven by spurious assignment.

Table 12. *Placebo Tests: Artificial Treatment Timing*

	-2 Years	-1 Year	+1 Year	+2 Years
	(1)	(2)	(3)	(4)
Pre avg.	-0.017	-0.024	0.014	-0.014
	(0.049)	(0.039)	(0.028)	(0.027)
Post avg.	0.121	0.117	-0.125	-0.006
	(0.084)	(0.080)	(0.104)	(0.097)
Pre-trend joint test	0.358	0.215	0.537	0.547
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Controls	Yes	Yes	Yes	Yes
Obs.	290,063	301,704	311,657	309,084

Notes: The dependent variable is TFPR (WLD) across all specifications. The table reports CSDID estimates with artificially shifted treatment timing. The pre-trend joint test reports the p-value for the null hypothesis that all pre-treatment coefficients are jointly equal to zero. All regressions include firm and year fixed effects and the full set of control variables. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Source: Statistics Estonia, author's calculations.

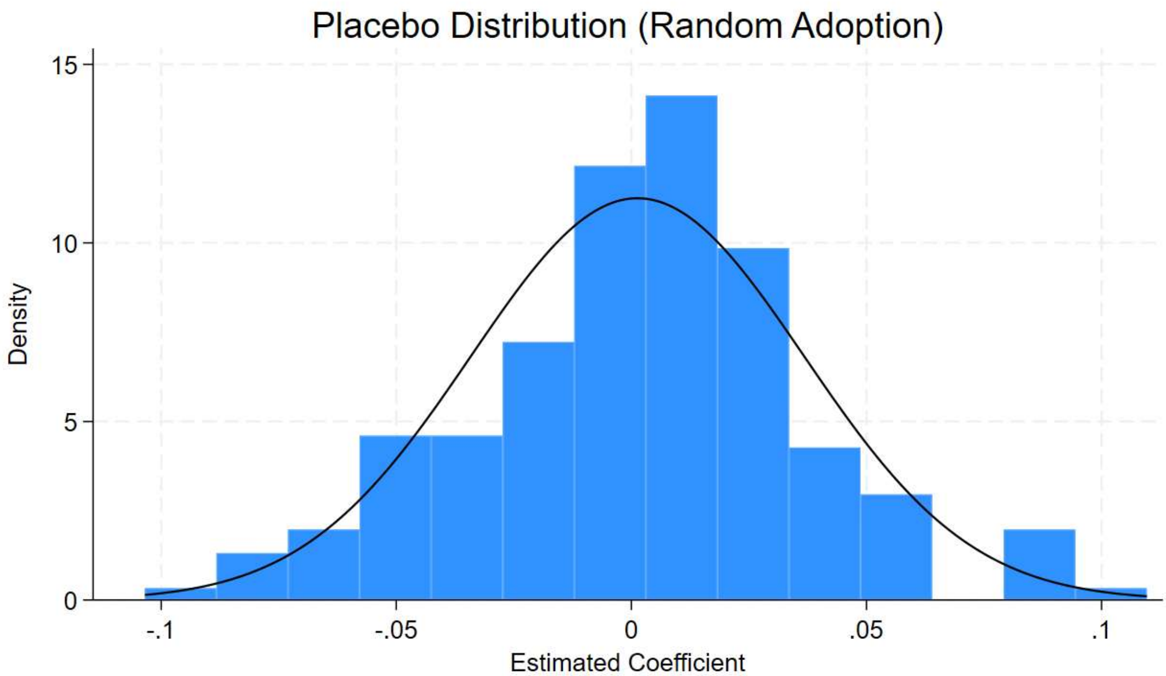

Figure 7. Placebo Distribution (Random Adoption)

Note: The figure displays the distribution of estimated ATT coefficients from 200 CSDID regressions in which treatment status is randomly assigned across firms. Each estimate is obtained using the same preferred first-adoption CSDID specification as in Column 2 of Table 7, with TFPR (WLD) as the dependent variable. The distribution is centered around zero, providing no evidence of systematic treatment effects under random assignment.

Source: Statistics Estonia, author's calculations.

5.6. Heterogeneous effects

This section conducts heterogeneous effects analysis by subgroups, including sector, region, firm age, and firm size.

Table 13 reports heterogeneous effects across sectors. Statistically significant average treatment effects are observed in manufacturing and services, with post-treatment ATT estimates of 0.340 and 0.164, respectively. Construction also shows a positive and marginally significant effect of 0.112. In contrast, the food and wood sectors show negative but statistically insignificant average effects, while the public and energy sectors show positive but insignificant average effects. The dynamic estimates suggest that productivity gains in manufacturing and services strengthen over time, reaching 0.849 and 0.325 by T = 5, respectively. Construction shows positive but less persistent effects, while the energy sector displays some positive medium-term estimates but no significant average effect. Overall, the sectoral results suggest that the productivity gains from green imports are concentrated mainly in manufacturing and services, with weaker evidence for other sectors.

