Three Essays on Digital Transformation

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In this dissertation, I investigate how firms leverage digital transformation initiatives to navigate environmental disruptions. Three studies explore this theme through the lenses of the COVID-19 pandemic, a severe environmental shock that profoundly impacted economies and organizations, and digitization of business processes. The first study examines the adoption of different digital configurations (e.g., online presence, delivery services, and remote work) across various phases of the pandemic, analyzing the causal impact of these configurations on sales growth. Building on this, the second study explores the adoption of remote work, a practice widely adopted during the pandemic, and the adaptations firms made to function remotely. This study investigates the relationship between remote work arrangements, firm agility, resilience, and key firm-level performance indicators. Finally, shifting focus to emerging economies undergoing digitization, the third study examines the association between transparency-enhancing information technologies and corruption. I investigate whether firms view bribe payments as a cost of doing business, even with the adoption of these technologies. These studies collectively contribute to a deeper understanding of how firms utilize digital transformation amidst environmental turbulence. They shed light on the crucial linkages between adopting new technologies and achieving positive performance outcomes.

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Preface

Thank you for all the support.

1.0 Introductory Overview

Over the past few decades, digital transformation, “a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies,” (Vial, 2021) has captured growing attention from both IS researchers and practitioners (Bharadwaj et al., 2013; Fitzgerald et al., 2014). Scholars have conducted extensive research on digital transformation, and a framework for digital transformation is gradually being established. Simultaneously, our understanding of digital transformation has also deepened.

One of the most widely discussed topics within digital transformation is its impact, which extends beyond the organizational level to society itself (Hanelt et al., 2021; Majchrzak et al., 2016). At the organizational level, digital transformation is linked to improvements in organizational performance (Karimi and Walter, 2015; Trantopoulos et al., 2017; Nwankpa and Datta, 2017). At a higher level, however, such as within industry and in society at large, both positive outcomes and potential issues have been noted (Agarwal et al., 2010; Srivastava and Shainesh, 2015; Newell and Marabelli, 2015). My dissertation contributes strong evidence to both sides. Furthermore, in the context of the COVID-19 pandemic, this has been an important opportunity to observe the effectiveness of digital transformation in response to environmental shock.

The COVID-19 pandemic stands as an extreme event in human history, disrupting the status quo and profoundly influencing both economies and organizations. When facing severe circumstances, companies have to navigate crucial decisions about how to realign themselves. Even now, organizations and individuals are still learning to live alongside the virus.

In times of crisis, the decisions and strategies that companies adopt can result in diverse consequences. When initially confronted with environmental shock, companies decided to pursue different digital transformation initiatives. These strategies involved bolstering their online presence, facilitating delivery services, and embracing remote work for their employees. Understanding the impacts of these strategies can empower companies to respond more effectively to crises, thereby simultaneously assisting researchers in studying the adoption processes of new technologies.

My dissertation includes three studies:

1. Digital Strategies and Sales Growth of Firms During Covid-19: Evidence From 27 Countries
2. Workforce Flexibility and Firm Resilience: An Exploration of Remote Work Adoption During Pandemic
3. Digitization and Corruption: How the Productivity-Transparency Tradeoff Distorts the Value Calculus

The key area of interest across all three studies is digital transformation, with a specific focus on analyzing its economic effects on firms, ranging from firm performance to bribe payments and more.

The first study focuses on firms' adoption of digital configurations during different phases of the Covid-19 pandemic. Responding to COVID-19, companies pursued new digital transformation initiatives, including those that increased their online presence, enabled new product and service delivery modes, and facilitated remote work for employees. This study adopts the paradigmatic lens of configurational theories and explores the relationship between firms' strategies related to their digital configurations and sales growth during the COVID-19 pandemic.

With firm-level data collected through the *World Bank Enterprise Survey* from 27 countries along with industry- and country-level data from other sources, this study estimates the impact of adopting specific digital configurations on sales growth. The results indicate that firms that pursued digitization during the COVID-19 pandemic period had about 5% higher sales growth, on average, relative to peers who did not pursue any digitization. Moreover, digital configurations that enabled new product and service delivery modes along with facilitating remote work for employees had the highest impact on sales growth (about 11% to 15%, on average) during the COVID-19 pandemic. Additionally, the results revealed heterogeneity in the effects of adopting specific digital configurations by firms on their sales performance, which can be attributed to industry- and country-level digitization and regulatory factors, such as business process digitization and ease of doing business. These results contribute to a better understanding of the adoption of digital configurations amidst environmental turbulence and about the linkages between these digital configurations and performance outcomes.

Furthermore, to reveal more details about how these impacts took place over time, I focused on remote work, an important technology which was widely adopted during the pandemic. Thus, in my second study, I investigated how remote work affects company performance. The proliferation of remote work has transformed the landscape of business operations during the pandemic and is considered an effective measure to cope with this crisis. The percentage of employees working remotely has experienced rapid growth in the US in recent years. Even since the pandemic, remote work is expected to remain prevalent as many companies have recognized its benefits. This study investigates the impact of remote work adoption on organizational performance and precisely documents the evolution of the situation over the course of the pandemic. The three consecutive waves of the *World Bank Follow-up Survey*, with one every six months, is our main dataset in this research. In the dataset, firms respond to 'whether the firm started or increased its remote work arrangement for its workforce' and 'the share of this establishment's workforce working remotely' in each wave. The different answers constitute different remote work technology-based adoption configurations that can be examined in terms of their effectiveness. By using the inverse probability of treatment weighting (IPTW) method and doubly robust (DR) estimator, along with causal tree and other machine learning techniques, I found that adoption of remote work had a positive impact on organizational performance during the pandemic. On average, firms that enabled remote work at the beginning of the COVID-19 pandemic period had about 3.3% higher sales growth relative to peers who did not adopt remote work. Furthermore, flexible workforce adjustment, such as changes in the share of employees who worked remotely following the adoption of remote work, positively impacts organizational performance. According to our observations, however, removing the flexible workforce arrangement entirely and calling all the existing employees back to the office negatively impacts organizational performance.

In my final study, I examined the association between the adoption of transparency enhancing digital technologies and corruption in emerging economies. Although the business value of IT literature is replete with evidence of the firm-level benefits of IT adoption, recent examinations have revealed that firms in emerging economies that encounter a challenging business environment with weak infrastructure and high corruption are reluctant to adopt transparency-enhancing technologies. This study examined the linkages between firm-level IT adoption, bribe payments, and performance by utilizing data from the *World Bank Enterprise Survey*. The analysis confirms the presence of a transparency-productivity tradeoff in emerging markets. On average, IT adoption is associated with an increase of about 1.76 million INR in Sales but also leads to around 38,000 INR in bribe payments. Both numbers surged even more in 2014. The results show that firms that adopted and used IT in their business operations substantially improved their performance, but they also paid more in bribes relative to their peers who did not adopt IT. However, since the bribe payments are a magnitude of order smaller than the quantum of productivity improvements, on average, firms are likely to treat the bribe payments as the cost of doing business in emerging economies. Such a distorted value calculus inflicts negative societal impact, and the study calls attention to this underexplored aspect of adopting digital technologies.

Collectively, these three studies contribute to a deeper understanding of the consequences of digital transformation for modern business. The insights derived from this research set the stage for making better decisions, which are crucial for ensuring sustainable growth for organizations in the long run.

2.0 Digital Strategies and Sales Growth of Firms During Covid-19: Evidence From 27 Countries

2.1 Introduction

Extreme events produce profound impacts on economies and organizations. The worldwide COVID-19 pandemic represents just such an event. Its impact on business was profound as it impacted supply chains, manufacturing, work locations, and delivery modes (Brodeur et al., 2021). Companies were compelled to make important choices about how to adjust, resulting in significant shifts in many cases. Some companies either chose or were required to move to virtual work set-ups. Factories needed to take new precautions to help ensure epidemic-related safety in the workplace. Retailers, service industries, and other face-to-face businesses enacted new policies and procedures that limited interaction and provided new, safer options for customers.

Information technology (IT) facilitated many of these changes. Indeed, the shock of COVID-19 and the regulatory and safety-related protocols, particularly those related to remote work, and product and service delivery, created for businesses a very sudden motivation to implement new technologies to address the impact of the crisis and alter their digital configurations. In this sense, much like other disruptive events of the past, the arrival of COVID-19 served as a call-to-action for companies to pursue new digital strategies or to accelerate planned ones. As such, it provided researchers with a unique opportunity to understand how businesses pursue digital adoption and related changes to their digital configurations amidst a severe shock to their operating environments.

Using this opportunity, and building on prior research on digital transformation, our study focuses on exploring the relationship between companies' digital configurations and a market-based performance outcome-sales growth-during a period of severe environmental shock. Prior studies have revealed that digital transformation programs, even during periods without any environmental shocks, feature paradoxical tensions in managing decisions related to IT portfolios and program management (Gregory et al., 2015). Organizations pursuing digital transformations are known to struggle with complexities arising from co-dependencies between various systems and between these systems and functional business processes, which constrain firms from achieving the desired performance improvements (Lauterbach et al., 2020). In addition, the malleability of digitized systems and processes contributes to dynamics of drift, that is, complexity arising from changes to process structures during transformative phases (Pentland et al., 2020). Environmental turbulence adds to these challenges and influences the relationship between firm-level digital initiatives and performance outcomes (Pavlou and El Sawy, 2006). Nevertheless, research is lacking on how firms respond to environmental shocks through digital transformation initiatives as well as how performance outcomes are affected by these digital transformation initiatives undertaken amidst environmental turbulence.

To better understand the dynamics at the confluence of environmental turbulence and transformational IT initiatives, researchers have called for studying them using the paradigmatic lens of configurational theories (El Sawy et al., 2010; Park et al., 2017). In this paradigm, a firm's digital assets and IT initiatives are not viewed in isolation but as configurations that embody complex interdependencies; the effects of these independencies are often non-linear, thus making assessment of configurations and their effects on performance effects difficult to assess (Anderson, 1999; Park and Mithas, 2020). Research that explains the relationships and outcomes relevant to digital configurations is still in its developmental stage. Notably to date, studies have discovered non-linear relationships between the organizational use of digital technologies and outcomes, such as organizational agility and ambidexterity (Park et al., 2017, 2020). These early studies qualitatively examined the linkages between digital configurations and outcomes using such methodologies as fuzzy-set comparative analysis and highlighted the existence of complex and equifinal pathways between digital configurations and performance outcomes. The formation of digital configurations during periods of environmental shock and their implications for firm performance, however, are still underexplored in this stream of literature.

We address this gap by focusing on specific digital configuration decisions made by 8,511 companies operating in 27 countries during the COVID-19 pandemic. We utilized data collected through the World Bank's Enterprise Survey and other sources to explore firms' decisions on their online presence, product or service delivery options, and/or remote work options for employees during the COVID-19 pandemic. The combination of decisions to either adopt or not adopt digital measures in the areas of (1) online presence, (2) delivery mechanisms, and (3) remote work options produces eight specific digital configuration options across these firms. Our empirical analysis sought to evaluate the performance implications of adopting these eight digital configuration changes in terms of sales growth during the COVID-19 pandemic.

Our results indicate that digital initiatives undertaken by firms during the COVID-19 pandemic had a positive impact on sales growth. Relative to firms that did not pursue any new digital initiatives, firms that implemented digital configurations that enabled online presence, new product or service delivery modes, or remote work for employees had about 5% higher sales growth. However, we noticed substantial heterogeneity across the different digital configurations as well as across firms located in different industry sectors and countries. For example, while the digital configuration decision to enhance online presence only did not have a significant impact on sales growth, the configuration decision to enable both remote work and new modes of product or service delivery had the greatest impact on sales growth (about 15%). When we unpacked the industry- and country-level fixed effects in our empirical models and examined the individual effects of representative digitization indices through causal trees, we noticed that these digitization indices could explain the observed heterogeneity in the impacts of various digital configurations on sales growth.

The study's main contribution is in rigorously examining and empirically documenting how firms' digital responses impact performance outcomes during periods of adverse environmental shocks. By adopting the configurational view, we go beyond the utilization of IT spending dollars as a proxy measure for firms' investments in digital transformation initiatives, and we consider the specific digital configuration through which a firm might attempt to transform its online presence, product or service delivery, and/or employee working modes. Large-scale empirical results that illustrate the linkages among specific digital configurations adopted by firms and performance outcomes during environmental turbulence, such as those presented in this study, are scarce in the IS literature. Finally, we contribute to an empirical illustration of digital ecodynamics by examining how various industry- and country-level digitization and regulatory indices influence the heterogenous impacts of firms' digital configurations on their sales performances (El Sawy et al., 2010), that is, the holistic confluence among environmental factors and digital assets that unfolded during COVID-19.

2.2 Data and Variable

We collated data from several sources as shown in column 1 of Table 1. Our primary data source is the World Bank's Enterprise Survey (ES), which is a '*firm-level survey of a representative sample*'[1] of a country's non-agricultural private firms in both manufacturing and service sectors. The ES is an ongoing World Bank project in which 185,000 firms have been surveyed in approximately 150 countries since the survey's inception in 2005-2006. Although the survey is administered every year, not every country is surveyed annually. Instead, a subset of these 150 countries is targeted in a particular year, which has implications for our sample selection as we describe later. The ES uses a standard global methodology for its surveys to ensure that survey data are comparable across countries and time periods.[2]

The aim of the ES is to collect representative data about private firms in its target countries. Specifically, the ES collects firm-level data such as their characteristics (e.g., ownership structure), behavior (e.g., rewarding worker performance), financial performance (e.g., sales growth), and perceptions about the business environment in order to enable researchers to analyze firm performance, firm productivity, and job creation in selected sectors. The ES survey collects data from both manufacturing and services sectors using standardized survey instruments and uniform sampling strategies across countries. Within each country, the ES uses stratified sampling following three stratification criteria, namely, sector of activity, firm size, and geographical location. The firm sample sizes within each country are chosen to be large enough to allow robust

[1] Additional information about the survey can be found at https://www.enterprisesurveys.org/en/about-us

[2] For additional details, please see https://www.enterprisesurveys.org/en/methodology

statistical analysis. The owners and senior managers of the targeted firms answer these surveys through interviews conducted by private contractors employed by WB. Furthermore, the WB promises to honor the confidentiality of the surveyed firms and their responses. These two factors—use of private contractors for interviews and the confidentiality of firms' responses—help ensure that the firms provide honest answers to the survey questions. Overall, this survey methodology results in minimizing measurement error and making the survey data comparable across countries and time.

