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Wired for Success: Exploring the impact of Digital Transformation Strategy on Firms and Employment in the Digital Gateway to Europe, The Netherlands

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Abstract

This paper aims to explore the impact of digital transformation strategies in firm and employment outcomes within the context of Europe's most wired economy- The Netherlands. With a paradigm shift towards digital readiness, there is a dire need to understand the implications of digital integration on firms and employees. With the help of a Difference-in-Differences, quasi-experimental design, this study analyzes firm and employment level data over the 40 COROP regions within the Netherlands with a focus on high and low Iot favoring industries between 2005 to 2020. An additional analysis of the differences in outcomes for the impact of digital transformation strategies, between 3 macro-economic zones within the country is also conducted. The results indicate a strong association between digital transformation strategies and the number of firms and jobs in IoT ready industries. This study contributes to the body of work that attempts to understand the dynamic nature of digital strategies, why digital transformations work, and what makes them successful.

Contents

1 Introduction

As technology evolves at a rapid pace, we witness a paradigm shift in our fundamental way of working. The digital transformation of societies call for the integration of digital technologies embedded deeply within our economies and the actors that make them run. Shifts in how we live, work, and interact with the world around us are driven by advancements in artificial intelligence and big data. This transformation therefore, plays a crucial role in shaping the future of firms and innovation.

The term "Digital Transformation" was first coined in the year 2000 (Patel and McCarthy, 2000) and much like technology, its definition has only evolved since. The concept resides on a similar wavelength of "digitization" or "digitalisation," but is generally considered as the broader transformation in comparison to the aforementioned terms (Veldhoven and Vanthienen 2021).

As the world spearheads towards an entirely digitally connected network, firms do not spare any opportunity to digitize their operations. A SAP business insight study conducted in collaboration with Oxford Economics found that leading companies that underwent digital transformations earn higher profits, revenues, and have a more competitive differentiation than their incumbents. They also expected such results to sustain in the future (SAP Center for Business Insight, 2017). Interestingly enough, 67% of the leading firms in the study were spread across a wide range of industries outside of technology. The study found around 84% of global industries considered a digital transformation strategy critical to their survival and growth in the coming decade. Given this shift in economic activity, it becomes of paramount importance to assess the relationship between digitisation and firm performance.

The deployment of a digital transformation strategy heavily relies on the firm's employees and impacts their behavior at the same time. (Weber et al, 2022). It is a common notion that increased automation and usage of technology will eventually make jobs redundant and effectively replace labor. This assumption alone could increase employees' resistance to change and undermine their identification with the firm (Braojos et al, 2024). The rise of artificial intelligence (AI), more importantly, generative AI, has exacerbated this fear. At the same time, the automation of repetitive jobs and the use of digital tools can streamline processes and allow employees to focus on higher value tasks. The access to real time data also results in better and more efficient decision making (Shwedeh et al, 2023). Another study also finds that employee involvement in the co-creation process of digital transformation and innovation offers opposing views to the idea that such a transformation strategy would not be in their favor (Niels et al, 2018). In order to properly inform not only policy but also employees on the impact of digital technologies on jobs, the impact of firms' digital strategies on employment outcomes also needs to be studied.

Consistent with China's lead in digitisation (Woetzel et al, 2017), existing literature dominantly studies Chinese firms. Empirical data is largely focused on Chinese digital strategies and outcomes dependent on the Chinese economic climate and governance style. While such studies present varied effects of digital transformation strategies on firm performance, there remains a gap in identifying these effects in different economic structures and stages, such as The Netherlands.

The Netherlands, marked as the digital gateway to Europe and one of the most wired countries in the world, boasts a strong digital infrastructure with top tier innovation ecosystems in cybersecurity and artificial intelligence (International Trade Administration, 2024). With a significant EU digital strategy accompanied by the national government's own Digital Economy Strategy, firms enjoy a booming entrepreneurial and innovative culture in the technological sector (Ministry of Economic Affairs and Climate Policy, 2022). This makes The Netherlands a suitable ground to assess the relationship between digital transformation strategies on firm and employment outcomes. Analyzing this relationship in this context as connectivity becomes increasingly important rather than in a mature state will present great benefits for lawmakers and firms creating their own strategies. This leads to the central question this paper aims to answer:

What is the impact of digital transformation strategies on firm and worker outcomes in The Netherlands?

This paper will first present an extensive literature review as part of its theoretical framework, outlining key concepts involved in this field of research and presenting the hypotheses to be tested. This will be followed by a description of the Data and Methodology used in the empirical analysis. The results will be presented along with a conclusion and discussion on the limitations of this paper and the scope of future research in digital transformation strategies.

2 Theoretical Framework

2.1 Digital Transformation Strategies

In the current, rapidly evolving digital landscape, digital transformation strategies (DTS) are assuming a crucial role for firms looking to adapt. The process breaks the conventions of traditional information systems (IS) planning, that often solely focuses on IT infrastructure, and spotlights a more all rounded approach to strategy making (Chanias, Myers, and Hess, 2018). This shift reflects the dynamic nature of digital technologies and their potential to constantly reshape industries and maintain a competitive environment (Henderson and Venkatraman, 1993).

According to Matt, Hess, and Benlian (2015), a DTS can be described as one that serves a central concept to integrate the entire coordination, prioritization and implementation of digital technologies within a firm. Such strategies are directly involved in transforming products, processes, and internal structures to engage with customers in new ways and make value creation more efficient (Downes and Nunes, 2013). Thus, DTS have the power to redefine a firm's business model, value proposition, and competitive landscape.

The existing IT strategies mostly define current and future operational activities. While essential for managing technological infrastructure, these strategies only address the necessary application systems and frameworks for providing IT that carry out business operations (Teubner, 2013). By restricting the product and customer centric opportunities that arise from new digital technologies, these often fail to drive innovation or facilitate the broader organizational changes required for a digital transformation. (Matt, Hess, and Benlian 2015). On the other hand, DTS has a broader scope and looks beyond process automation and optimization, into driving a total business model transformation.

However, despite the precedence DTS takes in modern business strategy making, it does not negate the importance of traditional IT strategies. Rather, a close alignment between DTS and IT strategies along with all active strategies within the workplace needs to be maintained (Henderson and Venkatraman, 1993). It is often found that while most existing studies and strategies discuss the future potential of the integration of digital technologies, they do fail to adequately translate this into the present context and how the individual firm will reach that potential. At the same time, some research finds that a community based strategy model can help create profitable revenue streams (Oestreicher-Singer and Zalmanson, 2013). A comprehensive digital business strategy should therefore pitch the potential of digital technologies, what the integration means for the firm and their impact on different stakeholders (Bharadwaj et al. 2013).

On that note, Matt, Hess, and Benlian (2015) highlight that while procedural and leadership aspects help form the development and evaluation aspects of the DTS, firms need to define the tangible content aspects they wish to include first. Owing to their firm subjective nature, DTS can differ on the bases of their contents itself, the order of contents implemented, the scale of implementation, etc... However, for most firms, the Internet of Things (IOT), almost always finds a significant spot in their DTS.

2.2 Internet of Things

Digital technologies are innovative, intelligent, and disruptive technologies. Among big data analytics, cyber-physical systems, and cloud computing, the Internet of Things (IoT) has made itself essential to most DTS (Ardolino et al. 2018) (Frank, Dalenograre, and Ayala, 2019) (Awan et al. 2022). It connects billions of devices through software, enabling a seamless data exchange over the internet and other communication networks, without any human intervention (Vass, Shee, and Miah 2020). This connectivity not only streamlines end-to-end processes but also acts as a critical indicator of a firm's commitment to remain competitive in the global market and that they have a solid DTS in place (Awan et al. 2022).

IoT stands out by playing a key role in the rapid expansion of Industry 4.0, by eliminating the need for manual labor as processes increasingly become automated (Edquist, Goodridge and Haskel, 2021). By closing the gap between the physical and virtual worlds, IoT enables real-time monitoring and data driven decision making, which are critical for optimizing business processes and performance (Vass, Shee, and Miah 2020) (Edquist, Goodridge and Haskel, 2021) (Zhang et al. 2024)

A 2021 Accenture report found that companies that integrate IoT into their supply chains experience better operational performance- with digitization strategy directly leading to a 10% reduction in loss of sales and higher revenue generation (Timmerman, 2021). IoT also contributes to smart manufacturing systems, flexible production processes, informed decision making, and tighter quality control- all contributing to the firms' operational excellence (Psarommatis et al, 2022) (Zhang et al. 2019).