Table 14 further explores heterogeneity within manufacturing and services. In manufacturing, productivity gains are concentrated in higher-technology industries, where the post-treatment ATT is 0.315 and statistically significant at the 5% level. Lower-technology manufacturing shows positive dynamic effects in later periods, but the average post-treatment effect is not statistically significant. In services, the effect is concentrated in less knowledge-intensive services, with a significant post-treatment ATT of 0.164, while knowledge-intensive services show no significant response. These results indicate that the productivity gains from green imports are strongest in sectors where imported green goods are more likely to be linked to tangible process upgrading and operational efficiency improvements.

Further heterogeneous effect analyses are reported in Appendix Tables A10 and A11. By region, the strongest productivity gains are found in North-Eastern Estonia, with a post-treatment ATT of 0.816. The dynamic estimates for this region also become larger over time, reaching 1.945 by T = 5. This may reflect the region’s heavier industrial base and greater exposure to pollution-intensive activities, which leave more room for productivity gains from green transition. In contrast, the estimates for Northern Estonia are positive but statistically insignificant, consistent with the idea that firms in the capital region and the most developed part of the economy may already operate closer to the efficiency frontier. By firm characteristics, the effects are concentrated among older firms and micro firms. Firms older than six years show a significant post-treatment ATT of 0.183, while micro firms show a smaller but marginally significant effect of 0.170. These patterns suggest that the productivity benefits of green imports are stronger among firms with accumulated operational experience and among smaller firms with greater room for efficiency improvement.

Table 13. *Heterogeneous Effects by Sectors*

Panel A: Average Effects							
	Sector						
	Mfg.	Services	Food	Wood	Const.	Public	Energy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pre avg.	0.016	-0.024	-0.007	0.059	0.066	-0.074	-0.078
	(0.055)	(0.037)	(0.102)	(0.137)	(0.034)	(0.063)	(0.200)
Post avg.	0.340**	0.164**	-0.309	-0.217	0.112*	0.011	0.382
	(0.163)	(0.081)	(0.219)	(0.401)	(0.068)	(0.156)	(0.323)
Panel B: Dynamic Effects							
T=0	0.168**	0.088	-0.130*	-0.199	0.055*	0.125*	0.245
	(0.071)	(0.056)	(0.077)	(0.188)	(0.032)	(0.073)	(0.256)
T=1	0.092	0.122*	-0.154*	-0.274	0.094*	0.099	0.351*
	(0.120)	(0.068)	(0.084)	(0.299)	(0.048)	(0.085)	(0.201)
T=2	0.120	0.125	-0.169*	-0.502	0.029	-0.135	0.492*
	(0.153)	(0.081)	(0.099)	(0.433)	(0.046)	(0.256)	(0.285)
T=3	0.238	0.129	-0.480	-0.223	0.077	-0.123	0.552
	(0.192)	(0.106)	(0.335)	(0.502)	(0.088)	(0.259)	(0.349)
T=4	0.571**	0.195	-0.470	-0.119	0.179	-0.147	0.625
	(0.263)	(0.130)	(0.422)	(0.617)	(0.117)	(0.312)	(0.488)
T=5	0.849**	0.325**	-0.450	0.017	0.240	0.244	0.025
	(0.430)	(0.145)	(0.524)	(0.668)	(0.189)	(0.333)	(0.888)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	18,717	159,041	13,982	12,181	46,139	11,932	7,459

Notes: The dependent variable is TFPR (WLD) across all specifications. The table reports CSDID estimates by sector. Industry classifications follow the Estonian value chain structure: Manufacturing covers EMTAK 13-33 excluding 16 and 17; Market services covers EMTAK 45-96 excluding 56 and 84-88; Food covers primary production (EMTAK 01, 03), processing (10, 11), and food services (56); Wood covers forestry (02), wood processing (16), and paper manufacturing (17); Construction covers EMTAK 41-43; Public sector covers

EMTAK 84-88; Energy and utilities covers EMTAK 05-09 and 35-39. Robust standard errors in parentheses.

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

Source: Statistics Estonia, author’s calculations.

Table 14. *Heterogeneous Effects by Technological Intensity in Manufacturing and Knowledge Intensity in Services*

Panel A: Average Effects				
	Manufacturing		**Services**	
	Higher tech	Lower tech	KIS	Less-KIS
	(1)	(2)	(3)	(4)
Pre avg.	0.039	0.049	0.051	-0.044
	(0.085)	(0.096)	(0.055)	(0.037)
Post avg.	0.315**	0.167	-0.028	0.164**
	(0.142)	(0.123)	(0.195)	(0.074)
Panel B: Dynamic Effects				
T=0	0.081	-0.012	-0.051	0.147***
	(0.083)	(0.069)	(0.114)	(0.052)
T=1	-0.024	-0.024	0.012	0.131**
	(0.134)	(0.095)	(0.144)	(0.064)
T=2	0.158	0.057	0.048	0.123
	(0.126)	(0.113)	(0.166)	(0.078)
T=3	0.282*	0.105	-0.069	0.132
	(0.154)	(0.155)	(0.216)	(0.099)
T=4	0.568***	0.383*	-0.087	0.087
	(0.217)	(0.220)	(0.286)	(0.126)
T=5	0.822*	0.492**	-0.022	0.363***
	(0.435)	(0.250)	(0.381)	(0.135)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	15,312	13,943	49,860	107,412