We used the 2019 Enterprise Survey to generate firm-level data about ownership structure, age, national sales percentage, sales per employee, annual sales change over a two-year period, product innovation, market innovation, and process innovation. Following the terminology used by the Enterprise Analysis Unit of the World Bank within the COVID-19 context, we will use the terms ES and Baseline Survey interchangeably. In 2020, the WB instituted a new survey, the ES Follow-up Survey on COVID-19, with the aim of measuring the impact of coronavirus on non-agricultural private sector firms across the globe. The ES Follow-up Survey on COVID-19, hereafter referred to as the Follow-up Survey (FS), collects data about firms' basic characteristics as well as COVID-19-related data on sales, production, labor (e.g., overall employment and changes), finance (e.g., solvency), policies, and expectations. We used FS data on whether the firm received support from the national or local government, whether the firm self-adjusted in response to COVID-19, and sales growth. Firms' sales growth is our outcome of interest, and is measured by comparing sales during a specific month during COVID-19 with the same month during the preceding year. As expected, the average sales growth is negative in this dataset, as sales declined for most of the observed firms during COVID-19. The FS also provides data for the firms' digital responses during COVID-19. Crucially for our study, the FS provides data on three firm policies, viz., (i) whether the firm started or increased its business activities online, (ii) whether the firm started or increased remote work arrangements for its workforce, and (iii) whether the firm started or increased delivery or carry-out of goods or services. These policies are the firms' digital responses to COVID-19 that we aim to study in this article. The Follow-up Survey was conducted throughout the calendar year 2020 and was administered across 42 countries. As we discuss later in the empirical section, data collected in the 2019 Baseline Survey was necessary for proper empirical analysis. Since we were able to match only 29 countries from the 2020 Follow-up Survey and the 2019 Baseline Survey, we dropped the remaining 13 countries in the FS. In addition, we dropped two more countries from our analysis because of missing data issues.[3] After these data cleaning steps, we were left with a data set that spanned 27 countries and 8,511 firms.

In addition to the ES and FS, we collected country-level data on digital adoption, ease of doing business, income and industry classification, and Covid-19-specific policies, such as mask mandates, lockdown measures, and stay-at-home policies.

The Digital Adoption Index (DAI) is a global country-level index created by the World Bank in 2016 to measure digital adoption across three dimensions: business, people, and government. The World bank creates separate sub-indices for these three dimensions, and the DAI, measured on a 0-1 scale, is a mean of these three sub-indices. The sub-indices are constructed by measuring technologies that are necessary for "increasing productivity and accelerating broad-based growth for business, expanding opportunities and improving welfare for *people*, and

[3] The FS for Lebanon did not have information on online business activities. Northern Macedonia had missing data on lockdown, which we will discuss momentarily.

increasing the efficiency and accountability of service delivery for *government*."[4] The DAI measure is available for all of the 27 countries in our FS sample.

The World Bank has been conducting annual studies that investigate the regulatory environment in a country and its impact on the ease of doing business. We source data from *Doing Business 2020*, which is the 17th study in this series of studies. As part of these studies, the World Bank generates a Doing Business Score (*DB Score*), which measures "the processes for business incorporation, getting a building permit, obtaining an electricity connection, transferring property, getting access to credit, protecting minority investors, paying taxes, engaging in international trade, enforcing contracts, and resolving insolvency."[5] The data used in Doing Business 2020 for creating the DB Score are current as of May 2019,[6] and the scores range from 20.0-86.8 for the 190 countries benchmarked in this study. The DB Score is available for all 27 countries in our sample.

We sourced government lockdown and stay-at-home information from Reuters, an international news organization that claims to be the world's largest multimedia news provider.[7] Reuters has been maintaining a COVID-19 global tracker,[8] which collates COVID-19 data for 240 countries from the official country and local government, and public health department websites. In addition to websites, Reuters also uses news conferences, press releases, and verified social media posts (e.g., X) by government officials. Furthermore, Reuters may also source data from

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[4] https://www.worldbank.org/en/publication/wdr2016/Digital-Adoption-Index

[5] https://tinyurl.com/z5j7p564

[6] Please see p. v of Doing Business 2020

[7] https://www.reutersagency.com/en/about/about-us/

[8] https://graphics.reuters.com/world-coronavirus-tracker-and-maps/

global health organizations such as the World Health Organization. Although the primary purpose of Reuters' COVID-19 tracker is to collate data about infections and deaths, it also reports data about governmental responses to this pandemic, such as lockdowns. As the severity of the COVID-19 pandemic became apparent, governments across the globe started responding by implementing lockdown measures which included restricting movement across international borders, closing down schools and workplaces, and ordering the population to stay at home. These governmental lockdown responses have important variations that may affect firm performances in different ways. Reuters has applied the following categorization scheme for these variations in government responses: (i) for schools: require closing all levels, require closing some levels, recommend closing, no lockdown measures; (ii) for workplaces: require closing all but essential workers, require closing some sectors, recommend closing, no lockdown measures; (iii) for stay-at-home orders: require not leaving home with few exceptions, require not leaving home with some exceptions, recommend not leaving house, and no lockdown measures; (iv) for borders: ban arrivals from all regions, ban arrivals from some regions, quarantine arrivals from some or all regions, screen arrivals, and no lockdown measures. Reuters also categorizes whether these lockdown policies were implemented at the national or local levels. We collected the lockdown data for the March to May period, which precedes the FS survey. During this relatively early period, the lockdown policies for the countries in our sample were nationally implemented (rather than more local policies), hence we do not use this distinction in our dataset.

We sourced data for country-level mask requirements from #Masks4All, which reports data on what countries require or recommend public mask usage to help contain COVID-19. These mask requirements may be implemented across the entire country or may be restricted to certain parts of the country. Another dimension of the mask requirement is whether masks are required everywhere in public or only in designated places (e.g., public transportation). We simplified the #Masks4All classification into two simpler binary classifications: mask requirement (whether the country required masks across the country) and mask requirement types (whether the country required masks everywhere in public).

Finally, we sourced data on country income levels from the United Nations (UN). The UN reported these data in the report *World Economic Situation and Prospects 2020*. Specifically, the UN classified countries into four income categories (high, upper-middle, lower-middle, and low) based on the per capita gross national income (GNI) in June 2019.

Table 2 summarizes these data by country. Most of the countries included are in the high-income category. Specifically, 14 countries are high income, 9 countries are upper-middle income, and 4 countries are lower-middle income.[9] The number of firms per country range from a low of 28 firms for Azerbaijan and a high of 842 firms for Russia. The DB Score ranges from 65-82 and the digital adoption index ranges from 0.34-0.86. Table 2 also shows the variation in lockdown measures and mask mandates across the sample countries.

2.2.1 Treatment Groups and the Outcome

Our data set consists of 8,511 firms in 27 countries. These firms adopted different digital strategies to cope with the business disruption caused by the COVID-19 pandemic. As discussed earlier, the FS surveys firms about changes in their online business activities, remote work arrangements, and delivery or carryout of goods or services in response to COVID-19. Recall that

[9] All of the high-income countries are part of the European Union.

the FS collects firm responses to: (i) whether the firm started or increased its business activities online, (ii) whether the firm started or increased remote work arrangements for its workforce, and (iii) whether the firm started or increased delivery or carry-out of goods or services. These changes constitute different technology-based business configurations that we can examine for their effects. We divide the firms in our sample into eight distinct groups, based on their responses around the three dimensions, namely, online, delivery, and remote work. Specifically, the eight distinct groups of firms are: (1) online only, (2) delivery only, (3) remote only, (4) online and delivery, (5) delivery and remote, (6) online and remote, (7) online, delivery, and remote, and (8) control. We abbreviate these groups as (O), (D), (R), (O+D), (D+R), (O+R), (O+D+R), and (C).

Our primary outcome variable is the firms' sales growth, and we are primarily interested in examining the impact of the firms' digital configurations on the sales growth of the firms. Specifically, the FS asks firms to report the percentage increase or decrease in firms' sales for one month during the COVID-19 pandemic relative to firms' sales in the same month in the previous year. Although the FS data set includes other potentially interesting outcomes (e.g., employment), these other outcomes have too many missing values and thus would not allow us to carry out a robust analysis.

2.3 Empirical Strategy

Our aim for this analysis is to estimate the impact on sales growth of various digital configurations that firms have adopted in response to the COVID-19 pandemic. Our unit of analysis is the firm since we observe the outcome at the firm level, and the treatment decisions are also at the firm level. Since firms self-select into these digital strategies, the treatment and outcome are likely to be confounded as we discuss below. Thus, our empirical strategy posits a plausible case for no unmeasured confoundedness (NUC) using various covariate adjustment methods for providing the best possible evidence.

Broadly, we can divide the potential confounders into two categories: country-level confounders and firm-level confounders. We note that our data are hierarchical in the sense that firms are located within countries, and thus the country policies will impact firms' treatment decisions and their realized outcomes. On the other hand, there will be no variation in country-level factors across firms that are located in the same country. A country's lockdown and mask policies are likely to have an impact on both the firms' choice of digital strategies and its sales growth. For instance, a strict country-wide lockdown is likely to induce firms to adopt remote work if the firms' business is conducive to remote work, and also likely to lead to a decline in the firms' sales growth. We can explicitly adjust for such country-level confounders, as they are likely to affect both sales growth (the outcome) as well as the firms' selection into the various treatment groups. Specifically, we can control for school lockdowns, workplace lockdowns, border lockdowns, stay-at-home orders, mask requirements, income levels, ease of doing business, and the digital adoption index. Alternatively, we can adjust for country-level fixed effects. In addition to these country-level confounders, firm-level variables may also impact the firms' outcome and treatment group selection. A firm's ownership structure (e.g., single influential decision maker as measured by percentage ownership of the largest owner) may have an impact on speed of decision-making and may correlate with both the choice of treatment groups and sales growth. Another example would be the industry that the firm operates in, which is likely to have an impact on both choice of treatment and the realized sales growth. For instance, a beauty service may decide that they may not have enough customers interested in receiving the service outside the salon and may not choose the delivery strategy.[10]

2.3.1 Inverse Probability of Treatment Weighting (IPTW)

Our first analysis uses the inverse probability of treatment weighting (IPTW) method to estimate the impact of the treatment on sales growth. Under the NUC assumption and given a set of potential confounders, the treatment, and outcome variable, the IPTW method creates a weighted sample[11] that has been adjusted for these potential confounders so that a mean difference between the treated and control group can be given a causal interpretation. The IPTW method works as follows: each unit is weighted by the probability of receiving the treatment level that the unit has actually received. For instance, to causally compare two groups, one that receives a treatment and the other that is in the control group, IPTW requires that the treated units be weighted by the probability of receiving treatment and that the control units be weighted by the probability of being in the control (which, in this dichotomous case, is one minus the probability of receiving treatment). The probability of treatment, also known as the propensity score, can be informally defined as the conditional probability of a unit to receive treatment given the observed pre-treatment values of a vector of covariates (Rubin, 2006). In an observational study, the true propensity score is not observed but can be estimated from the data. We estimate the propensity scores using the Toolkit for Weighting and Analysis of Nonequivalent Groups (TWANG), which

[10] For a counter example, please see https://glamsquad.zendesk.com/hc/en-us , which uses the customer service platform, Zendesk, to deliver beauty services to their customer.

[11] Also known as the pseudo-population. Please see Hernan and Robins (2020).

implements a generalized boosted regression model (GBM). GBM is an ensemble machine learning method which iterates through multiple functional specifications and uses boosting to assign higher weights to misclassified observations (McCaffrey et al., 2013). The TWANG package optimizes for covariate balance across the treated and untreated groups in its calculation of the propensity score, making it suitable for analysis that suggests a causal interpretation.

2.3.2 Doubly Robust Estimator

To augment the IPTW results, we use a doubly robust (DR) estimator which combines both an outcome model and a treatment model (i.e., the propensity score model) into a single estimator (Bang and Robins, 2005). The outcome model estimates the conditional mean of the outcome given treatment and a set of confounders either nonparametrically or by using a parametric model. Under the NUC assumption, the DR estimators can correctly identify the causal effect if either the outcome model or the treatment model is correctly specified. Thus, the doubly robust estimator gives the analyst two chances to get the model specification right (Hernan and Robins, 2020, Chapter 13). If both the outcome model and the propensity score model are correctly specified, the DR estimator is the most efficient estimator (Emsley et al., 2008).[12]

[12] A slight downside of using a DR estimator when the outcome model is correctly specified is that the DR estimator may have larger variance than the outcome model alone. However, it is not knowable if the outcome model is correct (or not) and thus the protection that DR provides may outweigh the slight downside in empirical analyses.

2.4 Results

2.4.1 Treatment Model using Inverse Probability of Treatment Weighting (IPTW)

We first estimate IPTW models using the TWANG package. For the estimation of the propensity score, we use 3-way fixed effects (i.e., country, industry, survey-month) as well as firm-level covariates such as *Firm Age*, pre-COVID *Sales per Employee, National Sales*, *Pre-COVID Sales Trend*, *Innovation Index*, *National Support*, and *Self Adjustment* (all of these covariates are taken from the pre-COVID baseline ES survey except the last two, i.e., received *National Support* and *Self Adjustment*).

Table 3 presents the estimated treatment effects using the IPTW estimator. Model (1) in Table 3 shows that firms that pursued any digitization strategy during the COVID-19 period had about 4.5% higher sales growth, on average, than firms that did not pursue digitization. Unpacking the binary digitization treatment into specific configurations, we observe positive and statistically significant effects on sales growth across all digital strategies except for the (O) and (O)+(R) treatment arms. The (D+R) strategy yields the highest economic impact with about 12% higher sales growth, relative to firms that did not pursue any digitization.

2.4.2 Conditional Outcome Model using Linear Regression with 3-Way Fixed Effects

Next, we estimate a conditional outcome model using linear regression with 3-way fixed effect (country, industry, and survey) and firm-level covariates. As in the case of the treatment model, the outcome model also relies on the NUC assumption. Nonetheless, the outcome model is useful for two reasons: (i) the outcome model uses a different model specification (cf. the treatment model), so getting consistent results would strengthen our confidence in observed effect size; (ii) the outcome model together with the treatment model provides a useful prelude for our main model, which uses a doubly robust estimator that combines the treatment model and the outcome model into a single estimator. For the conditional outcome model, the results are presented in Table 4 and are largely consistent with the results obtained with the IPTW model; the only treatment group in which the results are directionally different is the (O) group, but we note that these results are not statistically significant in either approach. When it comes to the (O+R) group, we obtained a larger positive and statistically significant effect on sales growth for the conditional outcome model, while the IPTW model presents an insignificant result.