However, the adoption of IoT is not devoid of its challenges, despite its rewarding potential. Beyond a large initial investment and uncertain profitability, IoT implementation requires over-coming high operating costs, long payback periods, and initial technical glitches, which often result in a short term financial loss (Brous, Janssen, and Herder, 2020) (Gawankar, Gunasekaran and Kamble, 2020) (Lin et al.2017). While existing studies discuss the impact of IoT on the performance of firms in different contexts- such as Chinese manufacturing firms, on its contribution to economic growth, or the market value of IoT in fortune 500 firms- the financial impact of IoT on firms remains insufficiently researched, especially from a supply chain and operations perspective (Yu et al. 2015) (Ceipek et al. 2021) (Edquist, Goodridge, and Haskel, 2021) (Tang, Huang, and Wang, 2018).

Nevertheless, Zhang et al. (2024) found that their control variable, firm size, played a substantial role on firm performance when investigating the impact of IoT on sustainable firm performance. By establishing firm size as an important factor in companies capitalizing on IoT technologies, it can be assumed that some industries are better positioned for IoT adoption. They can absorb the initial costs and complexities and unlock supply chain efficiency, improved customer engagement, and a greater potential to innovate (Confederation of Indian Industry, 2018) (Fendri et al. 2022). While some industries may hesitate due to their traditional practices or size, others- such as Healthcare, Automotive, and Building Automation- are becoming leading examples of such a digital transformation.

2.3 Digital Transformation Strategies: Industry analysis

Ross et al. (2016) discusses that while the evolving digital landscape makes room for innovation, it poses an existential threat to pre-digital organizations. Pre-digital organizations are those that were financially successful in the pre-digital economy and for which a digital transformation is critical for survival. However, unlike born digital organizations, for these firms, adopting digital technologies often involves reshaping entire business models. (Bharadwaj et al., 2013, Sebastian et al., 2017, Tumbas et al., 2017a). Often, the characteristics of the industry determine the need and capacity for a digital transformation. Industries that focus on day-to-day operations with a diverse client base, struggle to place demands on contractors and subcontractors due to competence discrepancies, and a product that inherently raises barriers to process innovations, effectively limit any efforts for digital transformation (Linderoth, Jacobsson, and Elbanna, 2018) (Hinings et al. 2018).

As these industries cope with the challenges of the evolving digital economy, an extensive digital transformation strategy consisting of the integration of digital technologies such as

IoT becomes imperative for maintaining their competitiveness and enhancing their operational performance (Ross et al. 2016). Due to recent advancements and industry characteristics, Healthcare, Automotive, and Building Automation are found to be the fastest growing use cases of IoT adoption.

2.3.1 Healthcare

With the recent developments in sensor and communication technology, the healthcare industry is a leader in digital transformations. Where detection and analysis of diseases was only feasible at hospitals, IoT has enabled health to be monitored at home (Yadav and Hasija, 2022). The Covid-19 pandemic led the surge of digital innovations in the industry, largely pushed by the urgency of making the industry more antifragile (Ramezani and Camarinha-Matos, 2020) (Cobianchi et al. 2020) (Denicolai and Previtali, 2022). The integration of IoT in healthcare enables continuous monitoring of patients through wearable and implanted sensors. Real-time data collection makes room for better diagnostics, disease prevention and personalized treatment, which ultimately leads to better clinical decisions and patient care (Yadav and Hasija, 2022). This operational intelligence ensures efficient utilization of healthcare resources and optimizes costs as well. Due to the rapid increase in patient level data, about 30% of the entire world's data volume is generated under the healthcare and related industries, making it a true big data sector, and ripe for large scale digital transformations (Faggella, 2018). This rise in big data analytics only accelerates the potential of IoT value generation in the industry and makes healthcare not only a leading example for digital transformations but also ripe for advanced digital strategies.

2.3.2 Automotive

The introduction and rise of connected and autonomous vehicles paired with the use of big data analytics in manufacturing is reshaping the Automotive industry- with IoT playing a central role. Firms underground digital transformations within the industry are able to offer new and innovative services and enhanced in-car digital experiences as well. (Llopis-Albert, Rubio, and Valero, 2020).

Lacking many restrictions that may be present in other more labor intensive industries, the automotive industry poses as a textbook example arguing in favor of digital transformations. Large scale manufacturing is considerably the easiest process to integrate with digital technologies as much of the process has heavy machine involvement already. As governments and consumers alike place greater importance on environmental issues, automotive manufacturers are cornered to shifting the entire process by which they can satisfy their needs as a for profit industry, maintain market share and competitiveness. Research finds that such a strategy and investment would result in greater profits, productivity, all while enhancing the individual customer experience (Llopis-Albert, Rubio, and Valero, 2020).

2.3.3 Building Automation

The building automation industry, while slower to adopt digital transformation strategies in comparison with healthcare and automotive, is beginning its journey with IoT and digital technologies. Unfortunately construction professionals lack knowledge of several automation techniques (Oke et al. 2023). A majority of existing research finds that project based parts of the industry are highly action oriented and require immediate and tangible results for any investment in digital technology be made (Jacobsson and Linderoth, 2010). However, Oke et al. (2022), in a closer assessment found that the clients in their study largely managed their facilities by monitoring with a wide range of different sensors and alarms. This is then complimented with the action oriented management through information transfer. Given this process, the authors of Musarat et al. (2021) argue that digital transformations within the industry actually enhance the productivity and efficiency of projects with better control over cost, time, and risk throughout the entire product life cycle. The use of IoT in building automation allows for real-time monitoring and control of various building systems such as heating, ventilation, and air conditioning (HVAC), lighting, and security.

2.4 Implication of varying regions on Digital Transformation Strategies

Understanding the impact of digital transformation strategies requires focus on the regional context in which these firms operate. Wu et al. (2023) emphasizes on an existing gap in research that fails to adequately address the role of regional digital infrastructure (RDI) in inter-organizational connectivity. Their research found that RDI is an external driver of enterprise digital transformation (EDT), more specifically having a stronger effect on mature enterprises undergoing digital transformations. They concluded that RDI enhanced EDT by providing strategy, resources, capabilities, and outputs, which differ amongst regions. Where the level of RDI increased, the EDT of firms in those regions rose consequently.

Following the perspective shared in Vial (2021), RDI also acts as an external driver of

EDT by improving the speed and breadth of knowledge acquisition and information processing capabilities. Isaksen at al. (2021) added that digital transformations in industries located in certain regions are related to the changes in regional innovation systems. A result of asset modification, asset reuse, and strategic destruction of outdated assets, digital transformations lead to different rates of developments in differing regions.

Additionally, regional virtual agglomeration helps reduce costs associated with information acquisition and negotiations conducted during the digital transformation process. This helps firms better allocate resources and emphasizes the role of knowledge spillovers and network effects (Yang and Wu, 2023). Closer collaboration with incumbents allows for collective digital transformation and firm growth within the same region but showed pronounced regional disparities.

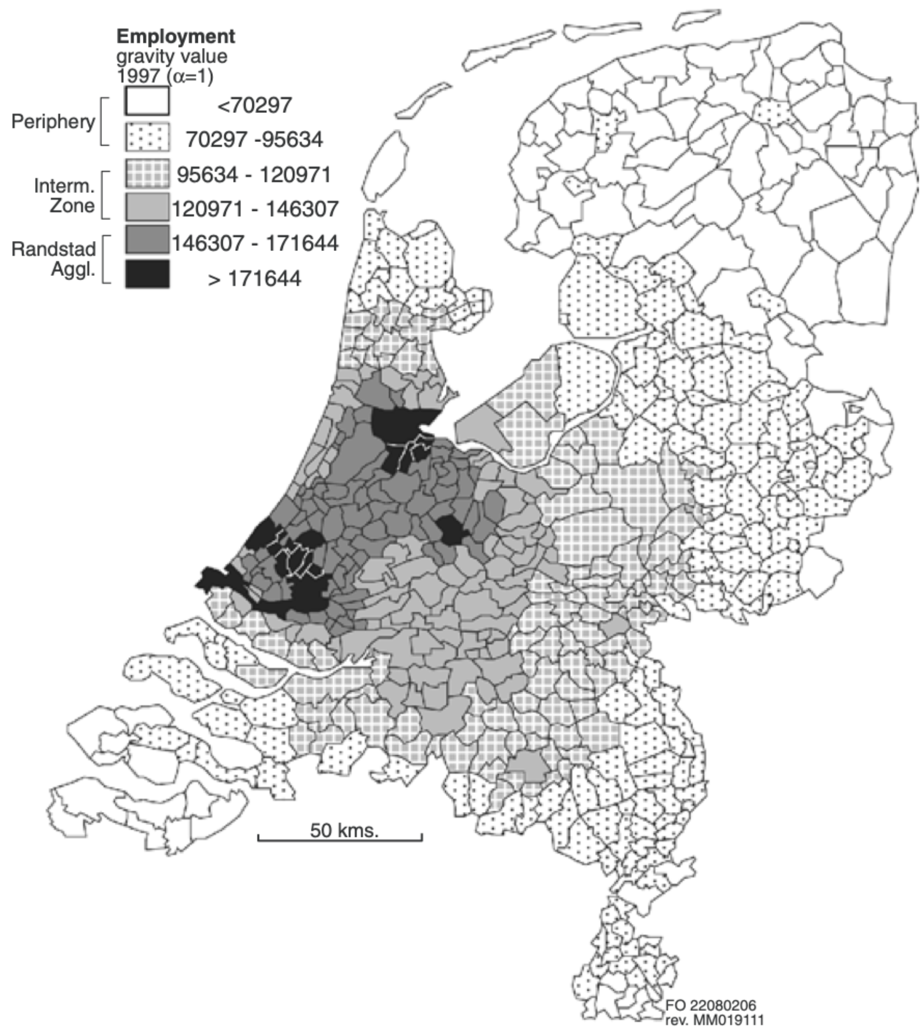

Figure 1: National Zoning Spacial Regime (Van Oort and Atzema, 2004)