Notes: The dependent variable is TFPR (WLD). The table reports CSDID estimates split by technological and knowledge intensity. Higher tech manufacturing includes high-technology and medium-high-technology industries (EMTAK 20, 21, 22-25, 26, 27, 28, 29, 30, 33). Lower tech manufacturing includes low-technology industries (EMTAK 13, 14, 15, 18, 19, 31, 32). Knowledge-intensive services (KIS) include information and communication (58-63), financial and insurance activities (64-66), and professional, scientific and technical activities (69-75). Less knowledge-intensive services (Less-KIS) include wholesale and retail trade, transportation, accommodation (45-56), administrative and support services (77-82), and other service activities (90-96). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Source: Statistics Estonia, author's calculations.

6. Discussion and Conclusion

Our results suggest that the productivity effects of green transition do not follow a simple one-directional logic. Instead, they combine direct gains with network frictions, and these effects are distributed unevenly across firms. On the one hand, green imports raise firm productivity, with gains appearing immediately after treatment and continuing to strengthen over time. On the other hand, the consequences of green transition are not confined to adopting firms themselves. They also travel through value chain linkages and generate short-run adjustment costs that are directionally asymmetric. Therefore, green transition is not well understood as either merely a compliance burden imposed by environmental regulation or an efficiency gain associated with technological upgrading. It is better seen as a dynamic process involving both technological upgrading and value chain adaptation.

A central finding is the directional asymmetry in how the green transition is transmitted through production networks. Green transition by upstream suppliers reduces the productivity of downstream firms in the short run, but this negative effect weakens over subsequent lags. By contrast, the green activities of downstream firms do not produce a significant effect on upstream firms. This finding is related to the production-network literature, which shows that shocks can propagate through input-output linkages (Acemoglu et al., 2012). Kashiwagi et al. (2021) further show that value-chain shocks can be transmitted through both supplier and customer linkages. At the same time, the result differs from the literature that usually emphasizes positive spillovers from upstream technological investment to downstream firms. For example, Guo et al. (2024) find that digital infrastructure promotes the green transformation of downstream firms, while Lin et al. (2025) show that digital transformation improves the green total factor productivity of upstream suppliers. By contrast, our evidence suggests that when the shock takes the form of upstream green transition, the immediate effect on downstream firms can be negative, because downstream firms may need time to adapt to changes in the inputs provided by upstream suppliers. These short-run frictions are consistent with our dynamic results, which show that the negative upstream spillover weakens over time. Moreover, this study complements recent work on green transition spillovers through upstream and downstream linkages (e.g. Guo et al., 2024; Lin et al., 2025) by incorporating Katz centrality and showing that the magnitude of spillovers also depends on firms' position in the production network.

The dynamic estimates reveal a clear pattern. Hart and Ahuja (1996) show that the economic returns to environmental investment often emerge with a lag. The results here point in a similar pattern, but they reveal a more specific trajectory. The positive effect of green imports does not simply appear later: it begins right after treatment and then becomes stronger over time. In other words, the gains from green transition are not realized all at once. They accumulate as firms gain experience with new technologies and move through a process of internal adaptation. Thompson (2012) offers a useful explanation by showing that accumulated experience can lower unit costs. This also implies that static estimators are likely to underestimate the longer-run productivity effects of the green transition.

The mechanism analysis points in a similar direction. Green imports affect productivity partly through changes in labor costs and capital intensity, but these channels account for only a limited share of the total effect. This does not contradict earlier work. Bello-Pintado et al. (2019) argue that skill upgrading is often accompanied by higher labor costs, while Zhang and Ke (2022) emphasize that green imports may induce capital deepening. The evidence here suggests, however, that these channels explain only part of the effect. Green imports do more than replace equipment and intermediate inputs. They also bring new knowledge, production routines, and managerial demands into the firm. The main driver appears to be not simply a reallocation of factor inputs, but a deeper process of technological absorption and organizational learning. In that sense, the learning-by-doing mechanism emphasized by Foster and Rosenzweig (1995) provides a plausible explanation: firms improve as they use the new technology and gradually turn experience into efficiency gains.