2.4.3 Results Using Doubly Robust Estimators

As stated earlier, our main analysis uses a doubly robust (DR) estimator with 3-way fixed effects (country, industry, and survey-month) and firm-level covariates that are potential confounders. By combining an outcome model and a separate treatment model, the DR estimator guards against bias due to model misspecification if either the outcome or the treatment model is correct. Table 5 presents the result from the DR analysis.

Once again, we observe that firms that pursued any digitization had about 5% higher sales growth, on average, than their counterparts who did not pursue digitization during the COVID-19 period. The strongest effects of digitization on sales growth are obtained through the (D+R), (D), and (O+D+R) configurations in that order. This ranking of effects obtained through the DR estimator is consistent with those obtained using IPTW and conditional outcome models. We also find a consistent null effect across various models for the (O) treatment. We do not get consistent estimates for firms that used (O+D) and (O+R) digital strategies; although the point estimates are mostly positive, these estimates lack precision for the doubly robust model.

2.4.4 Robustness with Firm-level Fixed Effects

Given that our analysis is based on one observation per firm, it is not possible to include firm-level fixed effects in an OLS model as such inclusion will require the estimation of more parameters than there are observations. In predictive analysis, it is common to use dimension reduction techniques such as the machine learning (ML) algorithm, least absolute shrinkage and selection operator, generally referred to as lasso (Tibshirani, 1996). However, for variable selection in causal inference models, the ML techniques can only be useful when the entire set of control variables necessary for unconfounding are a subset of a high-cardinality set of control variables. *A priori*, it is not known to the researcher which of the control variables are necessary for unconfounding, but effect estimation is possible under the assumption that the required set of control variables is a subset of a larger available set of control variables. For instance, Belloni, Chernozhukov, and Hansen have proposed an ML-based method for selection of control variables in a high-dimensional setting, which the authors refer to as "post-double-selection" (Belloni et al., 2013). Their goal is to estimate the treatment effect in a partially linear model, $y_i = d_i\alpha_0 + g(z_i) + \psi_i$, where d_i is the treatment, z_i is the set of control variables, and ψ_i is an unobservable that satisfies $E[\psi_i|d_i, z_i] = 0$. They approximate $g(z_i)$ with x_i, which consists of z_i and transformations of z_i. The dimension of x_i is allowed to be more than the number of observations, i.e., the number of control variables is allowed to be more than the number of observations. However, the post-double-selection method depends crucially on the assumption "that exogeneity of d_i may be taken as given once one controls linearly for a relatively small numbers $s < n$ of variables in x_i whose identities are *a priori* unknown" (Belloni et al., 2013, p.609). Under this assumption, their method provides inference that is uniformly valid over large classes of models. Briefly, the post-double-selection method proceeds in three stages: in the first stage, the researcher uses lasso to select a small number of variables that predict the treatment d_i; in the second stage, the researcher uses lasso to choose a set of variables that predicts the outcome y_i; in the third and final stage, the researcher runs a linear regression of y_i on d_i and the union of the set of variables selected in the first two stages to recover the causal parameter α_0. We use the post-double-selection procedure on our dataset with 4-way fixed effects, i.e., industry, country, survey time, and firm fixed effects.

Table 6 presents the result of this analysis. Once again, we see that firms that pursued any digitization strategy during the COVID-19 period outperformed counterparts who did not pursue digitization by about 5% in sales growth. Consistent with the IPTW, DR, and conditional outcome models, the lasso approach also shows that the highest economic benefits of digitization occurred in (D+R), (D), and (O+D+R) configurations in that order. This consistency in estimates across various empirical models provides high confidence in our results.

2.5 Heterogeneous Treatment Effects (HTE)

While our main results provide evidence for managers and policy makers about average effects of various digitization configurations, it would be useful to know if these treatment effects exhibit heterogeneity across other observed covariates. To recap, we have covariates in our data set that can be broadly divided into four categories, (i) industry characteristics, (ii) firm characteristics (e.g., labor productivity, national sales, firm age), (iii) country characteristics, and

(iv) a country's COVID-19-related responses. Identifying firm characteristics that lead to heterogeneous treatment effects will not only be helpful to managers and policy makers, but also allow us and other researchers to theorize and discuss the potential mechanisms that may underlie the observed effects. One firm characteristic, industry, has 27 possible values and this high-dimension does not lend itself well to analysis and subsequent interpretation. Thus, we closely followed Gandhi et al. (2016) and Manyika et al. (2015) and collapsed the industry designations into three dimensions or indices, viz., digital assets, digital business process usage, and labor digitization. The digital assets index measures how much firms in the industry spend on hardware, software, and IT services, and how much of their physical assets are digitized. For instance, if firms in the logistics industry had their entire fleets digitized and connected to the network, it would increase the digital assets measure for the logistics industry. Digital business process usage index refers to how much of the internal and external processes (i.e., interactions with suppliers, customers, and complementors) are implemented digitally. For instance, if all billing within the healthcare industry were to become digital, the digital business process usage measure would increase. Finally, the labor digitization index, one of the most important indices (Gandhi et al., 2016), is the extent to which the labor force in an industry uses productivity-enhancing digital technologies. Drawing on the work in the aforementioned references, we encoded the industries in our sample across the three indices—digital assets, digital business process usage, and labor digitization. As expected, the IT industry scored the highest on these measures with a score of “6” on digital assets and labor digitization indices, and a score of “5” on digital business process usage. In contrast, the Tobacco industry, which maps to McKinsey's categorization of agriculture and hunting, scores a “1” on all three indices.

We employed the causal trees approach introduced by Athey and Imbens (2016) for calculating heterogeneous treatment effects by recursively partitioning the covariate space into subspaces and estimating the treatment effect for each subspace. Although similar in some respects to the supervised machine learning algorithm classification and regression trees (CART), the causal tree (CT) algorithm crucially differs from CART as CT's focus is on estimating the conditional average treatment effects rather than predicting outcomes. This difference is crucial because the unit level treatment effects are not observed for any unit (cf., the observed unit-level outcomes in CART training data set). The estimand for CT is defined as follows: $\tau(x) \equiv \mathbb{E}[Y_i(1) - Y_i(0)|X_i = x]$, where $Y_i(.)$ are the potential outcomes for the individual i and X_i is a vector of covariates (Athey and Imbens, 2016). The estimated $\hat{\tau}(x)$ is based on the covariate subspace and does not vary for a particular partition of the covariate space.

The causal tree algorithm is implemented in the R package, *causalTree*, and the standard implementation assumes unconfoundedness. Thus, the standard implementation is only usable out-of-the-box for analysis of data generated in a randomized controlled trial (RCT).[13] In case of observational studies, we follow advice from Athey and Imbens (2016) and use propensity score weighting in our study. In particular, we used the propensity score we estimated earlier (for IPTW analysis) to create a weighted pseudo population (Hernan and Robins, 2020) that we fed into *causalTree* and created causal trees for all seven treatment levels.

For brevity, we discuss the HTE for the D+R configuration, which had the highest impact on sales growth in our main analysis. Figure 1 is the causal tree for the D+R digital strategy.

The figure shows that for firms that embraced the (D+R) strategy, the firm's age is the most

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[13] The TOT option for splitting rule in causalTree::causalTree function only allows a fixed propensity value, which is applicable when all units a priori have the same probability of receiving a treatment as in an RCT.

important factor. In particular, firms aged less than 14 years, and with a digital asset index of less than 3, which constitute about 12% of our sample, had a predicted sales growth of 40 percent. Another branch partition of firms that exhibit high sales growth are those whose older than 14 years, who operate in a location with an ease of business score of less than 72, and have a digital asset index of less than 3.8. Overall, the causal tree for the D+R configuration shows that even as the D+R configuration has a positive impact on sales growth, on average, there is substantial heterogeneity among firms that adopted the configuration. We highlight that there are specific conditions under which the D+R strategy did not yield a positive impact on sales performance (e.g., a firm with 14 or more years of operations in an area with relatively higher ease of doing business and which gets 62% or more of its revenues domestically).

2.6 Discussion and Conclusion

The COVID-19 pandemic represented an extreme shock to businesses. Unlike other recent recessionary periods, such as the financial crisis of 2008-2009 and the dot-com bubble burst of 2000-2001, firms faced government mandates to adopt employee and customer safety- and health-related measures while they were simultaneously tackling severe supply and demand disruptions. Market reports indicate that a majority of firms responded by accelerating their digitization efforts (Goasduff, 2020) and aimed to aggressively increase their online presence, adopt new product or service delivery modes, and enable remote work arrangements for employees.

While there is a dearth of literature that specifically examines the outcomes of digital transformation initiatives during adverse environmental shocks, prior studies have cautioned that paradoxical tensions in decisions related to IT portfolios and program management as well as the complexity in managing co-dependencies between systems and business processes are persistent hindrances in achieving successful digital transformations (Gregory et al., 2015; Lauterbach et al., 2020; Pentland et al., 2020). The presence of such hindrances in digital transformation initiatives, along with the immediate economic threats posed by an environmental shock, has the potential to induce organizational rigidities that negatively impact performance outcomes (Vial, 2021). Empirical results documented in the digital transformation literature are largely qualitative in nature and focus on specific case contexts, while generalizable evidence that showcases the causal impacts of digital transformation initiatives undertaken by firms during adverse environmental events is not readily available.

We aimed to fill this gap through our empirical examination. We embraced the paradigmatic lens of the configurational approach and examined the linkage between firms' sales growth during the COVID-19 pandemic and the digital configurations adopted by these firms with the aim of transforming their online presence, product or service delivery modes, and remote work arrangements. Utilizing data from the World Bank Enterprise Survey and other sources, we empirically assessed the relationship between various digital configurations adopted by firms and their sales performance during the pandemic. Our results indicate that digital transformations undertaken by firms during the COVID-19 pandemic were successful, on average. We noticed firms that pursued digitization efforts during the pandemic had, on average, about 5% higher sales growth than those that did not pursue any digitization. Additional results highlighted the heterogeneity in the impact on sales growth across different digital configurations as well as the influence of industry- and country-level digitization and regulatory factors.

While past research has not directly addressed the outcomes of digital transformation initiatives during adverse environmental shocks, we discovered through our analyses that concepts uncovered in previous studies nevertheless resonate within our context. We note that past research has shown that adopting new technical capabilities into an organization can be beneficial in a number of ways, including financial performance, firm growth, reputation, competitive advantage, and agility (Brynjolfsson and Hitt, 2000; Karimi and Walter, 2015; Vial, 2021). However, given the dearth of generalizable cost-benefit analyses that recommend specific changes to firms' digital configurations, many companies often lack improvisational capabilities and impetus to make such changes without an exogenous shock of some kind, such as government intervention (Hsu et al., 2006; Pavlou and El Sawy, 2010). Our study highlights firms' propensity to indeed adopt technology into their configurations while facing environmental turbulence. Our results support the idea of exogenous shock catalyzing organizational digitization efforts. Further, our study shows improved sales results for those firms who did so during this extreme global event, providing evidence that a global shock may augment the performance benefits of organizational digital transformation initiatives.

Furthermore, as we noted in the introduction, this research took a configurational approach. As noted by Park and Mithas (2020, p. 86), "digital business strategy cannot be fully understood by focusing on any single capability in isolation, and there is a need to focus on configurations of capabilities." We see considerable evidence to support this assertion. Indeed, while adding to digital configurations was generally positive for firms, the heterogeneity of our results suggests a need to consider adoptions within the broader context of the firm. Indeed, this corresponds closely with findings regarding complexity, whereby a portfolio of digital adoptions forms a complex system with interdependencies among elements, thus resulting in outcomes that are non-linear (Anderson, 1999; Park et al., 2017; Park and Mithas, 2020).

This finding also begs the question as to what elements within these complex systems result in heterogeneous results. While the dataset at hand does not provide the means for testing candidate theories, past research has raised interesting possibilities. For instance, the concept of threat rigidity, whereby firms tend to stick to past processes and priorities when faced with a new threat (Staw et al., 1981) could at least partially explain why some firms may be reluctant to change their digitization trajectories during environmental turbulence.

We would like to acknowledge a few limitations of the study that we hope future research can address. First, although we were able to utilize a sample that included 27 countries, there is a need to verify our results by including a wider array of countries in the developed and developing economies categories for broader generalization. Second, our study considers only the short-term impact of digital transformation initiatives as data was available only for the one-year period after the COVID-19 pandemic started. Examining longitudinal data that spans multiple years of adoption and use of digital configurations would enable us to have a better understanding of how the digital configurations evolve over time as well as about the long-term costs and benefits of digital initiatives. Third, while our study adopted a configurational approach, our data did not include the details of specific systems and their interdependencies with firms' business processes within the various digital configurations. Explicitly considering the system- and business process-level interdependencies would help researchers to estimate the impact of complexity arising from configurations on the performance outcomes of digital transformation initiatives.

We believe that the empirical results we have documented in this research note would facilitate further research inquiries and theoretical development. While there was substantial heterogeneity in the impacts of digital configurations on the sales growth of firms in our sample, firms that did not pursue any digitalization efforts had the greatest decline in sales revenue during the pandemic. This suggests that digital transformation initiatives undertaken during adverse environmental shocks can play an important role in improving organizational resilience, which is in contrast to theoretical models that predict the existence of threat-rigidity effects and paradoxical tensions that detract from the success of digital transformation initiatives. We hope that our results inspire further research on how firms overcome known hindrances to digital transformation and how they can develop resilience using digital configurations.

3.0 Workforce Flexibility and Firm Resilience: An Exploration of Remote Work Adoption During Pandemic

3.1 Introduction

The COVID-19 crisis is one of the most significant global challenges of our time, reshaping almost every aspect of our society. Since December 2019, the pandemic has strained healthcare systems, disrupted economics, and altered the way we work and live. Commuting with colleagues in the office has become less safe and more difficult, especially under lockdown policies. Firms' operations have been threatened internally due to labor disruptions. In order to alleviate the impacts of these disruptions and sustain business operations, many companies are offering employees the option to work remotely.

Prior to the pandemic, remote work was relatively uncommon and mostly limited to specific industries and job roles (Mateyka et al., 2012; Mas and Pallais, 2020). For example, according to the *2014 GSS Quality of Worklife Survey*,[14] only 12.22% of respondents reported having a formal work-from-home arrangement (Mas and Pallais, 2020). However, the COVID-19 pandemic forced many companies to adopt remote work as a safety measure, leading to a massive increase in its prevalence. The percentage of employees working remotely increased to around 42% during the height of the pandemic in 2020 and remained at 34% in 2022.[15] Even after the

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[14] https://gss.norc.org/Pages/quality-of-worklife.aspx

[15] https://www.washingtonpost.com/wellness/2023/06/22/remote-work-family-socialization-time-use/; https://www.bls.gov/tus/

pandemic, remote work is expected to remain prevalent as many companies have recognized its benefits, such as increased productivity, reduced costs, and improved work-life balance for employees (Brynjolfsson et al., 2020; Mas and Pallais, 2020). According to a report conducted by Upwork,[16] 36.2 million workers, or 22% of American workforce, will be working remotely by the year 2025. This is an 87% increase from pre-pandemic levels. Remote work will continue to be a significant aspect of the modern workforce.