Van Oort and Atzema (2004) present 3 zones within the Netherlands, varying in economic activity and agglomeration characteristics. Figure 1 from the aforementioned paper, distinguishes between the macro-economic zones in the Netherlands based on a gravity model of total employment. It shows that the Randstad region consists of the highest employment gravity values, which decrease as one moves to the Intermediate and National Periphery regions. The randstad is densely populated with industries and economic activity, making it the prime region for innovation and information spillovers. On the other hand, the National Periphery has relatively much lower industry density and economic activity, but can still be subject to knowledge spillovers from surrounding regions. The authors draw emphasis on the importance of spatial proximity in the growth of innovation, especially in ICT sectors. Based on this study, it can be argued that the Randstad region with its established infrastructure is likely to experience a differing effect of DTS on firm survival and employment growth compared to a rather rural region like the National Periphery.

In order to analyze the non-uniform impact of digital transformations across these macro-economic zones, this study conducts also conducts a regional analysis on the varying impact of DTS on firm and employment outcomes between The Randstad, the Intermediate Region, and the National Periphery.

2.5 Firm Performance

In the context of digital transformations, empirical evidence suggests that IoT implementation has a positive impact on firm performance- more specifically Tobin's Q and financial performance metrics. However, while IoT was shown to influence productivity in a positive way, the effect is less consistent than its financial impact, due to employee IT capabilities, and organizational culture (Tang, Huang, and Wang, 2018).

Digital transformation strategies also positively impact firm performance through a positive effect on global supply chain management practices (Zhang et al, 2024). An IoT enabled supply chain provides the necessary capabilities to increase its efficiency through a reduction in supply chain costs, lower inventory levels, and improved customer satisfaction levels (Argyropoulou et al. 2024)

On the other hand, not all findings are uniformly positive. Some empirical results find that IoT adoption has a negative effect on profit before interest and tax and profit after tax (Schinedejans and Hales, 2016) (Li, Dai, and Cui, 2020) (Yu et al. 2018). Conclusions made by Dash et al. (2023) justified these findings by highlighting the cost burden of technical complexities in IoT adoption for most firms.

Despite these challenges, the broader evidence suggests that effective digital transformation strategies driven by IoT adoption can significantly improve firm performance. An SAP (2017) survey revealed that 84% of global companies view a digital transformation as critical for their survival over the next 5 years. For this reason, the following empirical analysis of this study will measure firm performance through the number of firms in The Netherlands, and leads to the first hypothesis of this study:

H_1: Digital Transformation Strategies, proxied by IoT adoption will increase the number of firms within IoT favored industries, in The Netherlands

2.6 Employment Outcomes

A DTS requires continuous reassessment and adaptation. They depend not only on digital infrastructure but also active involvement of employees across the hierarchy and value chain. There is typically a high level of uncertainty and therefore employee resistance regarding DTS. This uncertainty calls for the DTS to have clear definitions, and measurement metrics to be put into place with thresholds upon which employees are to take corrective action. These methods are not only important to maintain credibility of leadership to drive such a long term strategy but also to avoid decision making biases like the sunk cost fallacy (Matt, Hess, and Benlian, 2015).

Contrary to the misconception that a digital transformation would displace the workforce, DTS consists of significant employee involvement. A successful and effective DTS is developed with the input of different stakeholders within the firm and is created "bottom-up.". The authors emphasize on the informal dynamics within firms that truly influence the outcomes during a DT, which in turn has a direct impact on employee outcomes. (Chanias, Myers, and Hess, 2018).

Though digital transformations do lead to employees continuously adapting with new skills and responsibilities, large financial investments can imply cost cutting through workforce reduction. Therefore, it is not possible to disregard the immediate impact on jobs. For the purpose of this study, the following empirical analysis measures employment outcomes through the number of jobs within each industry. This forms the second hypothesis of this study:

H_2: Digital Transformation Strategies, proxied by IoT adoption will increase the number of

jobs within IoT favored industries, in The Netherlands

3 Data

3.1 Data Source and Selection

All data in this empirical analysis was obtained through the LISA database, which provides a comprehensive repository of all employment and firm level data in The Netherlands. The database ranges from individual firms to country level data. For the purpose of this study, a regional categorization of data was obtained, segregated based on the 40 COROP regions in the country. Additionally, as emphasized by existing research, firm size plays an external role in the successful implementation of DTS. For this reason, only firms with more than 50 employees are considered.

The data set is bounded by a specific set of industries for both treatment and control groups, using their Standard Business Identification (SBI) codes (Central Bureau voor de Statistiek, 2022)

Treatment Group

Industries identified as the fastest growing use cases of IoT adoption

- **Building Automation:** 3512, 3513, 3514, 4321, 43222, 4329, 4334, 8020, 8110
- **Automotive:** 2910, 29201, 29202, 2931, 2932, 45111, 45112, 45191, 45192, 45193, 45194, 45201, 45202, 45203, 45204, 45205, 45311, 45312, 4532, 45401, 45402
- **Healthcare:** SBI codes 86101, 86102, 86103, 86104, 8621, 86221, 86222, 86231, 86232, 86911, 86912, 86913, 86919, 86921, 86922, 86923, 86924, 86925, 86929

Control Group

Industries with relatively low IoT adoption

- **Agriculture:** 011, 012, 013, 014, 015, 016, 017
- **Real Estate:** 6810, 6820, 6831, 6832
- **Hospitality:** 51101, 51102, 55201, 55202, 553, 559, 56101, 56102, 5621, 5629, 563

For the robustness check, all COROP codes were grouped into their respective regions.

- **The Randstad:** 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 40
- **The Intermediate Region:** 10, 11, 12, 13, 15, 16, 33, 34, 35, 36, 38
- **The National Periphery:** 01, 02, 03, 04, 05, 06, 07, 08, 09, 14, 31, 32, 37, 39

3.2 Treatment

The treatment period's focal point is the IoT boom which occurred between 2011 and 2014. This period signifies the introduction and exponential rise of IoT adoption among firms, which is considered the indicator of a digital transformation strategy for this study. For comparison, the study includes 5 years prior and 5 years post the treatment period, resulting in the assessment spanning over the years 2005 through 2020. The treatment variable is a dummy variable which indicates 0 for the control group and 1 for the treatment group.

3.3 Dependent Variables

To investigate the impact of DTS on firm and employment outcomes, two different dependent variables are used.

- **Firm survival:** measured by the number of firms greater than 50 employees within each industry in each COROP region. The number of firms serves as a proxy for firm survival and growth.
- **Employment growth (subject to firm survival):** measured by the number of jobs within each industry in each COROP region.

3.4 Summary Statistics

Table 1: Summary Statistics

Variable	Mean	Std. Deviation	Minimum	Maximum
Year	2012.5	4.68	2005	2020
Treatment	0.50	0.51	0	1
Firms	30.02	8.13	16.6	39.45
Jobs	7153.46	4865.97	1650.33	12593.83
Time	7.50	4.68	0	15

Table 1 presents the preliminary summary statistics of this research. The mean number of firms indicates an average of at least 30 firms in all industries and regions. Its standard deviation indicates some variability of this average suggests differences in industry density and regional economic activity. This can imply differing impacts of DTS on firm performance across regions and/or industries. The wide range of the observations also implies that the scale of industry presence might largely vary across regions, thereby impacting firm performance. The mean number of jobs reflects an average of at least 7153 jobs in all industries and regions. However, this average also has a large standard deviation which indicates regional discrepancies in the impact of DTS on employment outcomes. One way robustness is considered for this analysis is by comparing the effect of IoT adoption against non-adoption over the same period creates balance, through the binary treatment variable.

4 Methodology

4.1 Difference-in-Differences (DiD) Approach

The DiD method controls for all time-invariant unobserved heterogeneity which has the ability to estimate a causal effect of a treatment by comparing pre- and post- treatment differences in outcomes between treatment and control groups. It will isolate the effect of the IoT boom on both firm and employment outcomes before and after the IoT boom between the treatment and control industries. This method also provides this study with a quasi-experimental design. Since the data consists of observations over time from the LISA dataset, a randomized control trial is not possible. The DiD approach is therefore a suitable methodology to use the natural variations in the data and make causal estimates.