The heterogeneity results show that productivity gains are concentrated in manufacturing and market services. Within those broad groups, the strongest effects appear in high-technology manufacturing and less knowledge-intensive services, while small firms and mature firms also experience larger gains. This indicates that the returns to green transition depend not only on adoption itself, but also on firms' production structure, initial technological conditions, and absorptive capacity. In manufacturing, green imports are often directly embedded in production and can therefore more easily translate into gains through equipment renewal, energy savings, and process improvements. In some service industries, by contrast, green technologies are more likely to matter indirectly, through process optimization, better resource allocation, and changes in organizational and reputational dimensions (Ström, 2020; Aithal and Jeevan, 2016). Within services, the stronger effect for less knowledge-intensive activities may reflect their lower initial technological base and therefore their greater room for marginal improvement. Stronger gains are also found among small firms, which are in line with Cuerva et al. (2014) and Muangmee et al. (2021), who argue that SMEs may enjoy higher marginal returns from green innovation. By contrast, the larger gains among mature firms differ from the view advanced by Karpenko et al. (2021), who indicate that younger firms in the growth stage are better positioned to integrate green technologies. These results suggest that the benefits of green transition are not uniform, but depend on sectoral conditions and firm characteristics.

For firms, green imports should not be viewed merely as an added cost, but rather as an investment that may generate lasting productivity gains. Those gains, however, often come with a period of value chain adaptation. Firms undertaking green upgrading therefore need to look beyond the technology purchase itself and consider how adoption may affect production planning, input coordination, and relationships with both upstream and downstream partners. This is especially important for firms that depend heavily on upstream suppliers. For them, it is important to identify their exposure early, allow time for adjustment, and coordinate more closely with suppliers and customers to reduce short-run disruption.

For governments, the economic effects of green transition should not be assessed solely in terms of the direct gains accruing to adopting firms. Short-run costs within production networks also need to be taken into account. Since upstream green transition lowers downstream productivity in the short run, but the magnitude of this effect declines over time, broad long-term subsidies may be less appropriate than more targeted support aimed at transitional frictions. Downstream firms that are highly exposed to upstream green upgrading may need temporary adjustment assistance. Central firms that occupy systemically important positions in the network may also warrant closer monitoring and early-warning mechanisms.

These implications are especially relevant in the Estonian case. Survey evidence shows that many Estonian firms still see green transition more as a cost pressure than as a strategic opportunity (Kekkonen et al., 2023; Pesor et al., 2024). The results here suggest that this perception may reflect not only firms’ own investment costs, but also short-run external shocks transmitted through production networks. Given the highly interconnected structure of the Estonian economy, and the dominant role played by a relatively small number of central firms (Criscuolo et al., 2024), policies that overlook value chain structure and firm heterogeneity may underestimate transitional frictions and misjudge policy effectiveness.

Several limitations should be noted. First, green import-based measures provide a useful way to capture firm-level green transition, but they do not cover all forms of green upgrading, especially those achieved through R&D or non-trade channels. Second, although the mechanism analysis offers supportive evidence, it does not fully identify all the channels through which imported green technologies raise productivity. The interpretation of direct technology transfer and learning effects, therefore, rests more on indirect evidence and elimination logic than on direct causal identification. Third, the analysis focuses on Estonia, where imported technologies play an especially important role in firms’ green upgrading. Similar approaches have also been applied in larger countries (Domini et al., 2022; Pavlenkova et al., 2024). The more relevant question is therefore not whether the framework applies elsewhere, but how much the estimated effects depend on national context. Future work could extend this framework by incorporating other forms of green investment and green organizational change, comparing transmission patterns across countries, and examining more directly how firms’ internal capabilities, management practices, and absorptive capacity shape the productivity effects of green transition.

Overall, green transition is not simply a matter of environmental policy or compliance costs. It is also an economic process involving technology adoption, changing modes of production, and adaptation along the value chain. It can generate substantial productivity gains, but those gains do not arise automatically for all firms or at every stage of the process.

The short-run frictions, directional spillovers, and uneven distribution of effects that accompany transition are just as important for understanding its economic consequences. For small open economies, the overall efficiency of green transition may depend on how successfully policy can promote adoption while easing transitional costs within production networks.