Even before COVID, plenty of studies focused on remote work. Benefits and challenges have been well documented (Bloom et al., 2015; Gajendran et al., 2015; Bartel et al., 2012). With the new wave of working from home during the pandemic, remote work has once again attracted significant interest from researchers (Barrero et al., 2021; Garrote Sanchez et al., 2021).

Despite the continuous interest, the impact of remote work at the firm level has yet to be extensively explored. We identified three gaps in the existing literature concerning remote work at the firm level and seek to empirically investigate these by exploring the following research questions: First, what types of firms are more likely to adopt remote work in the face of environmental shock? Second, what are the impacts of adopting remote work on firm performance, specifically whether different remote work adoption configurations as a way of increasing workforce flexibility can lead to improved organizational performance? Third, remote work is not only a one-time short-term adjustment, but may serve as a long-term strategy to modify workforce flexibility. Thus, do different adjustments to remote work arrangement impact firms' performance, and if so, how? By examining this understudied dimension of workforce flexibility, we hope to

[16] https://www.upwork.com/press/releases/upwork-study-finds-22-of-american-workforce-will-be-remote-by-2025

provide insights into how organizations can adapt to changing business environments and remain competitive.

We first examine our data, a combination of *World Bank Enterprise Survey* and *Follow-up Survey* data, which consists of responses about remote work implementation status and operating conditions from 3,329 firms from different industries operating in 21 countries. The *Enterprise Survey* was conducted in 2019 and collected representative samples right before the outbreak of the pandemic. The *Follow-up Survey*, targeting the same firms that participated in the *Enterprise Survey* in 2019, documented the changes in the firms from different perspectives during the pandemic. It consists of three waves, each conducted every six months from June 2020. For our study, we felt it critical to construct various treatment groups. Our data reflects different decisions made by firms that offered remote work to employees during different periods of the pandemic. Among these firms, 751 companies immediately allowed employees to work remotely at the beginning of the pandemic, while 350 opted to wait and only allowed it when the situation worsened. Furthermore, among the 751 'first movers', around half of them continued to offer work-from-home as an option but adjusted the proportion of employees working remotely later on; the remaining half, in contrast, completely abandoned remote work. Ultimately, we observed eight different configurations.

Our empirical analysis involved three key steps. First, we investigated the factors that influenced firms' adoption of remote work. Next, building on the adoption model, we assessed the differences in firm performance between different remote work arrangement configurations. We utilized Inverse Probability of Treatment Weighting (IPTW) to create a weighted sample, which accounted for potential confounding factors, and then we estimated the causal effect of remote work arrangements on sales growth. To augment the results, the Doubly Robust estimator was also implemented to the same analysis. In the third step, we explored heterogeneity in treatment effects by employing causal decision trees to recursively partition the data into subpopulations (Athey and Imbens, 2016).

Our results reveal that the adoption of remote work has a positive impact on organizational performance, but there is a lag in the observable effects which becomes more apparent after a certain period. After adopting remote work, firms are equipped with a more flexible workforce and are better able mitigate uncertainties caused by COVID-19. On average, firms that pursued remote work right after the outbreak of the pandemic had about 3.337% higher sales growth in survey wave 2 than firms that provided no remote work options. Furthermore, they reaped even more benefits later on. In survey wave 3, they had about 3.934% higher sales growth than firms in the control group. We also found that dynamic adjustments of their remote work options, such as changing the percentage of employees working remotely, contributed significantly to their sales performance. However, firms that decreased the number of remote-work employees to zero or, in other words, decided to abandon remote work entirely and return to the pre-COVID stage, faced negative repercussions. Firms that terminated remote work availability in survey wave 2 had on average 7.020% lower sales growth than firms that kept remote work as an alternative for their employees.

Our findings make two main contributions to the literature. First, based on a cross-country and cross-industry data source, we provide strong firm-level evidence that remote work, as an arrangement to enhance workforce flexibility, contributes to business operations in the face of uncertainty and environmental shock. Our work thus enriches the existing literature on remote work. Second, through our research, we have gained insights into the importance of workforce flexibility and the potential dependence of employees on remote work given that a rapid shift in policy such as the abandonment of remote work may lead to dissatisfaction and eventual harm to the organization.

3.2 Theoretical Background

We draw inspiration from environmental shocks and remote work literature to develop our analysis on the impact of firms' work from home strategies. We begin by introducing the literature on environmental shocks, discussing how companies adjust their technological approaches in response to these shocks. We then consider the relationship between remote work and workforce flexibility, and what do we know from previous literature about remote work technology adoption and its impacts on business operations.

3.2.1 Environmental Shock and Technology Adoption

'Environmental shocks' have the potential to introduce considerable uncertainty to firms, arising as they do from significant physical and sociocultural changes, such as those in technology, the economy, politics, or the natural environment (Bretschger and Vinogradova, 2019; Crouzet et al., 2023). Firms that fail to realign themselves with new environmental actualities may encounter a decrease in performance, employment, and output that jeopardizes their long-term sustainability (Bloom, 2009). In light of these uncertainties, researchers are still debating about firms' responses and the actions that managers implement in response to environmental change. To cope with adversity and survive under varying environmental conditions, firms will modify their internal framework or implement measures to strengthen themselves in the moment (Thompson, 2017), and managers endeavor to establish more control within the company (Barker and Patterson, 1996). According to Staw et al. (1981), organizations ultimately end up alternations in 'both the information and control processes of a system', and the 'threat-rigidity' response depending on historical adjustment routines will limit the flow of external information.

Technological adaptation has long been a critical topic in the literature on Information Systems research, and the external environment plays a critical role within that. Past studies have demonstrated that information technology contributions to organizational performance (Brynjolfsson and Hitt, 1996; Kohli and Devaraj, 2003). However, the business value generated from IT can be shaped by competition and the macro environment (Melville et al., 2004). For example, firms in developing countries, a more challenging environment, encounter constraints when implementing IT (Jarvenpaa and Leidner, 1998). From an industry perspective, regulations may slow the adoption of technology (Riordan, 1992). Therefore, indicators such as regulation and competitiveness are important controls when conducting empirical studies on this topic (Bharadwaj, 2000).

Due to the importance of the external environment, environmental shocks can have a significant impact on IT adoption and its performance. In the context of India's demonetization of 2016, Crouzet et al. (2023) found that the shock of cash availability resulted in a surge in the adoption of digital payment solutions. Simultaneously, in response to the environmental shock, in such a scenario, it is not uncommon for firms to also adjust their IT portfolio. Digital technologies have the potential to enhance a firm's capability to understand the surrounding environment, enabling the establishment of strategic responses aimed at maximining the possibility of survival (Tanriverdi and Lim, 2017). According to my research data in chapter 2, in response to the pandemic, firms were increasing their online presence and enabling new products and services, such as providing delivery services and moving businesses online. Facilitating remote work for employees was also a practical internal choice. In summary, environmental shocks and technology adoption are closely interconnected and their relationship is dynamically intertwined.

3.2.2 Workforce Flexibility and Remote Work Configurations

The task of efficiently managing unpredictable, dynamic, and continuously evolving environments has been a focal point in operations research for many decades. (Upton, 1995; Vokurka and O'Leary-Kelly, 2000; Qin and Nembhard, 2015). Prior research has extensively discussed how flexible organizations may overcome external and internal difficulties, as well as the impacts of such flexibility on firms' performance (Swafford et al., 2006; Christopher, 2000; Gunasekaran and Yusuf, 2002; Kleindorfer and Saad, 2005; Shekarian et al., 2020; Yang, 2014). To measure organizations' ability to adjust and respond to change, six dimensions have been established: machine, labor, material handling, mix, new product, and modification (Koste et al., 2004). In terms of labor, in a changing business environment, an agile workforce is essential to quickly respond to unexpected events (Sherehiy et al., 2007). Within the domain of operations research and management sciences, workforce flexibility represents an organization's capacity to adapt its workforce in response to uncertainties in business processes and operations. This includes the ability to quickly scale the size of the workforce up or down, to adjust work schedules and job duties, and to use contingent workers as needed (Qin et al., 2015).

According to the literature, the majority of operations research has focused on one aspect of establishing workforce flexibility, namely, cross-training. This denotes training employees with multiple skills for flexible response to different tasks and these employees can be transferred between organizational units (Frye, 1974; Hopp and Oyen, 2004). Cross-training can increase adaptability to changing circumstances, enhance productivity, reduce downtime, mitigate the risk of staff shortages, and reduce costs (Iravani and Krishnamurthy, 2007; Mangiameli and Krajewski, 1983; Chakravarthy and Agnihothri, 2005; Hopp and Oyen, 2004). Another important method to create flexibility is flexible working time, i.e., flexible labor hours. This includes overtime, flexible workdays, and annualized hours (Akkan, 1996; Yang et al., 2002; Hung, 1997). In addition to cross-training and flexible working time, a few studies also examined other aspects of workforce flexibility, such as teamwork and floaters (Wise et al., 2020; Gnanlet et al., 2021). Most importantly, technologies used to assign workers, enhance teamwork, and build connections are included in workforce flexibility (Qin et al. 2015). Therefore, workforce flexibility encompasses the ability to adjust the percentage of employees who can work from home. At the same time, remote work technologies are also contributing to workforce flexibility.

Despite the increasing number and variety of remote work arrangements, however, research studying flexibility in where work is accomplished is still limited. By facilitating remote work for employees, organizations gain a potent tool for managing their labor resources in a flexible and adaptive way. Therefore, remote work is an essential dimension of workforce flexibility, giving organizations the potential to maintain resilience and adaptability in the face of uncertainty and change. At the individual level, researchers have well documented the benefits and challenges of remote work. Benefits include reducing work stress, increasing feelings of autonomy and organizational commitment, and improving job performance (Bloom et al., 2015, Gajendran et al., 2015, Gajendran and Harrison, 2007; Raghuram and Wiesenfeld, 2004, Kelliher and Anderson, 2008; Hunton and Norman, 2010). Challenges include reducing the potential for building work communities and relationships in the traditional workplace, reducing knowledge sharing, and increasing negative relationships with managers (Bloom et al., 2015; Golden, 2007; Golden and Raghuram, 2010; Golden and Fromen, 2011; Bartel et al., 2012).

Despite the dearth of literature on the subject, there are a few studies assessing the impact of remote work at the firm level. One of these is Ge et al. (2023), who study the impact of work-from-home policies on firm resilience. With a cross-industry dataset from China, they found that remote work policies enhance firms' resistance capacity by reducing the effect of COVID-19 on their operating revenue volatility and disruptions to their supply chain partners; however, it also decreases their recovery capacity by extending the time taken to return to normal. Another study collected data in India from 2021 to 2022., Raj et al. (2023) found that remote work indicators, such as the ability to communicate frequently and well, are positively related to firm performance. Some other studies used data from the United States, Jordan, and Morocco as well (Boutros et al., 2023; Bai et al., 2021).

These studies examine the impact of remote work on firms, mainly considering short-term coping strategies for dealing with the COVID-19 pandemic itself. This view, however, may neglect the long-term capabilities that organizations may need to prepare for future pandemic-like crises (Jones et al., 2021; Li et al., 2021). In fact, more than 50% of organizations report that since COVID-19, they still keep remote work policies so that employees may choose to work from home when necessary (Brynjolfsson et al., 2020; Mas and Pallais, 2020). Nevertheless, it is unclear how dynamically these firms are adjusting their remote work configurations since the “shutdown” stage. We also don't know the impact on company operations of the changes in workforce flexibility brought about by adjustments in remote work. In sum, from a workforce flexibility perspective, it is vital to understand not only the adoption of remote work, but also various configurations of remote work (i.e., dynamic adjustments to the percentage of employees that work remotely). Another limitation of these studies is that their research data often relies on sources from the same country. Different countries have completely different national conditions and corresponding COVID-19 policies. These factors not only affect the deployment of remote work but also influence its effectiveness. Data from a single country cannot help us delve into these crucial national factors and understand these macro environmental influences.

3.3 Data and Empirical Approach

3.3.1 Data Collection

In our research, the sources for data collecting were the World Bank's *Enterprise Survey* and *Follow-up Surveys*. As an ongoing World Bank project, the *Enterprise Survey* (ES) is 'a firm-level survey of representative samples of an economy's private sector,' which contains more than 174,000 interviews in 151 different countries conducted since 2005, on data about firms' basic characteristics. The surveys take place in different countries every year, so no given country is surveyed annually. Because of the Global Methodology that the *Enterprise Survey* uses, the data are comparable across time periods and countries.

To collect representative and circumstantial data from firms in different countries, the World Bank also sticks to their Global Methodology and reveals quite detailed information. In brief, first, when collecting data from both manufacturing and services sectors, the Enterprise Survey Unit uses standardized survey instruments— the Manufacturing Questionnaire and the Services Questionnaire, with many overlapping questions. Second, within a given country, stratified random sampling is used for the *Enterprise Survey*, with firm size, business sector, and geographic region strata. Overall, based on the Global Methodology, the Enterprise Survey Unit tries to minimize measurement errors and generate reliable datasets.

In our research, we first used the *2019 Enterprise Survey* to generate firm-level data describing firms' pre-COVID status, which included ownership structure, age, managers' information, financial data, and employment. Correspondingly, to capture the post-COVID portraits of these firms in the *Enterprise Survey*, the *Follow-up Surveys* have been of great theoretical and analytical importance in our research.

In 2020, the WB initialized a new survey, the *Follow-up Surveys* on COVID-19, aiming to measure the impact of coronavirus on non-agricultural private sector firms across the globe. The *Follow-up Surveys* (FS) collect data about firms' changes in sales, employment, and input purchases as well as financial responses, liquidity problems, and policies that have been implemented to address these problems. Furthermore, to precisely capture the progression of the pandemic, three follow-up survey waves have been conducted at six-month intervals since June 2020. The FS were administered to the full sample of recent ES data collected in 2019, which are considered as the baseline survey in our paper. We use FS data on whether a firm received support from the national or local government, whether the firm self-adjusted in response to COVID-19, the number of employees before COVID-19, remote work and sales growth. Sales growth is our outcome of interest and measures the average change in monthly sales compared to one year ago. As expected, the average sales growth is negative in this dataset, which demonstrates that sales declined for most of the observed firms during COVID-19. FS also provides data for the firms' remote work arrangements. The remote work capacity is documented by two questions in FS, viz., (i) Did this firm start or increase remote work arrangement for its workforce? and (ii) Currently, what is the share of this establishment's workforce working remotely?