DiD strongly makes the assumption of parallel trends which states that in the absence of an IoT boom, the treatment and control industries would have followed the same trend over time. Any unobserved differences between the two groups before the IoT boom should be constant over time. Since there is no method to test for this assumption, Figures 2 and 3 in the Appendix plot the average trends over time for treatment and control industries to visually confirm that the trends were parallel before the IoT boom.

DiD also assumes no simultaneous shocks which require no other major events or shocks to have occurred during the IoT boom. Post the crisis of 2008, the treatment period (2011-2014) was specifically identified as a time of rapid IoT adoption in the ongoing digital era with no other economic events affecting the jobs and firms in the selected industries.

Another assumption made by the DiD approach is a stable unit treatment value (SUTVA). This means that the impact of IoT adoption in one industry and/or region should not have spillover effects into other industry/region combinations. The industries selected carefully reduces the risk of violating the SUTVA assumption ensuring that the treatment group was directly impacted by IoT adoption while the control group, composed of industries that do not have favorable conditions for its adoption, were less likely to experience the indirect effects.

4.2 Model Specifications

Two DiD models were estimated to investigate the impact of DTS on firm performance and employment outcomes, respectively.

$$\begin{aligned} \text{firms}_{it} = \alpha &+ \beta_1 \,\text{treatment}_i + \beta_2 \,\text{post\_shock}_t \\ &+ \beta_3 \,(\text{treatment}_i \times \text{post\_shock}_t) + \delta_{\text{COROP}} + \gamma_{\text{year}} + \epsilon_{it} \end{aligned} \tag{1}$$

The first model, equation 1, focuses on the impact of IoT adoption on the number of firms within each industry-region-year combination. $firms_{it}$ represents the dependent variable which is the number of firms in each industry-region i at time T. $treatment_i$ is the binary indicator of the treatment group and measures pre-shock differences. $post\_shock_t$ is the binary indicator that indicates time period and measures the general changes during the post shock period. It equals 1 for observations during the IoT boom period and 0 otherwise. $treatment_i \times post\_shock_t$ is the interaction term which measures the differing effect of the post-shock period on the treatment group compared to the control group industries. $COROP$ controls for region fixed effects, and $year$ controls for year fixed effects. ϵ_{it} is the error term.

$$\begin{aligned} \text{jobs}_{it} = \alpha &+ \beta_1 \,\text{treatment}_i + \beta_2 \,\text{post\_shock}_t \\ &+ \beta_3 \,(\text{treatment}_i \times \text{post\_shock}_t) + \delta_{\text{COROP}} + \gamma_{\text{year}} + \epsilon_{it} \end{aligned} \tag{2}$$

The second model, equation 2, focuses on the impact of IoT adoption on the number of jobs within each industry-region-year combination. $jobs_{it}$ represents the dependent variable which is the number of jobs in each industry-region i at time T. The rest of the variables remain the same as in equation 1.

$$
\begin{aligned}
\text{firms}_{it} = \; & \beta_0 + \beta_1 \text{treatment}_i + \beta_2 \text{post\_shock}_t + \beta_3 \text{randstad}_i + \beta_4 \text{intermediate}_i + \beta_5 \text{periphery}_i \\
& + \beta_6 (\text{treatment}_i \times \text{post\_shock}_t) \\
& + \beta_7 (\text{treatment}_i \times \text{randstad}_i) + \beta_8 (\text{treatment}_i \times \text{intermediate}_i) + \beta_9 (\text{treatment}_i \times \text{periphery}_i) \\
& + \beta_{10} (\text{post\_shock}_t \times \text{randstad}_i) + \beta_{11} (\text{post\_shock}_t \times \text{intermediate}_i) + \beta_{12} (\text{post\_shock}_t \times \text{periphery}_i) \\
& + \beta_{13} (\text{treatment}_i \times \text{post\_shock}_t \times \text{randstad}_i) \\
& + \beta_{14} (\text{treatment}_i \times \text{post\_shock}_t \times \text{intermediate}_i) \\
& + \beta_{15} (\text{treatment}_i \times \text{post\_shock}_t \times \text{periphery}_i) \\
& + \delta_{\text{COROP}} + \delta_{\text{year}} + \epsilon_{it}
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
\text{jobs}_{it} = \; & \beta_0 + \beta_1 \text{treatment}_i + \beta_2 \text{post\_shock}_t + \beta_3 \text{randstad}_i + \beta_4 \text{intermediate}_i + \beta_5 \text{periphery}_i \\
& + \beta_6 (\text{treatment}_i \times \text{post\_shock}_t) \\
& + \beta_7 (\text{treatment}_i \times \text{randstad}_i) + \beta_8 (\text{treatment}_i \times \text{intermediate}_i) + \beta_9 (\text{treatment}_i \times \text{periphery}_i) \\
& + \beta_{10} (\text{post\_shock}_t \times \text{randstad}_i) + \beta_{11} (\text{post\_shock}_t \times \text{intermediate}_i) + \beta_{12} (\text{post\_shock}_t \times \text{periphery}_i) \\
& + \beta_{13} (\text{treatment}_i \times \text{post\_shock}_t \times \text{randstad}_i) \\
& + \beta_{14} (\text{treatment}_i \times \text{post\_shock}_t \times \text{intermediate}_i) \\
& + \beta_{15} (\text{treatment}_i \times \text{post\_shock}_t \times \text{periphery}_i) \\
& + \delta_{\text{COROP}} + \delta_{\text{year}} + \epsilon_{it}
\end{aligned} \tag{4}
$$

The robustness check, equations 3 and 4, focuses on the regional impact of IoT adoption on the number of firms and jobs. The definitions of the common variables between the models remain the same. "region name"_i measures the impact of the regions on the firms and jobs. $\text{treatment}_i \times \text{"region name"}_i$ is the interaction term which measures the differences in each region between the treatment group compared to the control group industries before the IoT boom. $\text{post\_shock}_t \times \text{"region name"}_i$ measures the difference before and after the IoT boom period for each region, regardless of treatment status. $\text{treatment}_i \times \text{post\_shock}_t \times \text{"region name"}_i$ measures the varying impact of the IoT boom on the treatment industries in each region.

5 Results

Table 2: DiD regression results for the effect of IoT adoption on number of firms

Variable	Coefficient
Treatment	15.496***
	(0.669)
post_shock	4.026**
	(1.738)
treatment × post_shock	-1.902
	(1.245)
Number of obs	1,280
F(56, 1223)	204.58
Prob > F	0.0000
R-squared	0.8863
Root MSE	10.132

Note. * p < 0.1, ** p < 0.05, *** p < 0.001

Table 2 shows the regression results for the effect of DTS strategies on the number of firms. The coefficient of the treatment variable is positive and highly significant reflecting that on average, the number of firms in the treatment industries is 15.496 more than in the control industries. The coefficient of the post shock variable is positive and significant as at a 5% level. This implies that during the post IoT boom period, the number of firms increased by 4.026 for the control industries. The coefficient of the interaction term is negative. It states that for the treatment industries, the number of firms decreased by 1.902 relative to the control industries, post the IoT boom. However, this result is statistically insignificant.

Table 3: DiD regression results for the effect of IoT adoption on number of jobs

Variable	Coefficient
Treatment	9566.063***
	(324.472)
post_shock	712.478
	(858.775)
treatment × post_shock	-65.406
	(641.410)
Number of obs	1,280
F(56, 1223)	60.86
Prob > F	0.0000
R-squared	0.7519
Root MSE	5007.3

Note. * p < 0.1, ** p < 0.05, *** p < 0.001

Table 3 shows the regression results for the effect of DTS strategies on the number of jobs.

The coefficient of the treatment variable is positive and highly significant reflecting that on average, treatment industries have 9566.063 more jobs than in the control industries. The coefficient of the post shock variable is positive. This implies that during the post IoT boom period, the number of jobs increased by 712.478 in the control industries. The coefficient of the interaction term is negative. It states that in the treatment industries, the number of jobs decreased by 65.406 relative to the control industries, post the IoT boom. However, the latter two coefficients were both statistically insignificant.

Additionally, the results in Table 6 in the appendix show additional coefficients on the effect of all COROP regions on the number of firms. The results showed positive and highly significant impacts of all regions on the number of firms with region codes 17, 23, 29, 36, 39 having the highest impact on the number of firms. Upon closer inspection, a pattern was determined. The aforementioned codes belong to The Randstad region. As a robustness check, a second set of difference-in-differences regression was conducted- focusing on the regional analysis of the impact of IoT adoption on firm survival and Job growth.