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Appendix

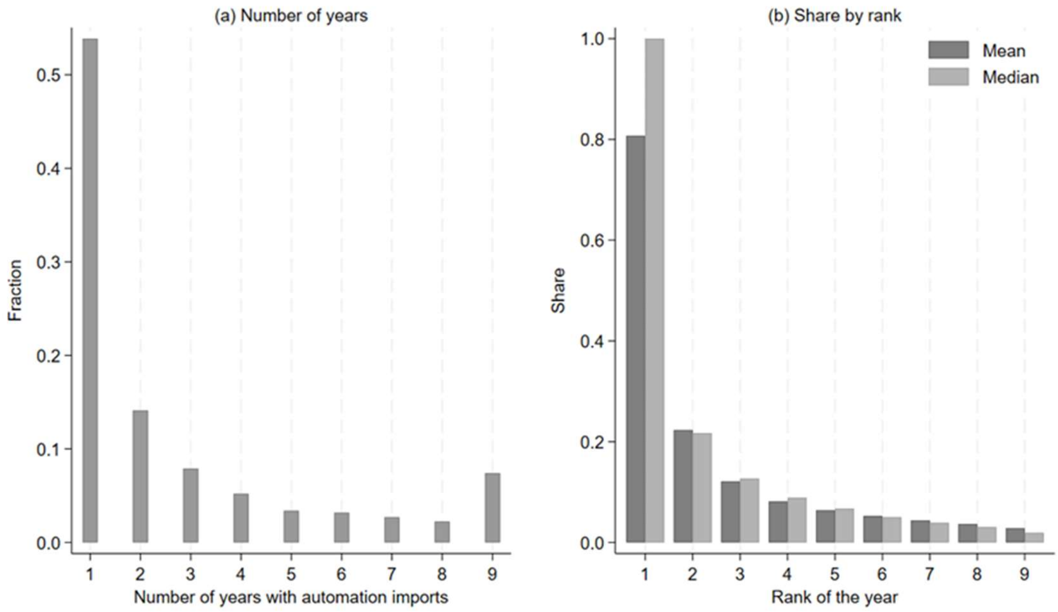

Figure A1. Lumpiness of Automation Imports

Notes: Panel (a) shows the distribution of firms by the number of years with positive automation imports during 2015-2023. Panel (b) shows the mean and median share of total automation import value accounted for by each ranked year. Automation imports are identified based on the classification of Acemoglu and Restrepo (2022), as operationalized by Domini et al. (2022), covering industrial robots (HS 847950), dedicated machinery (HS 847989), numerically controlled machine tools (HS 8456-8462), welding machines (HS 8515), weaving and knitting machines (HS 8446-8447), conveyors (HS 8428), regulating instruments (HS 9032), and 3D printers (HS 847780).

Source: Statistics Estonia, author's calculations.

Table A1. *Kolmogorov-Smirnov Tests for Outcome Variables*

Variable	Combined K-S	p-value
TFPR (WLD)	0.1141	0.000
Log LP (VA)	0.3652	0.000
Log LP (Sales)	0.4704	0.000
Log Elec.	0.2083	0.000

Notes: This table reports two-sample Kolmogorov-Smirnov tests comparing the unconditional distributions of firms with and without green imports for the main outcome variables. The reported statistic is the combined K-S statistic.

Source: Statistics Estonia, author's calculations.

Table A2. *Distribution of Green Imports by Industry*

Panel A: Cumulative 2015-2023						
Rank	By import value	Value (€ mil.)	Share (%)	By number of firms	N firms	Share (%)
1	Wholesale trade	415.8	21.5	Wholesale trade	2,027	23.4
2	Retail trade	193.5	10.0	Retail trade	850	9.8
3	Motor vehicle trade	126.1	6.5	Motor vehicle trade	524	6.0
4	Specialized construction	81.4	4.2	Specialized construction	335	3.9
5	Fabricated metals	68.2	3.5	Fabricated metals	314	3.6
6	Computer programming	64.8	3.3	Repair and installation	241	2.8
7	Repair and installation	51.8	2.7	Computer programming	228	2.6
8	Warehousing	43.2	2.2	Warehousing	215	2.5
9	Other professional services	41.1	2.1	Real estate	195	2.2
10	Real estate	39.8	2.1	Wood products	171	2.0
Panel B: 2015 vs 2023 (by import value)						
Rank	2015 Industry	Value (€ mil.)	Share (%)	2023 Industry	Value (€mil.)	Share (%)
1	Wholesale trade	122.0	31.2	Wholesale trade	206.0	30.7
2	Real estate	55.2	14.1	Civil engineering	102.0	15.2
3	Retail trade	19.4	5.0	Motor vehicle trade	81.7	12.2
4	Motor vehicle trade	19.3	4.9	Electronic products	31.3	4.7
5	Other non-metallic mineral products	16.9	4.3	Retail trade	27.7	4.1
6	Electrical equipment	14.5	3.7	Wood products	26.7	4.0
7	Fabricated metals	13.0	3.3	Motor vehicles manufacturing	25.5	3.8
8	Electronic products	11.6	3.0	Electrical equipment	22.0	3.3
9	Warehousing	9.6	2.5	Electricity, gas and steam supply	21.2	3.2
10	Repair and installation	7.7	2.0	Fabricated metals	13.5	2.0

Notes: Panel A reports the top 10 industries by cumulative green import value (left) and by number of distinct firms with positive green imports (right) over 2015-2023. Panel B compares the top 10 industries by import value in 2015 (left) and 2023 (right). Industries are classified by NACE Rev. 2 two-digit codes. Values are in millions of euros.

Source: Statistics Estonia, author's calculations.