The *Follow-up Surveys* were conducted three times between 2020 and 2021 and administered across 42 countries. To conduct empirical analysis in our research, variables from the *2019 Enterprise Survey* were also necessary. We were able to match 21 countries from the *2020 Follow-up Survey* and the *2019 Enterprise Survey*. All 21 countries are posted in Figure 2 with their corresponding sample size. Furthermore, we dropped missing values and were left with a data set that contains 3,329 firms in 21 countries. Table 7 summarizes all of the variables that we make use of in this paper.

3.3.2 Variable Construction

Among the 3,329 samples in 21 countries from our dataset, these firms tended to adopt different work-from-home strategies to cope with the business disruption caused by the COVID-19 pandemic. According to our previous discussion, FS collected firms' response to 'whether the firm started or increased its remote work arrangement for its workforce' and 'the share of this establishment's workforce working remotely' in each wave. The different answers constitute different remote work technology-based adoption configurations that we examined for their effectiveness. According to the two questions answered by firms in three different waves, we divided the firms in our sample into seven distinct groups: (1) Start 1, (2) Start 2, (3) Increase 2, (4) Same 2, (5) Decrease 2, (6) Quit 2, and (8) Control. We abbreviate these groups as (S1), (S2), (I2), (Sa2), (D2), (Q2), and (C).

The control group represents the firms that never adopted remote work technologies or arranged their employees to work from home before and after COVID-19. Accordingly, 'No' and '0' are their answers to the previous two questions in FS. Firms whose employees have been allowed to work from home since survey wave 1, which means an answer of 'Yes' and a positive value for the questions, constitute the treatment group ‘Start 1’. Meanwhile, later adopters who stayed put in survey wave 1 but embraced remote work in survey wave 2 are treatment group ‘Start 2’. Firms from group ‘Start 2’ responded to the two questions with ‘No’ and ‘0’ in survey wave 1, and ‘Yes’ and a positive value in survey wave 2. For further analysis and exploration on configurations which may cause dissimilar effects, we subdivided group ‘Start 1’ into four additional ones: ‘Increase 2’, ‘Same 2’, ‘Decrease 2’, and ‘Quit 2’. Firms in group ‘Increase 2’ increased the share of their workforce working remotely in survey wave 2 compared with survey wave 1. However, if the firms restricted remote work opportunities for employees in survey wave 2, they are taken as ‘Decrease 2’ group. For the firms who maintained their previous arrangements or totally withdrew their remote work permission in survey wave 2, we create ‘Same 2’ and ‘Quit 2’ to document their behaviors.

Our primary interest is the firms' sales growth as an outcome variable; thus we examined the impact of the firms' remote work arrangement on firms’ sales growth during COVID-19. Specifically, the FS asked firms to report the percentage increase or decrease in their sales for one month during the COVID-19 pandemic relative to their sales in the same month in the previous year.

Table 8 provides mean comparisons across the various treatment groups and the control group for a large set of variables. First, we notice that each of these groups has at least 150 firms except for the group ‘Same 2,’ with the largest treatment group having 751 firms and the control group having 2,228 firms. Second, as expected, most of the mean sales growth values in survey waves 1, 2, and 3 are negative across all groups. We observe that the values of mean sales growth are increasing from survey wave 1 to survey wave 3, which indicates that the firms are bouncing back from their economic predicaments during the pandemic. Not only throughout that period, but across various groups, the magnitude of the drop in sales growth, which ranges from 23.2 percent to 17.8 percent in survey wave 1, and from 20 percent to 9.64 percent in survey wave 2, provides quantitative evidence of the harsh economic impact of COVID-19 on the firms in our sample. Firms in almost all treatment groups (except 'Start 2' group in survey wave 2) report better mean sales growth than the control group. Alternatively stated, the associational mean differences among different groups across all three survey waves indicate that the mean sales growth of the treated firms is as good as or better than the control firms.

3.3.3 Summary Statistics

In order to directly observe the relationships among key variables of interest, we begin with descriptive analyses. Graphs have been created to illustrate the level of remote work strategies that firms were taking across multiple subgroups. Figure 3 and Figure 4 show the combo charts of different remote work adoption choices by industries or countries. These combo charts consist of a stacked bar part which indicates the percentage, and a scatter part which represents the sample size, within this subgroup. In figure 3, a closer look at the wholesale group reveals that the red dot means that the sample size in this group is 187. Around 30% of these wholesale firms acknowledged that they allowed their employees to work remotely according to their replies in wave 1 survey. In the seven groups that we constructed for analysis, these 30% firms fall into 'Start 1' group, and we can take them as the first movers in our dataset. Meanwhile, 9% of the wholesale firms chose to hold back in survey wave 1 but embraced remote work as the second mover in survey wave 2. The rest of the firms never accepted remote work; thus, they are marked as non-adopters in our research. Instead of summarizing the adoption choices by industry, Figure 4 illustrates remote work adoption choices of firms in different countries.

Figure 5 shows a box plot of the sales growth in survey wave 3 across different remote work strategy configurations. Whereas the overall sales growth in survey wave 3 is -3.03%, there is significant variation across configurations. On average, firms from the ‘Decrease 2’ group have the highest sales growth at 6.11% while control group firms are the lowest, -4.49%.

In terms of firm-specific characteristics, Table 8 also presents the summary statistics for a long list of variables that we use in our estimation. The average number of employees in a firm before COVID-19 is approximately 58, but there is a substantial standard deviation around the mean. For first movers, the number is 104. It is much bigger than the average number of employees for the control group, at 39. The average age of the firm is 23.8 years. Among these employees, on average, 69.7% completed secondary school, while only 19.1% achieved a university degree. The average experience of the firm manager is 24.1 years with little differentiation across treatment groups. 17.2% of the firms have a female top manager and 37% of the firms have at least one female owner.

3.3.4 Empirical Strategy

Our aim for this analysis is to estimate the impact of various remote work strategies that they took during different waves in response to the pandemic. In our paper, the research unit is the firm, as both outcome and treatment variables we collected are also at the firm-level. It is highly possible that the treatment and outcome are confounded since the firms themselves are choosing their adoption behaviors. Therefore, our empirical strategy is composed of four coherent steps.

First, to reveal the relationship between remote work adoption and features of the firm, we utilized a logit regression model to predict IT adoption of firms using an array of firm-related variables after controlling for country-level and industry-level fixed effects.

Second, in order to show the impact of different remote work strategies on firm performance, we introduce Inverse Probability of Treatment Weighting (IPTW) as our main results. The IPTW can generate a weighted sample called the pseudo-population, which is a new sample adjusted by weights derived from potential confounders. With pseudo-population, we can estimate the causal effect by comparing the mean value between treatment and control groups. To causally compare the treatment and control groups, the IPTW requires that the units in the treatment group be weighted by the probability of receiving treatment, while those in the control group should be weighted by the probability of not receiving treatment in a dichotomous case. The probability of receiving treatment, also known as a propensity score, can be generated by multifarious methods. In our case, although we could not observe the propensity scores directly, they can be estimated properly from data as well. In order to calculate the propensity scores, we use the Toolkit for Weighting and Analysis of Nonequivalent Groups (TWANG) embedded within the gradient boosting framework, a machine learning technique (Ridgeway et al. 2021). The TWANG package optimizes for covariate balance across the treated and control groups, making it suitable for conducting IPTW analysis.

Third, to augment the IPTW results, we use a doubly robust (DR) estimator which combines both an outcome model and a treatment model (i.e., propensity score model) into a single estimator (Bang and Robins, 2005). Under the no unmeasured confoundedness assumption, the DR estimators can correctly identify the causal effect when either the outcome model or the treatment model is correctly specified. Therefore, the doubly robust estimators give the analyst two chances to get the model specification correct (Hernan and Robins, 2020). Furthermore, The DR estimator is the most efficient and accurate estimator when both outcome and treatment models are correctly specified (Emsley et al., 2008).

Fourth, although our main model provides information about average effects of remote work strategies in different phases during the pandemic, it is useful to know whether the treatment effects exhibit heterogeneity. We employ causal trees to establish these heterogeneous treatment effects. Athey and Imbens (2016) introduced the causal tree to calculate heterogeneity by recursively partitioning the data into subpopulations based on covariates and simultaneously estimating differences between these sub-populations. There are some similarities between the causal tree and the machine learning algorithm classification and regression tree (CART). However, instead of predicting the outcome and accuracy, the aim of the causal tree is to estimate the conditional average treatment effects. According to Athey and Imbens's work (2016), conditional average treatment effect is defined as $\tau(x) \equiv E[Y_i(1) - Y_i(0)|X_i = x]$ where $Y_i(.)$ is the potential outcome of individual i conditional on vector of covariates X_i. In our research, we use CausalTree package in R. In particular, because the algorithm requires unconfoundedness, we will implement the pseudo population generated from step 3 as the sample for this heterogeneity analysis.

3.4 Analysis and Results

3.4.1 Remote work Adoption

Following our empirical strategy, we begin by discussing the findings from logit regression shown in Table 9. The set of the results is for the full sample. The second and fourth column exclude total annual sales, which is collected from the FS and adjusted to the US dollar with an average exchange rate from 2019. For the first two columns, we only consider first movers' remote work adoption behavior, whereas the third and fourth columns also include the second movers, firms who allow their employees to work remotely since survey wave 2. Almost all of the results in these four columns are consistent. As expected, firm size, which can be represented with both the number of employees and sales before COVID-19, is positively related to remote work adoption. Larger firms are more likely to adopt remote work technologies as firms are eager to find a substitutive way to maintain operation at the beginning of COVID-19 pandemic. Furthermore, considering affordability, firms with higher total annual sales are more inclined to permit their employees to work remotely. Interestingly, more experienced managers are less likely to adopt remote work. This may indicate that experience is an obstacle for new technology adoption. Unsurprisingly, remote work adoption is positively correlated with higher education. Firms tend to adopt remote work when they have more employees who have a university degree. Simultaneously, firms providing formal training programs to their employees are more willing to adopt remote work. When it comes to the *Innovation Index* that we created to measure a firm' innovation capability, it is obvious that higher innovation indices are positively related to remote work adoption. These firms are more open to new technologies. Inconsistency exists in *Power Outage* and *Business Organization*. *Power Outage* makes a significant impact on first movers' adoption behaviors but does not play an important role when taking all of the adoption measurements into consideration. In contrast, *Business Organization* has an overall influence on the remote work adoption decision but is not a factor that first movers pay attention to when facing environmental shock at the beginning. Finally, we find that remote work adoption is not related to ownership characteristics (private or government ownership, gender of owner), nor to top manager's political position.

3.4.2 Treatment Model Using Inverse Probability of Treatment Weighting (IPTW)

We utilize the TWANG package in R to estimate IPTW models. To estimate the propensity score, we use 2-way fixed effects (i.e., country and industry) as well as all firm-level covariates we listed in the logit regression model. Table 10 shows the estimated treatment effects with the IPTW estimator. In response to the potential endogeneity concerns in our survey, all of the models measure lagged effects. The dependent variable in model 1 (column 1 in Table 10) is sales growth from survey wave 2, while the corresponding remote work adoption dummy indicator is from survey wave 1. Therefore, a lagged effect can be estimated, and the measurement would be more accurate. Model 1 shows that the firms that pursued remote work right after the outbreak of the pandemic had about 3.337% higher sales growth in survey wave 2 on average than firms that adopted no remote work strategies. Furthermore, they reaped even more benefits from their remote work adoption decision later on. In model 2, instead of measuring the impact on sales growth in survey wave 2, the dependent variable now is sales growth from survey wave 3. On average, firms had about 3.934% higher sales growth than firms in the control group because they adopted remote work in survey wave 1. It seems that first movers (firm that adopted remote work in survey wave 1) benefited from their remote work adoption and were able to fight against the detrimental effects from the COVID-19 pandemic. However, some other firms had different considerations and took a distinct strategy. They hesitated at first and then took action as second movers. Model 3 shows that there is no evidence that adopting remote work in survey wave 2 has a statistically significant impact on sales growth in survey wave 3.

Even though all of the first movers chose to allow employees to work remotely in survey wave 1, as the pandemic continued, they varied greatly on preferences and the feasibility of remote work. To assess the different impacts brought about by adjustments in various follow-up remote work strategies, we unpack the first movers' follow-up decisions from survey wave 2 into 4 specific configurations: 'Increase,' 'Decrease,' 'Same,' and 'Quit,' based on the difference of share of workforce working remotely between survey wave 1 and survey wave 2. Among 751 first movers, 350 chose to increase the share of employees working remotely, and 63 opted to maintain the status quo. However, 166 firms required employees to return to the office, thus reducing the number of remote workers. Moreover, 360 firms went so far as to entirely eliminate the option of remote work.

Models 4, 5, 6 and 7 reveal the results of comparisons between the control group and corresponding treatment groups. Minor adjustments of remote work policies are still positively correlated with firms' performance. Nevertheless, completely eliminating remote work may not be an advisable choice. Additionally, we categorize all remote work adopted by firms into two groups based on whether they discontinued remote work or not in survey wave 2, and then assess the treatment effect of remote-work abandonment in Model 8. We observe that firms that still keep remote work as an alternative for their employees had about, on average, 7.020% higher sales growth than firms that terminate remote work availability.

3.4.3 Treatment Model Using Doubly Robust (DR) Estimator

As we discussed in empirical strategies, this part of the analysis uses the doubly robust (DR) estimator with 2-way fixed effects (country and industry), and firm-level covariates. By combining an outcome model and an independent treatment model, the DR estimator can guard against biases and help us augment the confidence of our IPTW estimation.

The estimation results are presented in Table 11. We still notice that firms that maintained remote work in survey wave 2 had on average 7.663% higher sales growth than firms that reversed their remote work policies. All of our estimates are still consistent with those obtained from IPTW estimators.

3.4.4 Heterogeneous Treatment Effects

While our main results illustrate that firms are motivated to accept remote work considering the improvement, it is still useful to know whether and how these treatment effects exhibit heterogeneity across covariates. Our datasets are full of firm-level covariates which are used to describe firm characteristics from diverse perspectives. Recognizing firm characteristics that lead to heterogeneous treatment effects is not only important for managers and policy makers, but also inspires researchers to explore the potential mechanisms within that context.