Table 4 shows the robustness check results for the regional effect of DTS strategies on the number of firms. The coefficient of the treatment variable is positive and highly significant reflecting that on average, treatment industries have 9.054 more firms than the control industries do. The coefficient of the post shock variable is positive and significant as well, indicating that post the IoT boom, the number of firms in the control industries increased by 3.437. The national periphery was taken as the reference region. The main interaction terms for both The Randstad ($treatmentxRandstadxpost\_shock$) and The Intermediate region ($treatmentxIntermediatexpost\_shock$) were positive but statistically non significant. These results are consistent with those presented in table 2, proving them to be robust.

Table 5 shows the robustness check results for the regional effect of DTS strategies on the number of jobs. The coefficient of the treatment variable is positive and highly significant reflecting that on average, treatment industries have 5622.571 more jobs than the control industries do. The coefficient of the post shock variable is positive but insignificant. The national periphery was once again taken as the reference region. The main interaction term for The Randstad region ($treatmentxRandstadxpost\_shock$) was positive but insignificant. The main interaction term for The Intermediate region ($treatmentxIntermediatexpost\_shock$) was negative but statistically insignificant as well. These results are consistent with those presented in table 3, proving them to be robust.

Table 4: DiD regression results for Regional Analysis of IoT adoption impact on Firms

Variable	Coefficient
Treatment	9.054***
	(0.692)
post_shock	3.437**
	(1.731)
treatment × post_shock	-0.661
	(1.425)
Randstad	13.375***
	(2.225)
treatment × Randstad	8.485***
	(1.611)
post_shock × Randstad	1.762
	(2.134)
treatment × Randstad × post_shock	-2.212
	(3.022)
Intermediate	6.324***
	(1.516)
treatment × Intermediate	11.856***
	(1.171)
post_shock × Intermediate	-0.259
	(1.576)
treatment × Intermediate × post_shock	-1.498
	(2.233)
Number of obs	1,280
F(56, 1223)	204.58
Prob > F	0.0000
R-squared	0.8863
Root MSE	10.132

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

The extended versions of all regression result tables consisting of individual coefficients per year and COROP region can be found in the appendix, along with their respective graphical visualizations.

Table 5: DiD regression results for Regional Analysis of IoT adoption impact on Firms

Variable	Coefficient
Treatment	5622.571***
	(347.567)
post_shock	629.723
	(835.982)
treatment × post_shock	-8.679
	(652.867)
Randstad	404.803
	(813.947)
treatment × Randstad	5715.662***
	(743.796)
post_shock × Randstad	208.477
	(1036.76)
treatment × Randstad × post_shock	60.729
	(1477.539)
Intermediate	-627.121
	(828.352)
treatment × Intermediate	6545.883***
	(630.129)
post_shock × Intermediate	16.641
	(866.427)
treatment × Intermediate × post_shock	-289.094
	(1206.413)
Number of obs	1,280
F(56, 1223)	204.58
Prob > F	0.0000
R-squared	0.8863
Root MSE	10.132

Note. * p < 0.1, ** p < 0.05, *** p < 0.001

6 Conclusion and Discussion

The aim of this research was to evaluate the impact of Digital Transformation Strategies on firm and worker outcomes, through the adoption of Internet of Things technology. Through a difference-in-differences approach, this study measured the impact of the IoT boom- a period of significant IoT adoption, on fastest growing industry use cases for it [IoT adoption].

The first hypothesis tested the impact of DTS on firm performance. Results showed that while, on average, high IoT adoption industries have more firms compared to low IoT adoption industries, the interaction term between the treatment and post shock periods is negative and statistically insignificant. This implies that there is no significant change in the number of firms in IoT favorable industries compared to traditional industries post the IoT boom between 2011-2014. For this reason, the first hypothesis cannot be accepted nor rejected.

The second hypothesis tested the impact of DTS on worker outcomes. The results indicated that high IoT adoption industries tend to employ 9566 more people, on average, than low IoT adoption industries. However, similar to the firm performance analysis, the interaction term between the treatment and the post shock periods for this model was also negative and statistically insignificant. This also implies that there is no significant change in the number of jobs in IoT favorable industries compared to traditional industries post the IoT boom between 2011-2014. The second hypothesis cannot be accepted nor rejected either.

These results evidence an association between the adoption of IoT technologies in IoT positioned industries and both firm and worker outcomes, compared to low IoT adoption industries. Due to lack of statistical significance, these results cannot establish causation.

Interestingly, the results of the robustness check for the regional effect of DTS on firm survival and employment growth were also statistically insignificant. This means that the effect of DTS, proxied by IoT adoption, does not significantly differ between The Randstad, The Intermediate region, and The National Periphery, nor does it differ between industries with different stages of IoT adoption. This insignificance also implies that regional factors like urbanization do not impact the effect of DTS in firm survival and employment growth. However, both the robustness check and the initial analysis resulting in insignificant interaction term coefficients suggest that this is not due to an anomaly in the initial analysis, and consistency is maintained across all models. This helps improve the credibility of the empirical analysis. It is likely that the insignificance is a product of other factors outside of the scope of this paper, requiring a more extensive investigation.

One possible reason as to why results may be negative and insignificant, could be the presence of time lags in the positive effects of DTS. IoT adoption is a costly process both in terms of time and money. It requires not only a lot of hardware and software, but technical skill, training, and minimal resistance to change. At the same time, DTS are often long term strategies that may often allow short term losses for long term gain. The time period considered and available, given the recent occurrence of the IoT boom, is not a sufficient time period to observe any long term benefits yet. In the short run, due to the financial burden or lack of readiness of firms undertaking a digital transformation, an easy way out, is often conducting layoffs or shutting down entirely. It may also be possible that the integration of digital technologies as part of DTS, impacts firm and worker outcomes indirectly rather than in a direct and immediate way as measured in this study. These ideas may also affirm that successful DTS, beyond the initial adoption, require continuous learning and adaptation to other firm strategies and goals, owing to the very dynamic nature of technology.

The study is not devoid of its limitations. The use of the DiD approach involves holding very strong assumptions such as parallel trends. Due to there being no official means to test if this assumption holds, there is no guarantee that the results of the DiD model are the most accurate they can be. Additionally, though playing a pivotal role, limiting DTS to IoT adoption poses a threat to the generalisability of this study's results. DTS, as previously mentioned, is subjective to a firm and its stakeholders' visions, and existing strategies. The implementation of DTS therefore varies and largely relies on other factors like cloud computing, Big Data Analytics, machine learning, Generative AI, among people centred strategies. This study also only considers firms that employ more than 50 people as existing literature finds firm size to play an important role in mediating the impact of DTS on firm outcomes. However, a size of greater than 50 employees is considered huge in The Netherlands, and results may possibly differ when observing the behaviour of regularly large firms as well. The most important limitation of this study remains the statistically insignificant results, which impede the establishment of a causal effect of DTS on firm and worker outcomes.

This study aims to add onto the growing body of research on digital transformation strategies. While it begins to explore how DTS affect firm and worker outcomes using IoT adoption as a proxy, it has much room for further analyses and exploration. The general purpose of digital transformation strategies aims to make end-to-end processes within the firm more efficient and aid sustainable growth. For this reason, studying the impact of DTS on firm and employment productivity may help better understand the true impact of DTS on firm and employment outcomes. The high variation in the results for differing regional effects on firm and worker outcomes highlights the room to conduct closer regional analyses, possibly comparing only those with the greatest variations. Further research can also make distinctions between Business-to-Consumer sectors and Business-to-Business sectors in these industries. The adoption of digital technologies and the formation of DTS would presumably differ greatly between these two sectors as they cater to very different consumer bases who have very different individual needs- due to which the way, timing, and if at all DTS is implemented may greatly differ too. Lastly, there are many other important aspects to DTS, both people and technical focused, such as change management, Big Data Analytics, machine learning, etc... The impact of which can individually be tested to narrow down on a possible standard DTS that could eventually prevail amongst firms- especially those unsure of the DTS approach to sustainable growth. Essentially more longitudinal studies with granular data much like those obtained through IoT and big data analytics, would improve this study and others adjacent to it in the field.