Table A3. *The Share of Firms Importing Green Goods by Category*

Grouping variable	Green importer (%)	APC (%)	CRE (%)	EPP (%)	HEM (%)	MON (%)	NRP (%)	NVA (%)	REP (%)	SWM (%)	SWR (%)	WAT (%)
Whole sample	6.30	1.34	0.98	0.23	2.38	2.15	0.07	0.47	3.40	2.11	0.24	3.23
2015	6.52	1.34	0.90	0.26	2.57	2.20	0.07	0.45	3.57	2.05	0.22	3.49
2019	6.45	1.41	1.02	0.23	2.51	2.12	0.06	0.47	3.47	2.17	0.25	3.32
2023	5.41	1.20	0.89	0.21	1.88	1.90	0.05	0.46	2.88	1.79	0.21	2.69
Mfg.	2.13	0.25	0.11	0.02	0.55	0.25	0.01	0.03	0.73	0.43	0.02	0.95
Services	2.42	0.36	0.27	0.09	0.82	0.74	0.00	0.07	1.34	0.51	0.06	0.92
Food	4.12	0.39	0.14	0.10	1.32	0.79	0.05	0.06	1.28	2.00	0.16	1.69
Wood	4.97	0.70	0.19	0.07	1.93	1.11	0.02	0.07	2.41	2.06	0.07	1.93
Const.	18.91	3.48	1.41	0.42	7.39	6.09	0.09	0.76	10.05	7.29	0.36	10.19
Public	6.80	1.66	1.40	0.31	2.65	2.53	0.10	0.67	3.87	2.19	0.33	3.64
Energy	0.97	0.05	0.06	0.01	0.19	0.32	0.00	0.02	0.23	0.08	0.00	0.33

Notes: The table report the percentage of firms with positive imports in the indicated OECD environmental goods category within each group. "Green importer" denotes firms with positive imports of OECD environmental goods. Mfg. = manufacturing; Food = food industry; Wood = wood industry; Const. = construction; Public = public sector; Energy = energy sector. APC = air pollution control; CRE = cleaner and renewable energy; EPP = environmentally preferable products; HEM = heat and energy management; MON = environmental monitoring; NRP = natural resources protection; NVA = noise and vibration abatement; REP = renewable energy plant; SWM = solid waste management; SWR = sewerage and wastewater recycling; WAT = water supply and treatment.

Source: Statistics Estonia, author's calculations.

Table A4. *Baseline Fixed Effects Estimates Excluding ROE*

	TFPR (WLD)	*Log LP (Sales)*	*Log LP (VA)*	*Log Elec.*
	(1)	(2)	(3)	(4)
Green Imp.	0.014***	0.017***	0.012***	0.016**
	(0.005)	(0.001)	(0.001)	(0.007)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Obs.	327,058	327,058	327,058	3,644

Notes: ROE is excluded from the control set. Robust standard errors clustered at the firm level are reported in parentheses. All specifications are estimated using firm fixed effects and region-by-year fixed effects. *** p<0.01, ** p<0.05, * p<0.10.

Source: Statistics Estonia, author's calculations.

Table A5. *Dynamic Treatment Effects: Alternative Productivity Measures*

	Log LP (VA)	*Log LP (Sales)*	*Log Elec.*
	(1)	(2)	(3)
Pre avg.	0.024***	0.023***	0.078*
	(0.007)	(0.007)	(0.041)
Post avg.	0.019	-0.003	-0.082
	(0.013)	(0.012)	(0.252)
year = 0	0.026**	0.035***	-0.007
	(0.012)	(0.010)	(0.050)
year = 1	0.043***	0.024*	-0.126
	(0.014)	(0.013)	(0.163)
year = 2	0.018	-0.004	-0.306
	(0.016)	(0.015)	(0.245)
year = 3	-0.000	-0.023	-0.155
	(0.019)	(0.018)	(0.354)
year = 4	0.012	-0.036*	-0.003
	(0.021)	(0.020)	(0.413)
year = 5	0.012	-0.011	0.104
	(0.027)	(0.024)	(0.525)
Pre-trend joint test	0.024	0.001	0.002
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Obs.	291,754	291,754	2,364

Note: All regressions include firm and year fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Source: Statistics Estonia, author's calculations.

Table A6. *Baseline Fixed-Effects Estimates Using Green Imports per Employee*

	TFPR (WLD)	*Log LP(Sales)*	*Log LP(VA)*	*Log Elec.*
	(1)	(2)	(3)	(4)
Green Imp.	0.017***	0.023***	0.016***	0.026**
	(0.006)	(0.001)	(0.001)	(0.012)
Size	0.242***	-0.356***	-0.257***	-0.145
	(0.037)	(0.009)	(0.010)	(0.198)
$Size^2$	0.004	0.004	-0.002	-0.015
	(0.014)	(0.003)	(0.004)	(0.035)
Age	0.329***	0.374***	0.381***	0.112
	(0.044)	(0.012)	(0.013)	(0.656)
Age^2	-0.049	-0.054***	-0.075***	0.151
	(0.032)	(0.007)	(0.008)	(0.246)
ROE	0.098***	0.102***	0.178***	-0.010
	(0.006)	(0.002)	(0.002)	(0.022)
Capital	0.038***	0.074***	0.077***	0.036
intensity	(0.007)	(0.002)	(0.002)	(0.040)
Foreign	0.008	0.023*	0.011	0.225***
owned	(0.046)	(0.013)	(0.014)	(0.081)
Market share	0.376***	0.250***	0.206***	0.010
	(0.070)	(0.007)	(0.006)	(0.039)
Firm FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
Obs.	327,058	327,058	327,058	3,644

Notes: The key explanatory variable is the log of green imports per employee, defined as ln(1 + green imports / number of employees). All specifications are estimated using firm fixed effects and region-by-year fixed effects. Standard firm-level controls are included in all regressions. Robust standard errors clustered at the firm level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Source: Statistics Estonia, author's calculations.