We first examine heterogeneous treatment effects for the treatment in models related to the first movers. Figures 6 and 7 display the causal tree for firms that adopted remote work along with the control group (non-adopters). According to Figure 6, which reveals the heterogeneous treatment effects on Sales growth in survey wave 2, on average, the total treatment effect caused by remote work is 3.3%. This is consistent with the result generated under our IPTW model. The coherence reinforces the reliability of our heterogeneous treatment effect estimation, and the consistency is maintained in all our causal tree results. In Figure 7, which represents the heterogeneous treatment effects on sales growth in survey wave 3, the most important factor is *University Degree*. On average, these firms with more highly-educated employees (with university degrees) achieve more benefits from remote work.

Next, we examine the heterogeneous treatment effects for second movers. According to our previous logit regression results, experienced managers are more conservative; thus it is less likely for these firms to adopt remote work. In Figure 8, we gain further insight into the impact of

Manager Experience. Once they provide work from home as an option for employees, firms with more experienced managers can better manage the more flexible workforce and glean a more positive impact from remote work on their sales growth.

3.5 Discussion and Conclusion

The COVID-19 pandemic has been widely viewed as a global threat. To maintain business performance and survive the crisis, firms have used remote work as a crucial strategy to resist labor disruption. Remote work thus continues to be a hot topic and the pandemic has provided a great opportunity for researchers to rethink the role of this working format (Barrero et al., 2021; Garrote Sanchez et al., 2021; Ge et al., 2023). However, most studies only focus on the individual-level, while the exploration of remote work's impact at the firm level remains limited, especially on performance across industries and countries. It turns out that firms in such an unpredictable environment can take remote work as a long-term strategy to stabilize their operation. This long-term strategy has not been widely discussed, and the effects of dynamically adjusting this strategy during environmental shocks remains under-examined.

This is thus a great opportunity for us to delve into the role that remote work plays as a response to environmental shocks, leading to important contributions to the gaps in the literature. By investigating the relationship between remote work and productivity, our study empirically explores the impact brought about by the changes in workforce flexibility across different industries in multiple countries during the pandemic. Specifically, by utilizing a large survey database from the World Bank with additional complementary datasets, we identify configurations of several different remote work adoption choices. After empirically analyzing the impact of these configurations on firms' productivity, we find evidence that, overall, remote work has a positive impact on productivity. On average, firms that embraced remote work immediately following the onset of the pandemic experienced approximately a 3.337% increase in sales growth during the second survey wave compared to firms that did not offer remote work options. Over time, these firms saw increased profits as early adopters, with an average sales growth in survey wave 3 approximately 3.934% higher than the non-adopters. Even more interestingly, according to our estimations of causal inference brought about by the different configurations, we found that completely abandoning remote work dealt a significant blow to firms. Those that discontinued remote work options during survey wave 2 experienced, on average, a 7.020% decrease in sales growth compared to those that continued to offer remote work alternatives for their employees.

Overall, our study provides solid evidence supporting the adoption of remote work as an effective response to environmental crises, especially during the COVID-19 pandemic. We not only enrich the literature by directly measuring the impact of remote work adoption configurations on firms' productivity with real-world, firm-level data, but we also provide managerial implications.

The debate over whether employees should return to the office rather than continuing to work remotely is multifaceted and has sparked discussion among stakeholders with different opinions. Many CEOs emphasize the importance of returning to the office because of collaboration and have thus expressed their skepticism about the effectiveness of remote work for certain industries. Others meanwhile treat the hybrid format as the future of work and highlight the long-term viability of remote work. The effectiveness of remote work may therefore depend on various factors, such as culture and employee preferences. From the perspective of firm productivity, our study provides a strong signal to top managers that reasonably adjusting remote work policies while retaining it as an option for employees is the optimal choice at the moment. Hastily removing this option can have significantly negative effects on a firm's productivity.

We would like to conclude our discussion with a few limitations and potential opportunities for further exploration. First, our study only measures the effect of remote work based on 3 survey waves from June 2020 to June 2021. We can gain a deeper understanding of how these effects change over time by using longitudinal data with more survey waves. With more data released by the World Bank over the next several years, we can conduct an even more thorough exploration. Second, our data for this study mainly concentrates on Eastern European countries. We hope to have a more diverse data pool in the future to explore additional potentially significant factors on the role of remote work.

4.0 Digitization and Corruption: How the Productivity-Transparency Tradeoff Distorts the Value Calculus

4.1 Introduction

The transformative role of digital technologies at the level of firms, markets, and societies is well documented (e.g., Brynjolfsson and Hitt, 2000; Brynjolfsson and Saunders, 2013; Majchrzak et al., 2016). The bulk of this literature has focused on the positive aspects of digital transformation, such as increased productivity, reduced information asymmetry, greater economic participation, and higher consumer welfare, which arise from the adoption and use of computer technologies. However, studies have also painted a more complex picture of digital technology adoption with uncertain outcomes. For example, in economies where myriad challenges to business growth in the form of weak infrastructure, regulatory hurdles, and corruption exist, it is unclear whether adoption of computer technologies have led to any tangible performance benefits. In fact, prior studies have even raised concerns that firms operating in developing economies might be reluctant to adopt productivity-enhancing technologies in light of the idiosyncratic business hurdles they face (Sudhir and Talukdar, 2015). It has also been reported that the anti-corruption potential of information technology is often constrained by established configurations of administrative and institutional practices in developing economies (Adda and Avgerou, 2021).

A key hurdle for improvements in both business performance and social welfare in emerging economies is the prevalence of higher levels of corruption and bribery in those countries (Shleifer and Vishny, 1993; Svensson, 2005; Jung and Lee, 2023). Businesses operating in these environments are known for managing complex regulatory procedures (e.g., company registration, access to public utilities, customs and border control, and tax payments) but also for paying bribes to appease corrupt officials. While firms may treat such bribe payments as the cost of doing business, these payments further engender corruption and degradation of public services. For example, bribe payments contribute to unreported incomes ("black money"), and concealing economic activities based on these incomes from public authorities reduces the overall revenues collected by the state, which could otherwise be deployed for enhanced public services. Moreover, appeasement of corrupt officials contributes to a weakening of regulatory structures that govern, for example, minimum wages, maximum working hours, and safety standards. In this way, the prevalence of corruption and bribery in a society is inextricably linked to the underlying social welfare of its citizenry.

Our study seeks to examine the complex linkages between IT adoption and bribe payments, thereby deriving insights into issues related to IT adoption and social welfare. We build upon prior work on the productivity-transparency trade-off in IT adoption, which posits that gains in productivity from adoption of IT may be offset by the attendant costs of making transactions more transparent, thereby subjecting them to burdensome regulatory scrutiny by corrupt officials (Svensson, 2003; Sudhir and Talukdar, 2015). Firms may, therefore, limit their IT investments especially if the relative productivity gains are underestimated relative to the transparency costs. Using data from a large-scale World Bank survey of retail merchants in India, Sudhir and Talukdar (2015) showed that computer technology adoption was indeed lowered by motivations to avoid transparency. Specifically, technology adoption was lower when state-level corruption was higher, but higher when there was better enforcement and auditing.

Despite the evidence of lower IT adoption in high corruption regimes, what is not clear is whether IT-adopting firms still benefit from overall gains in productivity. In other words, are the productivity gains sufficient to overcome the cost of additional bribes? If so, the adopting firms may still benefit from computer technology, but the societal welfare losses may also increase with more bribes being collected. We seek to empirically investigate this by posing the following research questions: What is the overall economic impact to IT-adopting firms given the existing corruption regimes in their environments? Are there higher costs to the adopting firms due to the increased transparency of transactions resulting from computer adoption? By empirically examining the effects of IT adoption on productivity as well as bribes paid, we can examine if there are private gains to be had for IT-adopting firms even as they increase the social costs in the form of higher bribe payments.

Following Sudhir and Talukdar (2015), we first conducted a detailed examination of the World Bank's *2006 India Enterprise Survey* data, which consists of responses about computer adoption, operating conditions, and bribe payments of 1,948 retail stores operating in 41 Indian cities. We augmented this core dataset with data from the *2006 India Corruption Study* conducted by Transparency International and the *2006 India Human Development Report* published by the Indian Government. Then, for broader generalization of our results, we replicated our analysis with the *2014 India Enterprise Survey* data. In addition, we utilized the latest published version of the *Enterprise Survey* data prior to the Covid-19 outbreak to explore broader cross-country patterns in the impact of computerization on bribe payments.

Our empirical analysis involved four key steps. In the first step, we examined the factors that influenced the adoption of computers by firms. Next, building on the adoption model, we assessed the differences in bribe payments between the firms who adopted computers for their business operations and those that did not. We employed regression models and controlled for potential confounding variables such as operating environment and prior performance. In addition, we utilized Inverse Probability of Treatment Weighting (IPTW) to generate a weighted sample (pseudo population) that controlled for potential confounders, and then estimated the causal impact of computer adoption on bribe payments. In our third step, we replicated our analysis with the *2014* and *2022 India Enterprise Survey* data for broader generalization of our results. In the fourth step, we explored treatment effect heterogeneity using causal decision trees to recursively partition the data into subpopulations and to estimate the effect of computer adoption in these subpopulations (Athey and Imbens, 2016).

Our results reveal that adoption and use of computer technologies by firms significantly improves their sales performance. Our estimations indicate that adoption of computers increased sales revenues, on average, by about 1.83 million INR (Indian Rupees) in 2006 and about 143 million INR and 115 million INR, respectively in 2014[17] and 2022[18]. The prevalence of corruption in the operating environment of firms, however, significantly hinders the adoption of computers, thereby confirming the transparency-productivity tradeoff in emerging markets that has been documented in prior literature (Sudhir and Talukdar, 2015). Firms that adopt and use computers in their business operations indeed pay more in bribes than their peers who do not adopt computers. Our estimates show that computer-adopting firms paid on average 24 thousand INR more in bribes in 2006 and as much as 288 thousand INR more in 2014[19] as bribe payments than their peers who did not adopt computers. These results indicate that firms that invest in transparency-enhancing technologies are more vulnerable to extraction of bribes by corrupt public officials.

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[17] About 80 million INR in 2006 values after deflation.

[18] About 45 million INR in 2006 values after deflation.

[19] About 162 thousand INR in 2006 values after deflation.

A key implication of our results is that there is an economic rationale for treating bribe payments to corrupt public officials as the cost of doing business in emerging markets. Although computer adoption makes firms vulnerable to greater bribe payments, the impact of computer adoption on sales revenues is much larger than its impact on bribe payments. Hence, the net benefit of computer adoption for firms is positive. However, greater bribe payments inflict a negative societal impact, and our study calls attention to this underexplored aspect of adopting transparency-enhancing information technologies in emerging economies.

4.2 Background Literature

4.2.1 Information Technology adoption and Firm Performance

Back in the 1980s, the relationship between information technology and firm performance was a controversial subject. Since then, by using a variety of methodological approaches, the researchers have studied the topic widely. At early stages, the perception that IT failed to bring significant improvement on firm productivity prevailed. Researchers were not able to provide evidence to support the claim that information technology can exert positive influence on firm performance (Strassman, 1990; Loveman, 1994). As more new convincing data and systematic methodologies were applied, however, more and more researchers found a positive impact of IT on firm performance (Peffers and Dos Santos, 1996; Chatterjee et al., 2001; Nicolaou, 2004; Albadvi et al., 2007). Among these prior studies, from the input side, researchers sought to document a firm's IT status with different IT factors, such as IT investment, IT capability, and IT alignment (Brynjolfsson and Hitt, 1993; Sabherwal and Jeyaraj, 2015). Instead of using these aggregated measures, some studies also focused on concrete IT adoptions. For example, ERP systems are one of the most examined information technologies, and most studies have posited that there was a positive impact on firm performance after implementing ERP systems from 1999 to 2014, especially over a long period of time (Mangin et al., 2015). Besides ERP systems, knowledge management systems (Wang et al., 2013) and supply chain management systems (Dehning et al., 2007) can also contribute to the improvement of firm performance.

As for the output side, profitability-based measures are the most commonly used for firm performance (Sabherwal and Jeyaraj, 2015). Return on assets (ROA), return on equity (ROE), and revenue are all appropriate indicators to represent the comprehensive efficiency of a firm (Huang and Wang, 2013; Bharadwaj, 2000). In contrast, productivity-based measures, such as inventory turnover and labor hours, represent other small realms that are connected to business performance; furthermore, researchers also have evidence that firms benefit from IT under these measures (Barua et al., 1995; Mukhopadhyay et al., 1997). The implementation of these measures enriches the description of firm performance and enhances the confidence that IT improves firm performance in diverse ways.

Persuasive evidence such as that discussed above underscores the significance of IT and its benefits for firms; thus, information technology is clearly a crucial element in achieving competitiveness. To realize the full benefits that IT can bring to firms, adoption is essential. Therefore, it is critical to understand the determinants of IT adoption. With the efforts of researchers in recent decades, two main adoption models have been developed and being widely applied at the firm level: diffusion of innovation (DOI) (Rogers, 1995) and the technology-organization-environment (TOE) framework (Tornatzky et al., 1990). Based on DOI theory, organizational innovation is driven by three characteristics: individual characteristics, internal organizational structural characteristics, and external characteristics of the organization (Rogers, 1995; Oliveira and Martins, 2011). Simultaneously, TOE frameworks identify technological, organizational, and environmental contexts as the three conditions which kindle technological innovation (Tornatzky et al., 1990). Multiple studies have followed DOI theory and the TOE framework to reveal different IT adoptions, such as ERP systems (Pan and Jang, 2008; Ramdani et al., 2013) and E-commerce (Zhu et al., 2006). Factors that influence firms' adoption of IT have also been explored. According to Ramdani et al. (2013), top management support, ICT experience, and firm size are all key factors. The bigger the firm, the greater the preparedness for the adoption of new technology. Peltier et al. (2012) explored the impact of owner-related factors on ERP adoption and found that the education level of the owners or managers has a positive impact on adoption. Owners or managers with more IT knowledge are inclined to adopt more innovative technologies. They also draw the same conclusion that the probability of IT adoption is higher when the firm is larger.