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A Appendix

A.1 Parallel Trends

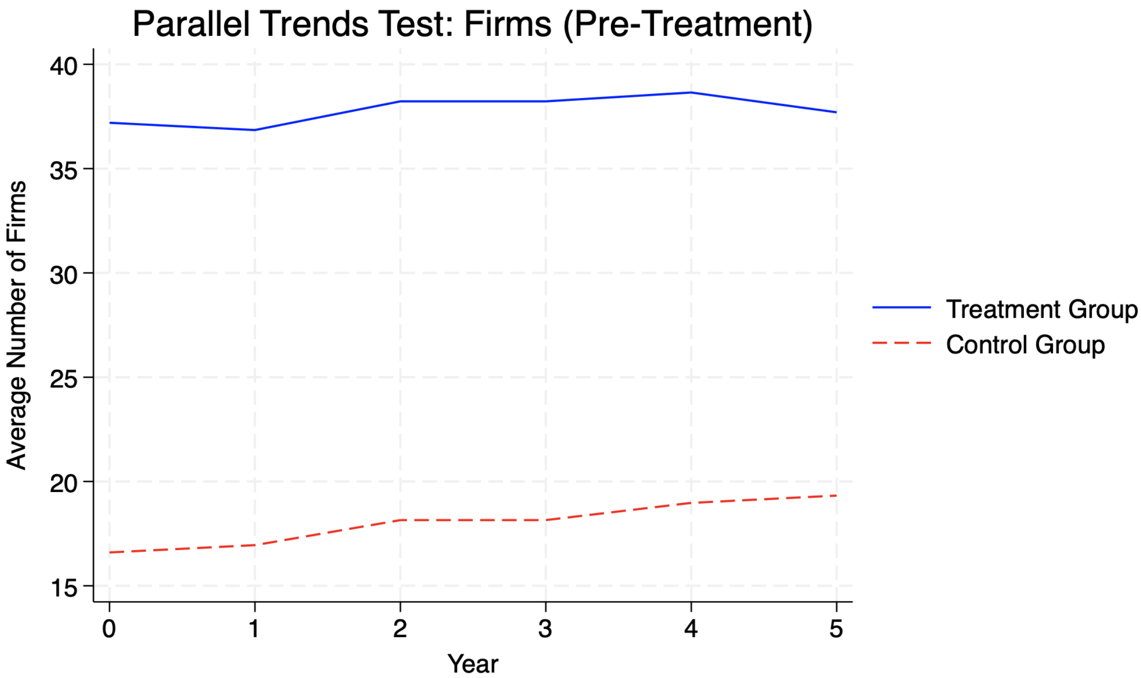

Figure 2: Parallel Trends Test on Firms

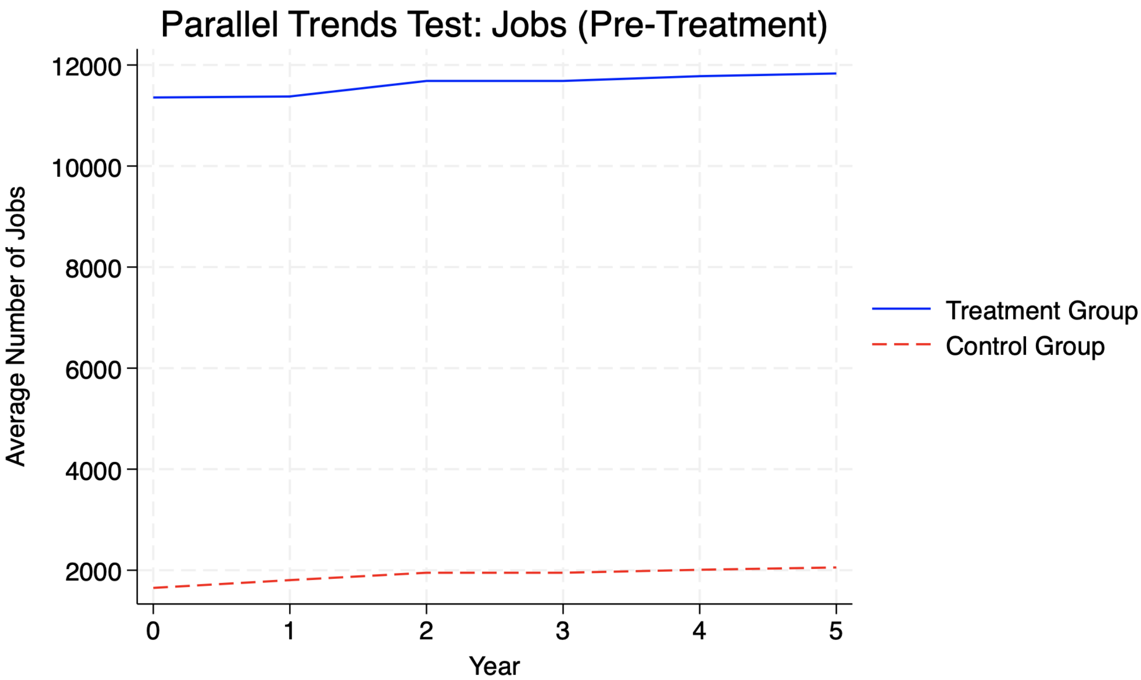

Figure 3: Parallel Trends Test on Jobs

A.2 Regression Results for Main Analysis

Table 6: DiD regression results for the effect of IoT adoption on number of firms

Variable	Coefficient
Treatment	15.496***
	(0.669)
post_shock	4.026**
	(1.738)
treatment × post_shock	-1.902
	(1.245)
COROP (ref:1)	
2	-1.902
	(1.760)
3	31.875***
	(1.764)
4	20.031***
	(1.249)
5	2.531
	(2.206)
6	10.938***
	(1.307)
7	6.875***
	(1.313)
8	7.094***
	(1.888)
9	6.5***
	(1.325)
10	27.188***

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Variable	Coefficient
	(1.337)
11	10.625***
	(1.480)
12	42***
	(1.516)
13	41.625***
	(1.983)
14	21.5***
	(1.439)
15	48.406***
	(2.369)
16	12.031***
	(1.591)
17	96.625***
	(6.119)
18	15.907***
	(2.044)
19	10.813***
	(1.454)
20	5.438**
	(1.825)
21	5.5***
	(1.708)
22	6.719***
	(1.487)
23	112.094***
	(2.347)
24	6.562***
	(1.364)

Continued on next page

Variable	Coefficient
25	22.5***
	(1.509)
26	41.688***
	(1.349)
27	21.469***
	(3.226)
28	17.563***
	(1.403)
29	102.719***
	(4.872)
30	20.219***
	(1.479)
31	2.5*
	(1.513)
32	15.969***
	(1.309)
33	42.5***
	(1.801)
34	27***
	(1.455)
35	45.375***
	(2.393)
36	57.406***
	(2.495)
37	22.156***
	(2.801)
38	12***
	(1.413)
39	37.594***

Continued on next page

Variable	Coefficient
	(2.100)
40	17.781***
	(2.096)
year (ref:2005)	
2006	4.82
	(1.723)
2007	1.288
	(1.776)
2008	1.288
	(1.776)
2009	1.913
	(1.750)
2010	1.613
	(1.676)
2011	0.975
	(1.478)
2012	0.725
	(1.451)
2013	0.388
	(1.430)
2015	2.963*
	(1.601)
2016	3.488**
	(1.613)
2017	4.313**
	(1.620)
2018	5.562***
	(1.695)

Continued on next page

Variable	Coefficient
2019	7.188***
	(1.707)
2020	5.962***
	(1.721)
constant	-7.183***
	(1.761)
Number of obs	1,280
F(56, 1223)	204.58
Prob > F	0.0000
R-squared	0.8863
Root MSE	10.132

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table 7: DiD regression results for the effect of IoT adoption on number of jobs

Variable	Coefficient
Treatment	9566.063***
	(324.472)
post_shock	712.478
	(858.775)
treatment × post_shock	-65.406
	(641.410)
COROP (ref:1)	
2	-724.813
	(1053.9)
3	10595.78***
	(1129.139)
4	3604.563***
	(739.350)
5	25.063
	(1059.589)
6	1602.969*
	(861.826)
7	1582.75*
	(845.284)
8	903.625
	(1013.206)
9	951.625
	(891.169)
10	7221.5***
	(765.649)

Continued on next page

Table 7: (Continued) DiD regression results for the effect of IoT adoption on number of jobs

Variable	Coefficient
11	1907.094**
	(923.957)
12	7694.906***
	(733.028)
13	7460.781***
	(749.374)
14	3806.063***
	(814.143)
15	16337.66***
	(1905.638)
16	896.313
	(974.320)
17	22696.69***
	(2508.117)
18	2244.969**
	(974.677)
19	2271.594**
	(801.501)
20	696.969
	(960.61)
21	1119.938
	(905.609)
22	474.625
	(964.267)
23	31240.63***
	(2216.109)
24	1320.344

Continued on next page

Table 7: (Continued) DiD regression results for the effect of IoT adoption on number of jobs

Variable	Coefficient
	(864.499)
25	7286.594***
	(850.9455)
26	9719.969***
	(888.699)
27	3524.969***
	(984.400)
28	2022.063**
	(856.911)
29	22842.94***
	(2316.299)
30	3460.5***
	(731.078)
31	-34.469
	(987.823)
32	2763.688***
	(792.793)
33	8044.875***
	(721.683)
34	5326.969***
	(712.229)
35	8261.625***
	(741.757)
36	16584.78***
	(1641.283)
37	4236.406***
	(927.769)