Table A7. *Green Import Identification Funnel*

Filtering Stage	Transactions	% of Total
Total import transactions (2010-2023)	3,107,414	100.000
HS6 on green candidate list	110,934	3.570
HS6 × NACE strict match	2,403	0.077

Notes: A transaction is classified as green only when both its 6-digit HS code and the importing firm’s 4-digit NACE industry code jointly satisfy the green-technology taxonomy. The NACE industry screen filters out 97.834% of HS6-candidate transactions.

Source: Statistics Estonia, author’s calculations.

Table A8. *Industry Coverage of the HS6 × NACE Green Rule*

NACE section	Description	Unique 4-digit codes	HS6 × NACE pairs
C (10-33)	Manufacturing	50	593
D (35)	Electricity and gas	7	151
E (36-39)	Water, waste, remediation	9	127
F (41-43)	Construction	8	50
H (49-52)	Transport and storage	11	40
M (71-72)	Professional and scientific	4	31
G (45, 47)	Motor vehicles and non-specialized retail	2	8
G (46)	Wholesale trade	0	0
Others	Administrative services and miscellaneous	6	20
Total		97	1,020

Notes: This table reports the industry coverage of the green-technology rule, aggregated by NACE section. The rule contains 1,020 HS6 × NACE 4-digit pairs across 97 unique four-digit industries. Manufacturing, utilities, and waste-management sectors account for 85.4% of rule entries. Wholesale trade, NACE division 46, is entirely absent from the rule by design.

Source: Statistics Estonia, author's calculations.

Table A9. *Top Importing Industries for HS6 Green-Candidate Transactions*

NACE 4-digit	Industry Description	Transactions
4669	Wholesale of other machinery and equipment	8,735
4690	Non-specialized wholesale trade	5,545
4511	Sale of cars and light motor vehicles	3,124
4652	Wholesale of electronic and telecom equipment	3,007
4531	Wholesale trade of motor vehicle parts	2,686
4674	Wholesale of hardware and plumbing equipment	2,552
4719	Other retail sale in non-specialized stores	2,122
4646	Wholesale of pharmaceutical goods	2,060
4711	Retail sale in non-specialized stores with food	1,926
4661	Wholesale of agricultural machinery and equipment	1,848
4675	Wholesale of chemical products	1,490
4778	Other retail sale of new goods in specialized stores	1,448
4673	Wholesale of wood and construction materials	1,349
4519	Sale of other motor vehicles	1,338

Notes: This table reports the industries most frequently associated with imports of HS6 green-candidate products after removing re-export transactions. Excluding observations with missing industry records, 13 of the 14 named top importing industries are not covered by the HS6 × NACE green rule. The only covered industry among them is NACE 4719, which contributes only one rule entry.

Source: Statistics Estonia, author's calculations.

Table A10. *Heterogeneous Effects by Region*

Panel A: Average Effects					
	Region				
	Northern	Central	North-Eastern	Western	Southern
	(1)	(2)	(3)	(4)	(5)
Pre avg.	-0.005	-0.081	0.312	0.074	0.025
	(0.039)	(0.191)	(0.248)	(0.100)	(0.093)
Post avg.	0.123	0.435	0.816**	0.168	0.226
	(0.105)	(0.377)	(0.394)	(0.272)	(0.216)
Panel B: Dynamic Effects					
T=0	-0.020	0.447*	0.319	0.276*	0.164
	(0.057)	(0.259)	(0.338)	(0.147)	(0.136)
T=1	0.098	0.243	0.699*	0.215	0.201
	(0.074)	(0.334)	(0.396)	(0.189)	(0.177)
T=2	0.082	0.549	0.194	0.082	0.209
	(0.108)	(0.369)	(0.369)	(0.255)	(0.222)
T=3	0.140	0.551	0.766*	-0.245	0.028
	(0.149)	(0.467)	(0.419)	(0.335)	(0.270)
T=4	0.083	0.245	0.923*	0.220	0.267
	(0.181)	(0.554)	(0.561)	(0.463)	(0.305)
T=5	0.353	0.578	1.945**	0.457	0.488
	(0.226)	(0.726)	(0.823)	(0.518)	(0.418)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	162,122	25,346	14,690	35,089	65,953

Notes: The dependent variable is TFPR (WLD) across all specifications. The table reports CSDID estimates. All regressions include firm and year fixed effects and the full set of control variables. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Source: Statistics Estonia, author's calculations.