4.2.2 Culture of Corruption

Corruption is an all-too-common global phenomenon that undermines economic productivity and development in both developed and developing countries. It increases the cost of doing business and discourages investment as firms prefer to devote their resources to informal activities such as rent-seeking (Lambsdorff, 2002). According to the *Foreign Bribery Report* (OECD, 2014), the analysis of 427 cases globally from 1999 to 2014 reveals that on average, the value of bribes equals 34.5% of profits. The large number of bribes raises the uncertainty of the business environment and decreases the attractiveness of entrepreneurship. According to Transparency International, in developing countries, corruption is more widespread than in developed countries.[20] The African Union has estimated that, on average, the African economies lose over 148 billion dollars per year, which is around 25% of Africa's GDP, because of corruption (VOA, 2009). Therefore, more and more governments and organizations are realizing that it is crucial to address corruption.

When bribing government officers is a viable option, firms prefer to pay bribes in order to evade taxes and other costs (Alm et al., 2016). Corruption makes it easier for these firms to hide their revenue and achieve illicit competitiveness against other competitors. Meanwhile, with the benefit gained from tax evasion, taxpayers may seek additional opportunities for more corruption. Alm and his colleagues (2019) found that firms who participated in bribery usually report a smaller amount of sales for tax purposes and the percentage of reported sales decreases by 5% with the help of bribery. Furthermore, in order to conceal the risk of tax evasion, firms need to engage in more bribery. Thus, a vicious cycle is formed. Besides tax evasion, firms may make bribe payments for a range of purposes, including securing government contracts, gaining access to utilities, acquiring permits, and so forth (Pelizzo et al., 2016). These firms' choices have prompted researchers to explore the relationship between corruption and firm performance. In the long run, the literature consistently argues that bribery is detrimental to firms, impacting not only firm performance (Fisman and Svensson, 2007; Jung and Lee, 2023) but also market value (Cheung et al., 2021; Zeume, 2017) and investment (Birhanu et al., 2016; O'Toole and Tarp, 2014). Although some researchers argue that corruption can potentially reduce distortions and improve performance when firms are facing low quality of institutions and poor governance, which negatively impacts the business environment (Beck and Maher, 1986; Jiang and Nie, 2014), paying bribes can impose

[20] https://www.transparency.org/en/cpi/2016

an increasing burden on private agents and contribute to increaseingly unfair resource allocation (Shleifer and Vishny, 1993; Baumol, 1996). Ultimately, corruption hinders economic development. Therefore, researchers are actively exploring effective measures to mitigate the effects of corruption.

4.2.3 Corruption and IT

Perspectives regarding the role that information technology plays in reducing corruption diverge widely, and we are just beginning to understand their ramifications. Some researchers support the view that IT is an effective way to combat corruption (Srivastava et al., 2016; Vu and Hartley, 2018). Other studies argue that IT cannot be considered as a cure-all for corruption (Masiero and Prakash, 2015; Basyal et al., 2018; Park and Kim, 2020). Furthermore, evidence suggests that even similar IT lead to different anti-corruption outcome when facing different types of corruption (Žuffová, 2020; Sheryazdanova and Butterfield, 2017) Furthermore, its effectiveness also varies across countries (Pathak et al., 2007; Choi, 2014). Given these mixed findings, it is challenging to ascertain the overall relationship between IT and corruption. Thus, there is no clear theoretical explanation as to how of why IT can mitigate corruption under different circumstances.

For its part, e-government, which refers to the government's use of information technologies to provide information and services to citizens, businesses, and public agencies (Nam, 2014), has been widely studied. It has become an effective method to promote transparency in government processes and to mitigate the risk of corruption (Park and Kim, 2020). In a different case with firms, however, there has been limited research on the relationship between firm-level IT adoption and corruption. This gap in the literature is what we aim to fill.

4.3 Data Collection and Methodology

4.3.1 Data Collection

Building on prior work (Sudhir and Talukdar, 2015; Jung and Lee, 2023), our primary data source is the *World Bank Enterprise Survey* (WBES). The WBES follows a global methodology and covers a representative sample of firms in the private sector in more than 150 countries.[21] Since the survey touches upon sensitive topics about business environments, such as corruption, crime, and access to finance, survey respondents' confidentiality is strictly enforced. As a result, since researchers utilizing the WBES data cannot identify private firms. In contrast, confidentiality helps to improve the accuracy of survey responses to sensitive questions about topics, such as bribe payments, and ensures data integrity and quality.

Although WBES follows standard instruments and methods across the globe, the survey periodically includes country-specific questions, and in 2006 the WBES India questionnaire featured a question about computer adoption[22]. Executives of 1,948 retail stores operating in 41 different Indian cities responded to the survey. Sudhir and Talukdar (2015) used the 2006 India WBES data for their investigation on the productivity-transparency tradeoff. In order to create common ground with prior studies, we begin our analysis with the 2006 India WBES data. To the best of our knowledge, WBES did not feature the direct computer adoption question in any other

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[21] Detailed documentation about the survey methodology, including sampling and execution strategies, can be found here: https://www.enterprisesurveys.org/en/methodology

[22] The featured question in the 2006 WBES survey was "does this store use its own/hired computer for running its business?"

country or year. However, a few other iterations of the WBES data collection did pose, questions about the online presence of firms and email use[23]. As expected, responses to the online presence and email use questions were highly correlated; we thus leverage these responses as a proxy for firm-level IT adoption and use. Filtering the WBES data for the Indian context and the presence of any of the IT adoption-related responses resulted in 9,281 firms across 27 industries for the 2014 survey year and 9,375 firms from 26 industries for the 2022 survey year. Thus, after removing all of the missing values, the sample consisting of 1,124 representative Indian firms in 2006, 6,932 Indian firms in 2014 and 8,810 Indian firms in 2022 constitutes our main dataset.

We augmented our WBES data of Indian firms with additional information from the *India Corruption Study* (ICS), conducted by Transparency International[24]; the *Human Development Report* (HDR), published by the Planning Commission of India[25]; *Telecom Statistics India*, reported by the Department of Telecommunications in India[26]; the *Handbook of Statistics on Indian States*, created by the Reserve Bank of India[27]; and the *National Multidimensional Poverty Index Baseline* Report, generated by the National Institution for Transforming India[28]. The *India*

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[23] The featured questions were (1) "does the firm have its own website?", and (2) "does the firm use email for communication?"

[24] https://www.transparency.org/en/countries/india

[25] The report was published by the institute of applied manpower research and can be accessed here: http://www.im4change.org/docs/340IHDR_Summary.pdf. The institute was part of the planning commission of India when the report was published, but it has recently been organized as an autonomous institution under the Government of India and is now called the National Institute of Labor Economics Research and Development.

[26] https://dot.gov.in/reportsstatistics/telecom-statistics-india-2020

[27] https://m.rbi.org.in/scripts/AnnualPublications.aspx?head=Handbook+of+Statistics+on+Indian+States

[28] https://niti.gov.in/sites/default/files/2023-07/National-Multidimentional-Poverty-Index-2023-Final-17th-July.pdf

Corruption Study provides reliable state-level corruption data from which we generated state-level corruption indices to measure the corruption environment in which the firms in our sample were operating. These state-level indices measured the prevalence of corruption in three critical public services related to computerized land records, electricity provisioning, and public distribution systems used by state actors to distribute major commodity items, such as staple food grains and essential household fuels. To capture the overall socioeconomic development environment in which a firm operates, we utilized the state-level human development index from the Planning Commission of India and ease of doing business rank collected in the *Handbook of Statistics on Indian States*. Additionally, the poverty rate from the *National Multidimensional Poverty Index Baseline Report* is also included as a state-level environmental control. Furthermore, we also introduced the Internet Subscription Rank by calculating the percentage of people who subscribed to Internet services within different states from the data collected in the *Telecom Statistics India Report*. The Internet Subscription Rank represents the state-level internet penetration. Table 12 summarizes all the key variables that we make use of in our dataset.

Table 13, 14 and 15 show the summary of statistics of all the variables we used in our research. In 2006, all firms were from the retail industry and responded to the question '*Does this store use its own/hired computer for running its business?*' Following Sudhir and Talukdar (2015), we used the response to this survey question as an indication of firms' IT adoption and digitization of business processes. The 2014 and 2022 sample featured firms from diverse industries across India, but the survey did not feature the direct computer adoption and use question. Instead, the survey asked firms about their online presence (website) for business operations, which we used as a proxy for IT adoption and digitization of business processes.

To assess bribe payments, we utilized firms' responses to the survey question about informal payments/gifts to government officials to complete tasks ('get things done') related to services such as customs clearance, business taxes, licenses, and regulations. In WBES, most of the respondents provided either the percentage of *Sales* or the exact value they spent on bribe payments (*Bribe Value*). For firms who provided bribe payments as the percentage of their sales, we generated the absolute value of bribe payments (*Sales* x *Bribe Percent Sales*). To assess the prevalence of corruption in a firm's operating environment, we utilized data from the *2005 India Enterprise Survey*, which featured 2,286 firms from 50 Indian cities. For each of these cities, we derived the proportion of firms located in the cities who paid informal payments/gifts to public officials in exchange for 'getting things done' as the *City Corruption* variable. At the state-level, *Computerized Land records*, *Electricity* and *Public Distribution System* served as a proxy for the level of corruption in a firm's broader operating environment. Finally, we measured firm performance by assessing *Sales* reported for the fiscal year in relation to *Sales* reported three fiscal years previous.

The descriptive table also shows firm-specific characteristics: the average number of employees was approximately 3 in 2006, 110 in 2014, and 93 in 2022, while average years' of managerial experience for 2006 and 2014 samples were close— 13.8 years in 2006 and 13.7 years in 2014. As expected, most of the firms in 2006 were owned by one owner. The largest shareholders owned an average of 96.1% of the shares. Meanwhile, in both 2014 and 2022, compared with the samples in 2006, the ownership structure of the firms was more scattered, with the mean value of firm shares held by the largest owner at around 77.5% in 2014 and 87.7% in 2022. For samples from all three years, more than 99% of the firms were not government-owned.

4.3.2 Analysis Approach

The main goal of our study is to assess the economic impact of firm-level IT adoption taking into account the corruption regimes in which the firms operated and to evaluate whether these IT-adopting firms encountered higher operating costs due to the increased transparency of their operations. It is highly possible that the treatment (IT adoption) and outcomes (Sales performance and bribe payments) were confounded since the firms chose their IT adoption and bribe payment behaviors by themselves. Therefore, we carefully assessed the interlinkages between the focal variables in four steps.

First, we examined the impact of corruption regimes on IT adoption by firms. Similar to Sudhir and Talukdar (2015), we utilized a probit regression model to predict IT adoption of firms using an array of corruption-related variables, namely, corruption incidence in computerized land records, electricity, and public distribution systems, after controlling for other firm-level and city-level environmental factors.

In the second step, we sought to assess the causal impact of IT adoption on both sales performance and bribe payments made by firms. We utilized a regression model with state and industry fixed effects to establish a baseline association between IT adoption and sales revenues, and IT adoption and bribe payments made by firms. Then, we derived average treatment effects of IT adoption on sales revenues and bribe payments using the potential outcomes framework and inverse probability of treatment weighting (IPTW) approach (Rosenbaum 1987, Austin and Stuart 2015). We used the propensity scores or the probability of a firm adopting IT conditional on the baseline covariates to derive weights for firms that are equal to the inverse of the probability of receiving the treatment (i.e., adopting IT or not adopting IT)[29]. Then, weighting by the inverse probability of treatment, we generated a pseudo population in which the baseline covariates are independent of treatment status. This enabled us to compare the IT adopting and non-IT adopting firms, and thereby, estimate the causal effect on sales revenues and bribe payments. Once we derived these average treatment effects, we compared the positive outcomes (sales revenues) and negative outcomes (bribe payments) and assessed the overall economic impact of IT adoption.

4.4 Results

4.4.1 Corruption and IT Adoption

Table 16 presents the results of a probit regression that we used to predict computer adoption using the corruption variables and other baseline covariates. The only difference between the specifications in the two models (1) and (2) shown in Table 16 is the omission of prior sales performance in model (2), which serves to test the sales performance-related sensitivity of the associations between the other covariates and computer adoption. We observe consistent results irrespective of the inclusion or omissions of prior sales performance. We see that the four indices representing corruption in the environment in which a firm operates, namely, *Computerized Land Records*, *Electricity*, *Public Distribution System*, and *City Corruption* are negatively associated

[29] We utilized the toolkit for weighting and analysis of nonequivalent groups (TWANG) package along with a gradient boosting machine learning approach for deriving weights (Ridgeway et al., 2021).

with computer adoption. These results corroborate the findings reported by Sudhir and Talukdar (2015), that corruption hinders adoption of transparency-enhancing technologies.

Among the control variables, we observe that higher intensity of regulatory inspections acts as a catalyst for computer adoption. Similarly, firms that utilized independent external auditors for financial certification had a higher probability of adopting computers for business operations. Variables representing size of operations, such as store size and employee headcount, are also positively associated with computer adoption. Firms utilizing their own generators for electricity supply were also more likely to adopt computers, which is not surprising. These results are consistent with general expectations that coordination with external agencies as well size and complexity of operations engender computer adoption.

4.4.2 IT Adoption, Sales Performance, and Bribe Payments

In Table 17 we present the fixed-effects regression results that reveal the association between IT adoption and sales performance, and between IT adoption and bribe payments utilizing the sample of firms in the 2006 dataset. Results shown in column 1 of Table 17 confirm that firms that adopted computers for their business operations had better sales performance on average. The positive coefficient on *IT Adoption and Use* indicates that IT adoption is associated with an increase of about 1.76 million INR in *Sales* on average. At the same time, as shown in Column 2, IT adopting firms also paid more bribes than their non-IT adopting peers—38,000 INR more on average. We also note that this increased level of bribe payments accounts for only about 2 percent of the benefits realized as additional sales earned by the IT-adopting firms. Among the control variables, *Top Manager Experience* had positive and significant coefficients in the *Sales* model but remained insignificant in the *Bribes* model, while *Auditor* had positive and significant coefficients in both models. These results suggest that while strong management controls may have aided sales performance, their impacts on deterring bribe payments varies among internal and external formats. External management controls may better handle corruption, while internal management controls may not be very effective.

As in Table 16, we still omit prior sales performance in models (3) and (4) in Table 17. In the last four columns, instead of taking both state and industry fixed effects, we utilize all state level controls that we collected as well as industry fixed effects in the model. From most of the coefficients on state-level corruption-related controls in Table 17, an unfavorable business environment harms sales performance and may cause more bribe payments.