Continued on next page

Table 7: (Continued) DiD regression results for the effect of IoT adoption on number of jobs

Variable	Coefficient
38	2613.844**
	(831.594)
39	11055.81***
	(1202.382)
40	3322.344***
	(829.1925)
year (ref:2005)	
2006	87.038
	(769.969)
2007	313.4
	(775.044)
2008	313.4
	(775.044)
2009	390.038
	(780.928)
2010	439.688
	(778.419)
2011	58.563
	(784.191)
2012	61.15
	(785.786)
2013	72.075
	(792.141)
2015	708.5
	(785.844)
2016	766.225

Continued on next page

Table 7: (Continued) DiD regression results for the effect of IoT adoption on number of jobs

Variable	Coefficient
	(789.604)
2017	891.488
	(793.251)
2018	1039.288
	(813.837)
2019	1283.675
	(815.839)
2020	1247.088
	(826.949)
constant	-4203.107***
	(907.518)
Number of obs	1,280
F(56, 1223)	60.86
Prob > F	0.0000
R-squared	0.7519
Root MSE	5007.3

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

A.3 Graphical Visualization of Main Analysis

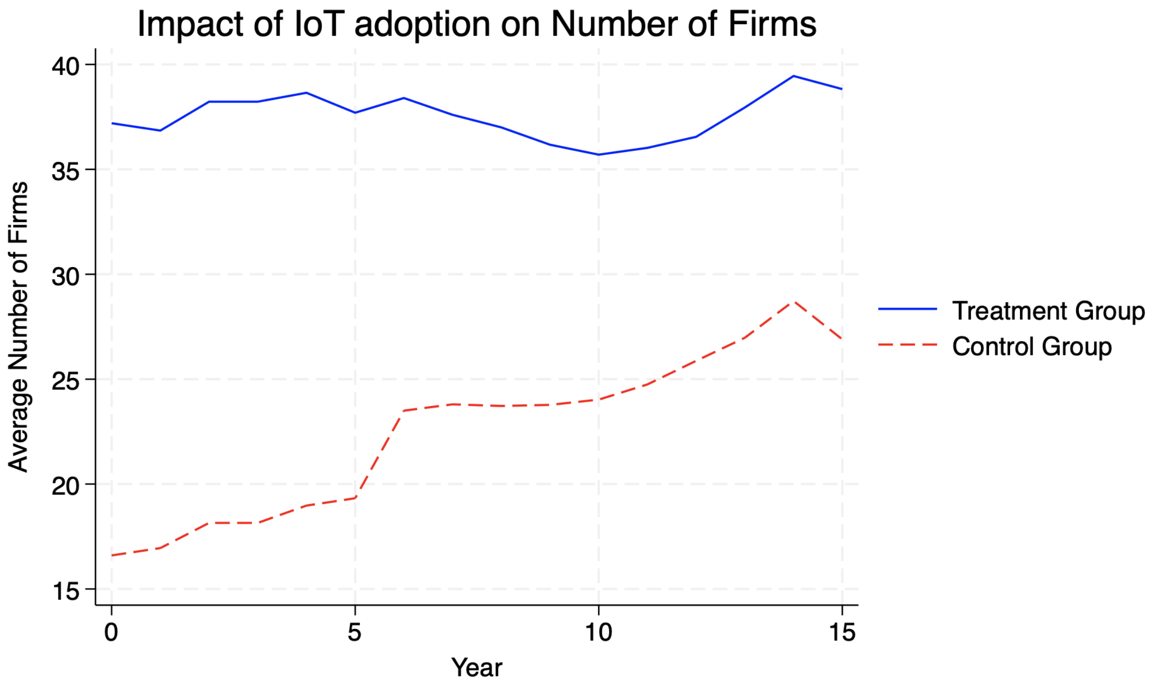

Figure 4: Effect of IoT adoption on Firm Survival

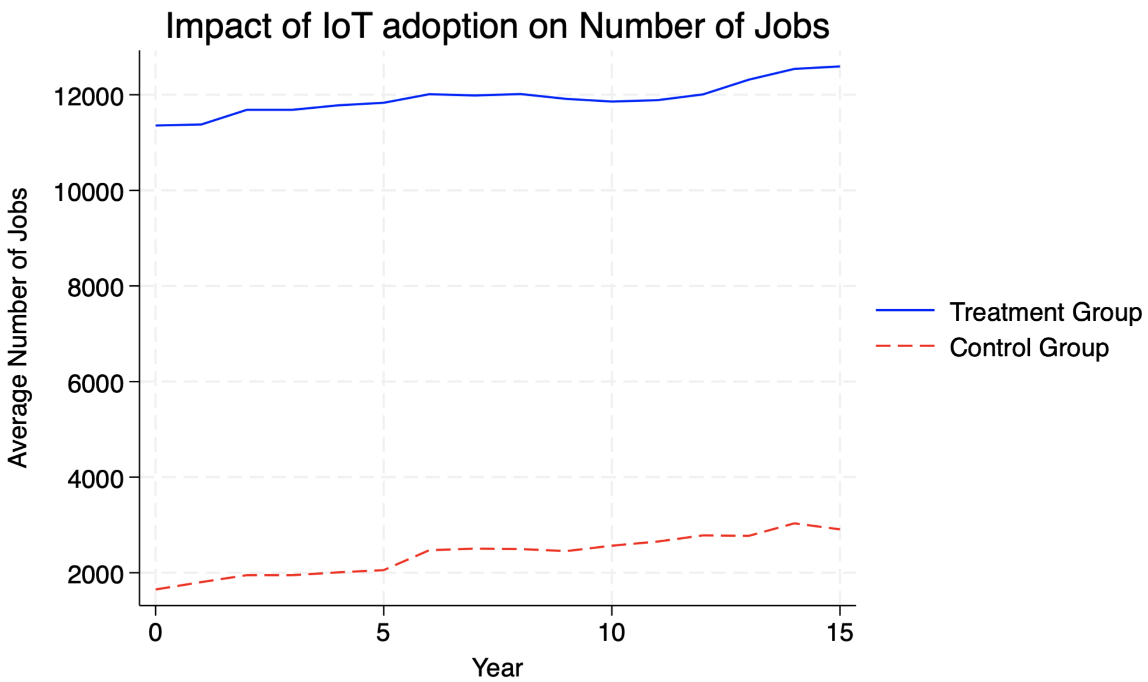

Figure 5: Effect of IoT adoption on Job Growth

A.4 Regression results for Regional Analysis Robustness Check

Table 8: DiD regression results for Regional Analysis of IoT adoption impact on Firms

Variable	Coefficient
Treatment	9.053571***
	(0.692)
post_shock	3.436756**
	(1.731)
treatment × post_shock	-0.661
	(1.425)
Randstad	13.375***
	(2.225)
treatment × Randstad	8.485***
	(1.611)
post_shock × Randstad	1.762
	(2.134)
treatment × Randstad × post_shock	-2.212
	(3.022)
Intermediate	6.324***
	(1.516)
treatment × Intermediate	11.856***
	(1.171)
post_shock × Intermediate	-0.259
	(1.576)
treatment × Intermediate × post_shock	-1.498
	(2.233)
COROP (ref:1)	

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Variable	Coefficient
2	-1.906*
	(1.072)
3	31.875***
	(1.841)
4	20.031***
	(1.048)
5	2.531*
	(1.505)
6	10.938***
	(0.924)
7	6.875***
	(0.818)
8	7.094***
	(1.184)
9	6.5***
	(0.906)
10	15.188***
	(1.255)
11	-1.375
	(1.718)
12	30***
	(1.377)
13	29.625***
	(1.705)
14	21.5***
	(0.908)
15	36.406***
	(1.963)
16	0.031

Continued on next page

Variable	Coefficient
	(1.868)
17	78.844***
	(6.144)
18	-1.875
	(2.583)
19	-6.969***
	(2.100)
20	-12.344***
	(2.413)
21	-12.281***
	(2.315)
22	-11.063***
	(2.116)
23	94.313***
	(2.739)
24	-11.219***
	(2.022)
25	4.719**
	(2.0212)
26	23.906***
	(1.948)
27	3.688
	(3.648)
28	-0.219
	(1.988)
29	84.9375***
	(4.941)
30	2.438
	(2.000)

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Variable	Coefficient
31	2.5**
	(0.858)
32	15.96875***
	(0.954)
33	30.5***
	(1.827)
34	15***
	(1.679)
35	33.375***
	(2.054)
36	45.406***
	(2.094)
37	22.156***
	(2.191)
39	37.594***
	(2.390)
year (ref:2005)	
2006	4.820
	(1.639)
2007	1.288
	(1.697)
2008	1.288
	(1.697)
2009	1.913
	(1.675)
2010	1.613
	(1.605)
2011	0.975