Table A11. *Heterogeneous Effects by Firm Age and Size*

Panel A: Average Effects				
	Firm age		**Size**	
	Age ≥ 6 years	Age < 6 years	Micro firms (0-9)	Non-micro firms (≥10)
	(1)	(2)	(3)	(4)
Pre avg.	-0.019	-0.024	0.012	-0.020
	(0.046)	(0.072)	(0.040)	(0.068)
Post avg.	0.183**	0.036	0.170*	0.098
	(0.094)	(0.212)	(0.099)	(0.165)
Panel B: Dynamic Effects				
T=0	0.118*	0.125	0.056	0.071
	(0.062)	(0.106)	(0.055)	(0.100)
T=1	0.172**	0.165	0.183**	0.086
	(0.077)	(0.196)	(0.072)	(0.120)
T=2	0.133	0.224	0.141	0.091
	(0.093)	(0.256)	(0.098)	(0.156)
T=3	0.112	-0.370	0.117	0.232
	(0.121)	(0.560)	(0.138)	(0.219)
T=4	0.172	—	0.171	-0.009
	(0.146)	—	(0.175)	(0.262)
T=5	0.393**	—	0.353*	0.115
	(0.180)	—	(0.214)	(0.339)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	212,549	69,106	262,800	43,435

Notes: The dependent variable is TFPR (WLD) across all specifications. The table reports CSDID estimates. All regressions include firm and year fixed effects and the full set of control variables. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Source: Statistics Estonia, author's calculations.

Declaration of AI Use

I used ChatGPT as an auxiliary tool during the preparation of this thesis. The tool was used mainly for language editing, improving academic clarity, checking the structure of selected paragraphs, assisting with the wording of the Estonian summary, and debugging and improving parts of the Stata and R code used for data processing and empirical analysis. The empirical design, data construction, estimation choices, interpretation of results, tables, figures, and final conclusions were developed and checked by the author. All references included in the thesis were manually verified, and no AI-generated references were used without independent checking.

A typical prompt used was: “Please revise the following paragraph to improve academic clarity and grammar while preserving the original meaning and empirical interpretation.

Resümee

ROHEÜLEMINEK EESTI ETTEVÕTETES JA SELLE MÕJU ETTEVÕTETE TEGEVUSEDUKUSELE

Jiahao Zhu

Dekarboniseerimissurve tugevnemise tõttu peavad ettevõtted üha enam kohandama oma tootmisstrateegiaid roheülemineku tingimustes. Üha olulisemaks on muutunud mõista, kas selline kohanemine parandab ettevõtete tootlikkust ning kuidas selle mõjud kanduvad edasi tootmisvõrgustikes ning väärtusahelates. Käesolev magistritöö lähtub raamistikust, mille kohaselt mõjutab rohepööre ettevõtte tulemuslikkust tehnoloogilise uuendamise ja õppimise kaudu, tekitades samal ajal ajutisi kohanemisraskusi ostja-tarnija seostes.[6] Kasutades Eesti administratiivandmeid aastatest 2015-2023 Äriregistrist, detailsest ettevõtte ja toote põhisest väliskaubanduse statistikast ning käibemaksudeklaratsioonidest ettevõtete-vaheliste tehingute kotha, mõõdetakse ettevõtte tasandi roheüleminekut keskkonnakaupade impordi kaudu ning selle mõjusid hinnatakse Callaway ja Sant'Anna (2021) erinevuste erinevuse (*differences in differences*) meetodi abil koos ettevõtete võrgustike põhiste roheülemineku mõjudele avatuse näitajatega. Tulemused näitavad, et roheimport suurendab ettevõtte tootlikkust ning see mõju tugevneb ajas. Seevastu vähendab ülesvoolu ettevõtete rohepööre lühiajaliselt allavoolu ettevõtete tootlikkust, kuigi see negatiivne ülekandeefekt taandub ettevõtete kohanemise käigus. Tööjõukulude ja kapitaliintensiivsuse muutused selgitavad vaid piiratud osa kogumõjust. Tulemused viitavad sellele, et roheüleminek on laiem tehnoloogilise ja organisatsioonilise kohanemise protsess, mille positiivsed mõjud ilmnevad aja jooksul ning mille kohanemiskulud võivad kanduda kliendi ja tarnijasuhete kaudu seotud ettevõteteni. Need tulemused niisiis rõhutavad vajadust, et nii teadlased kui ka poliitikakujundajad liiguksid ettevõttepõhisest analüüsist kaugemale ning arvestaksid rohepöörde laiemat ettevõtete võrgustiku põhist konteksti.

[6] Näiteks võivad sellised kohanemisraskused tekkida sisendite tehniliste spetsifikatsioonide muutumisel, tootmisprotsesside kohandamisel või uute tarnetingimustega kohanemisel.

Märksõnad: rohepööre; ettevõtte tootlikkus; väärtusahela ülekandemõjud; roheimport; dünaamilised mõjud.

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Jiahao Zhu

17/05/2026