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Variable	Coefficient
	(1.442)
2012	0.725
	(1.416)
2013	0.388
	(1.401)
2015	2.963*
	(1.543)
2016	3.488**
	(1.553)
2017	4.313**
	(1.559)
2018	5.562***
	(1.636)
2019	7.188***
	(1.648)
2020	5.962***
	(1.653)
constant	-3.970**
	(1.417)
Number of obs	1,280
F(62, 1217)	247.14
Prob > F	0.0000
R-squared	0.8929
Root MSE	9.8577

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table 9: DiD regression results for Regional Analysis of IoT adoption impact on Jobs

Variable	Coefficient
Treatment	5622.571***
	(347.567)
post_shock	629.723
	(835.982)
treatment × post_shock	-8.679
	(652.867)
Randstad	404.803
	(813.947)
treatment × Randstad	5715.662***
	(743.796)
post_shock × Randstad	208.477
	(1036.76)
treatment × Randstad × post_shock	60.729
	(1477.539)
Intermediate	-627.121
	(828.352)
treatment × Intermediate	6545.883***
	(630.129)
post_shock × Intermediate	16.641
	(866.427)
treatment × Intermediate × post_shock	-289.094
	(1206.413)
COROP (ref:1)	
2	-724.813
	(562.078)

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Variable	Coefficient
3	10595.78***
	(1285.952)
4	3604.563***
	(384.654)
5	25.063
	(566.438)
6	1602.969***
	(386.296)
7	1582.75***
	(377.908)
8	903.625*
	(520.106)
9	951.625**
	(411.811)
10	4607.656***
	(682.028)
11	-706.75
	(1068.615)
12	5081.063***
	(672.934)
13	4846.938***
	(677.173)
14	3806.063***
	(375.700)
15	13723.81***
	(1687.102)
16	-1717.531
	(1129.304)
17	19374.34***

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Variable	Coefficient
	(2331.351)
18	-1077.375
	(1035.716)
19	-1050.75
	(819.989)
20	-2625.375**
	(1020.393)
21	-2202.406**
	(953.972)
22	-2847.719**
	(1024.627)
23	27918.28***
	(2040.982)
24	-2002**
	(902.154)
25	3964.25***
	(685.771)
26	6397.625***
	(718.842)
27	202.625
	(1043.756)
28	-1300.281
	(892.419)
29	19520.59***
	(2137.542)
30	138.1563
	(706.819)
31	-34.469
	(493.461)

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Variable	Coefficient
32	2763.688***
	(369.271)
33	5431.031***
	(679.731)
34	2713.125***
	(752.123)
35	5647.781***
	(682.878)
36	13970.94***
	(1426.157)
37	4236.406***
	(440.542)
39	11055.81***
	(1374.039)
year (ref:2005)	
2006	87.038
	(730.511)
2007	313.4
	(735.499)
2008	313.4
	(735.499)
2009	390.038
	(743.377)
2010	439.688
	(740.998)
2011	58.563
	(750.671)
2012	61.15

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Variable	Coefficient
	(752.623)
2013	72.075
	(759.824)
2015	708.5
	(751.336)
2016	766.225
	(753.952)
2017	891.488
	(758.197)
2018	1039.288
	(779.363)
2019	1283.675
	(781.379)
2020	1247.088
	(791.704)
constant	-2217.764***
	(648.799)
Number of obs	1,280
F(62, 1217)	152.24
Prob > F	0.0000
R-squared	0.7737
Root MSE	4794

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

A.5 Graphical Visualization of Regional Analysis Robustness Check

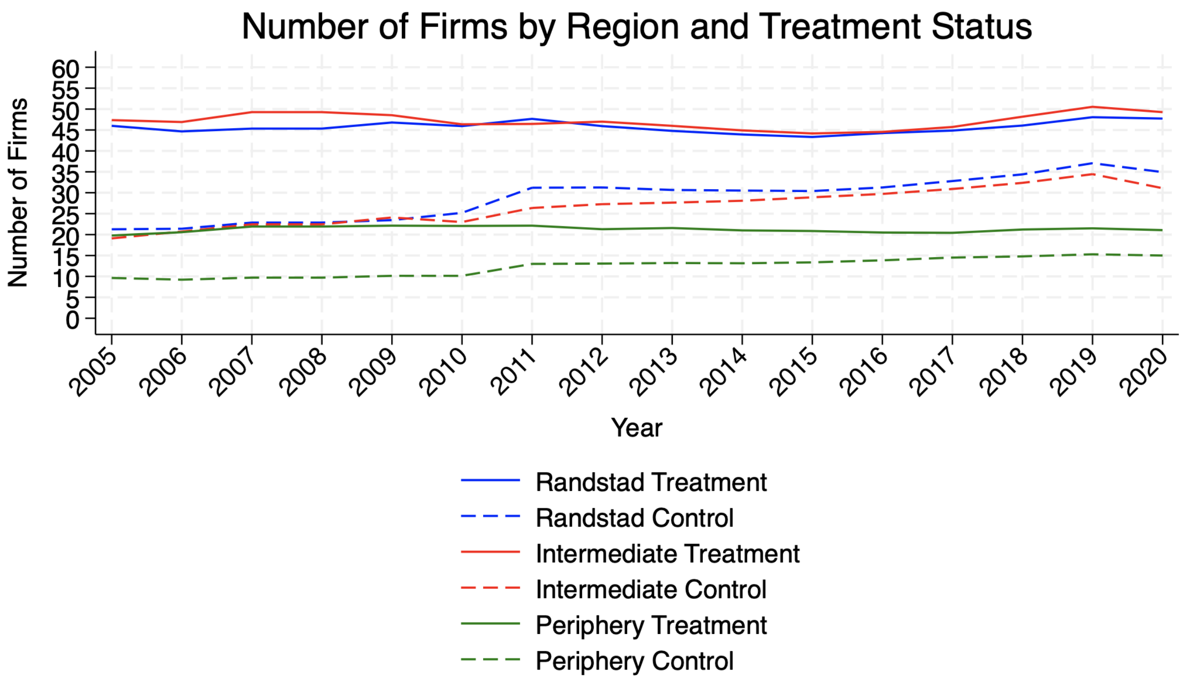

Figure 6: Effect of IoT adoption on Number of Firms, by region

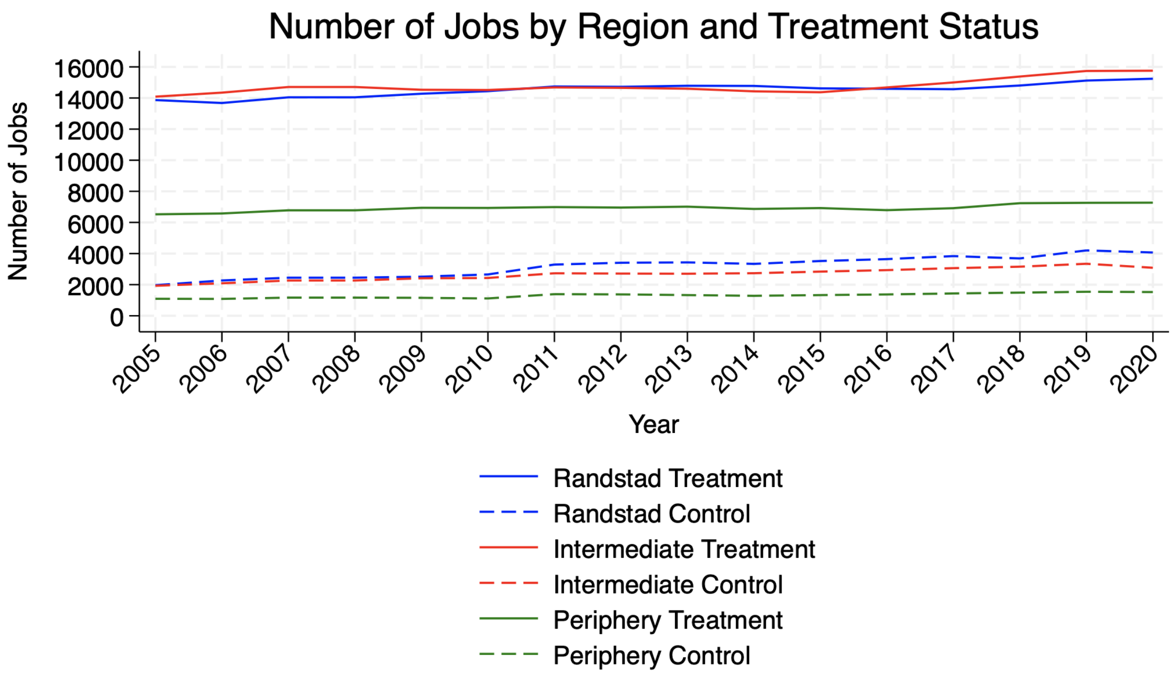

Figure 7: Effect of IoT adoption on Number of Jobs, by region