The estimates derived using the IPTW approach are presented in Table 18. Consistent with the OLS results, we can observe positive and statistically significant effects of IT adoption on both *Sales* and *Bribe Value* according to all models. Furthermore, the constant terms in Table 18 indicate the average *Sales* and *Bribe Value* paid by firms in the control group. It is obvious that the impacts on *Sales* and *Bribe Value* brought by IT adoption and use are tremendous compared to the magnitude of constant terms. Overall, both OLS and IPTW results provide strong evidence that while IT adoption helped the firms improve their sales performance, it also made them vulnerable to coercive bribe payments. Because the improvement in sales performance is orders of magnitude higher than the bribe payments, adopting productivity-enhancing technologies is likely to be seen as the rational decision for firms despite the presence of vulnerability to corruption.

We replicated the analysis using both the 2014 and 2022 India datasets. These results are presented in Tables 19, 20, 21 and 22. Tables 19 and 20 illustrate the factors that influence IT adoption and use in 2014 and 2022, respectively. Similar to the results in 2006, we see that *Poverty*, *Internet Subscription Rank*, and *Ease of Doing Business Rank* are all negatively associated with

IT adoption, and these results still support the findings that corruption hindered adoption of transparency-enhancing technologies in 2014. Nevertheless, the impact diminished in 2022, and Table 20 provides mixed results. *Internet Subscription Rank* is negatively related to IT adoption, on the contrary, while *Ease of Doing Business Rank* is positively related to IT adoption.

Compared with the coefficients in Table 18, the magnitude of the coefficient values in Table 21 are much higher, which indicates that technology adoption ushered in both increased sales (additional 143 million INR) and higher bribe payments (288,000 INR). On average, the ratio of bribe payments to additional sales decreased to about 0.2 percent in 2014 from about 1.3 percent in 2006. This indicates that firms' economic rationale to adopt IT only grew stronger even as they paid a higher level of bribes to corrupt officials. However, although the positive impacts still exist when considering firm performance, *Bribe Value* is not significantly related to IT adoption in Table 22, and the ratio of bribe payments to additional sales has turned to -1.6%. We present Figure 9 to demonstrate the overall trend of ratio's movement.

As stated earlier, we restrict our analysis in India as a whole to 2006, 2014 and 2022 sample data. Given the diversity of public policy and the business environment in different states, it is reasonable to explore the connections between IT adoption, productivity and bribery by state. Based on the data we collected in different years, it is reasonable to compare the mean value of *Sales* and *Bribe Value* between treatment group (technology adopters) and control group (non-adopters) in different states along with IT adoption rate. The comparisons are presented in Figure 10, 11, and 12, which represent years 2006, 2014 and 2022, respectively. States marked with different shades of green represent the percentage of firms who adopted IT. Black numbers indicate the mean value differences of sales between treatment and control groups, while red numbers capture bribery.

4.5 Discussion and Conclusion

Corruption is widely considered to be a global phenomenon which does damage to the business environment, especially in developing countries. To improve business performance and social welfare, recent studies are exploring the anti-corruption potential of information technology (Srivastava et al., 2016; Vu and Hartley, 2018). However, most studies only focus on the government side of IT adoption, and the results are quite mixed. From the firms' perspective, they may avoid adoption because of the transparency concerns in developing countries (Sudhir and Talukdar, 2015). Firms in such a corrupt environment take bribe payments as part of the cost of stabilizing their operations and of gaining benefits over their competitors. Moreover, regulatory structures are undermined due to the concealed relationship between corrupt officers and firms.

This is therefore a great opportunity for us to tease out the role that IT plays for a firm in such an environment. Our contribution to the literature is in investigating the linkages between IT adoption, bribe payments, and productivity, and exploring the possible impact on social welfare brought by IT adoption.

Specifically, utilizing data from the *World Bank Enterprise Survey* and other sources, we empirically investigate whether increased transparency of transactions will lead to higher costs. For firms that adopted IT in India, on average, sales increased by about 1.86 million INR in 2006 and 159 million INR by 2014[30] while simultaneously having to pay 24 thousand INR more in 2006 and 288 thousand INR more in 2014[31] as bribe payments than firms did not adopt IT. Our results

[30] About 89 million INR in 2006 values after deflation.

[31] About 162 thousand INR in 2006 values after deflation.

show that transparency-enhancing technologies can significantly improve firm productivity but also bring unwanted harassment from officers who demand more bribe payments.

Although these technologies are double-edged swords, the benefits they bring to the firms far outweigh their damages. By admitting a small amount of bribe payments, firms can make a large improvement in their sales performance. Both corrupt officers and existing firms will benefit from this game even while larger bribe payments have a detrimental impact on society. Based on our heterogeneity analysis results, a larger amount of bribe payments is required when firms are in more unfair and impoverished societies. After more informal requirements are satisfied, society becomes even more unfair, and the investment environment worsens. That is why we call for more attention to this aspect of adopting transparency-enhancing information technologies. Our further exploration based on global data from 2019 to 2022 also posits that this harmful pattern not only causes harm in developing countries but may also exist in developed countries. It is important to conduct more research to uncover the details.

We would like to conclude with a discussion of a few limitations of our study, which can provide opportunity for future research. First, our study only measures short-term effects of transparency-enhancing technologies on bribe payments and productivity based on cross-sectional data sets in 2006 and 2014. We can gain keener insights into how these effects evolve over time with longitudinal data. Second, our findings in India should be replicated in other developing countries; thus it is necessary to examine the linkages between adoption and bribe payments in developed countries as well.

We believe that the empirical findings presented in this study will provide a foundation for further research and the advancement of theoretical frameworks. We hope that our results will inspire further research on what role transparency-enhancing technologies play in society and how firms' adoption behaviors reshape the business environment.

5.0 Conclusion

In my dissertation, these three studies have provided a comprehensive examination of digital transformation and its multifaceted impacts across various countries and industries. Through an analysis of empirical research, several key findings have emerged.

First, contributions have been made to the literature related to the impact of digital transformation. At the organizational level, the first study suggests that firms that undertook digitalization efforts during the pandemic experienced much better performance compared to their counterparts who did not engage in any digitalization initiatives. It supports literature that posits that digital transformation is associated with the improvement of organizational performance. Furthermore, the first study also indicates that, in face of environmental shock, digital transformation such as increasing online presence, enabling new product and service modes, and facilitating remote work for employees, is practical and effective. Our second study also provides more detailed exploration about remote work and estimates the impact of different configurations. At the societal level, the third study demonstrates that firms leveraging IT in their business operations achieved substantial performance gains, yet they also exhibited a higher tendency to pay bribes, an admittedly small price to pay compared to their gains. However, from this perspective, digital transformation directly leads to undesirable outcomes that compromises society as a whole.

Second, researchers have also been curious about how digital technologies transform the value creation process. One idea is that digital technologies facilitate swift adaptation to shifts in environmental conditions by enhancing organizational agility (Hong and Lee, 2017; Kohli and Johnson, 2011). Besides the discussion relative to the impact of remote work, my second study also provides evidence in support of these researchers by introducing workforce flexibility and exploring the connection between flexible workforce adjustment and sales growth.

I wish to wrap up by pointing out several limitations of my dissertation and offering avenues for future research. First, all three studies assess the impact of digital transformation using cross-sectional datasets from the same data source, the *World Bank Enterprise Survey*. A more comprehensive understanding could be gained by employing longitudinal data from different sources. Second, explorations from my dissertation are mainly limited to short-term effects due to the short time that has elapsed since the pandemic itself, particularly for the *Follow-up Survey*. With more datasets that will inevitably be released in the future, we will be able to reveal more about the long-term impact of digital transformation in this context.

As we venture into the future amidst the rapid growth of Artificial Intelligence, the landscape of explorations related to digital transformation is poised for evolution. Compared to technologies we have thus far observed as a proxy of digital transformation, AI possesses revolutionary differences and will no doubt redefine industries and, reshape economies. I believe the future of research in the realm of digital transformation will be intertwined with AI; thus, it is imperative for researchers to seek to understand the socio-economic implications of AI-driven digital transformation. AI clearly holds significant potential to aid firms in combating environmental shocks. By leveraging advanced algorithms and data analytics, AI can enable businesses to anticipate and respond effectively to environmental challenges. The future is replete with opportunities for research and exploration.

6.0 Figures and Tables

6.1 Tables

Table 1 Variable Description

Source	Variables	Description	Type
2020 FS	Sales Growth	Comparing sales with the same month last year, by what percentage did the sales increase, decrease or remain the same? (if decrease, Sales Growth is negative)	Continuous
2020 FS	Online	Did this establishment start or increase business activity online in response to the COVID-19 outbreak? 0=No; 1=Yes	Binary (0: no; 1: yes)
2020 FS	Delivery	Did this establishment start or increase delivery or carry-out of goods or services in response to the COVID-19 outbreak? 0=No; 1=Yes	Binary (0: no; 1: yes)
2020 FS	Remote	Did this establishment start or increase remote work arrangement for its workforce in response to the COVID-19 outbreak? 0=No; 1=Yes	Binary (0: no; 1: yes)
2019 ES	Largest Owner	What percentage of this firm does the largest owner or owners own?	Continuous
2019 ES	Government Ownership	What percentage of this firm is owned by government or state?	Continuous
2019 ES	Firm Age	How many years since the establishment started operation?	Continuous
2019 ES	National Sales	what percentage of this establishment's sales were national sales?	Continuous
2019 ES	Sales per Employee	(Sales in the last completed fiscal year)/(the number of Permanent, full-time workers at the end of last fiscal year)	Continuous
2019 ES	Performance Difference	Sales in the last completed fiscal year - Sales in the (last fiscal year - 2)	Continuous
2019 ES	Pre-COVID Sales Trend	1 if Performance Difference> 0, 0 if Performance Difference >=0, -1 if Performance Difference <0	1/0/-1
2019 ES	Website	At the present time, does this establishment have its own website? 0=No; 1=Yes	Binary (0: no; 1: yes)
2019 ES	Innovation Index	Index represents a firm's innovation ability through the following items: • During the last three years, has this establishment introduced new or improved products or services? • Were any of the new or improved products or services also new for the establishment's main market? • During the last three years, has this establishment introduced any new or improved process? 0=No for all three questions; 1=Yes for one of the questions; 2=Yes for two of the questions; 3=Yes for all of the questions	0/1/2/3
2020 FS	National Support	Since the outbreak of COVID-19, has this establishment received any	Binary (0:

		national or local government support in response to the crisis? 0=No; 1=Yes	no; 1: yes)
2020 FS	Self Adjustment	Has this establishment adjusted or converted, partially or fully, its production or the services it offers in response to the COVID-19 outbreak? 0=No; 1=Yes	Binary (0: no; 1: yes)
2020 FS	Industry Number	Industry sectors	Categorical
2020 FS	Country Number	Country names	Categorical
2020 FS	Survey Number	the month when the firms took the survey	Categorical
Masks4All	Mask Requirement	country level mask required or not. 0= Not full country mask required; 1=Full country mask required	Binary (0: no; 1: yes)
Masks4All	Mask Requirement Type	type of mask requirement. 0=Not everywhere; 1= Everywhere in public	Binary (0: no; 1: yes)
Reuters	Workplace Lockdown	0=No lockdown measures; 1=Recommend closing; 2=Require closing some sectors; 3=Require closing all but essential workers	0/1/2/3
Reuters	Borders Lockdown	0=No lockdown measures; 1=Screen arrivals; 2=Quarantine arrivals from some or all regions; 3=Ban arrivals from some regions; 4= Ban arrivals from all regions	0/1/2/3/4
Reuters	Schools Lockdown	0=No lockdown measures; 1=Recommend closing; 2=Require closing some levels; 3=Require closing all levels	0/1/2/3
Reuters	Stay-at-home	0=No lockdown measures; 1=Recommend not leaving house; 2=Require not leaving home with some exceptions; 3=Require not leaving home with few exceptions	0/1/2/3
United Nations	Country Income Classification	0=Low-income; 1=Lower-middle-income; 2=Upper-middle-income; 3=High-income	0/1/2/3
World Bank	Digital Adoption Index	country level digital adoption index	Continuous
World Bank	Doing Business Score	country level Doing Business Score	Continuous

Note: Data sources are World Bank Enterprise Survey 2019 (ES) and World Bank Follow-up Survey 2020 (FS).

Table 2 Descriptive Statistics on Included 27 Countries

Income	Country Name	Firms	DBI	DAI	Work LD	Border LD	School LD	Stay Home	Mask	Mask Type
LM	Moldova	244	74.4	0.61	RS	BA	RA	RS	FC	NE
LM	Mongolia	254	67.8	0.54	RA	BA	RA	RM	FC	EIP
LM	Morocco	514	73.4	0.56	RA	BA	RA	RS	FC	EIP
LM	Zambia	427	66.9	0.34	RA	BA	RA	RS	FC	EIP
UM	Albania	258	67.7	0.61	RS	BA	RA	RS	NF	NE
UM	Azerbaijan	28	76.7	0.59	RA	BA	RA	RM	FC	NE
UM	Bosnia and Herzegovina	159	65.4	0.60	RA	BA	RA	RM	FC	EIP
UM	Bulgaria	366	72.0	0.63	R	BA	RA	RS	FC	EIP
UM	Georgia	306	83.7	0.60	RA	BA	RA	RM	FC	NE
UM	Jordan	136	69.0	0.55	RA	BA	RA	RM	NF	NE
UM	Kazakhstan	402	79.6	0.67	RA	BA	RA	RM	FC	NE
UM	Russia Federation	842	78.2	0.74	RA	BA	RA	RM	NF	NE

UM	Serbia	212	75.7	0.69	RA	BA	RA	RM	FC	NE
H	Croatia	338	73.6	0.65	RA	BA	RA	RS	FC	NE
H	Cyprus	138	73.4	0.68	RA	BA	RA	RS	NF	NE
H	Czech Republic	388	76.3	0.72	RA	BA	RA	RS	FC	NE
H	Estonia	211	80.6	0.83	RA	BS	RA	RS	NF	NE
H	Hungary	569	73.4	0.69	RS	BA	RA	RS	FC	NE
H	Italy	315	72.9	0.76	RA	BS	RA	RM	FC	NE
H	Latvia	164	80.3	0.73	RS	BA	RA	R	FC	NE
H	Lithuania	148	81.6	0.79	RA	BA	RA	R	FC	EIP
H	Malta	169	66.1	0.86	RS	BA	RA	RS	FC	NE
H	Poland	278	76.4	0.69	RS	BA	RA	RS	FC	EIP
H	Portugal	648	76.5	0.79	RA	BS	RA	RS	FC	NE
H	Romania	465	73.3	0.64	RS	BA	RA	RS	FC	NE
H	Slovak Republic	311	75.6	0.69	RS	BA	RA	RS	FC	NE
H	Slovenia	221	76.5	0.71	RA	BS	RA	R	FC	NE

Note: Income categories are lower-middle (LM), upper-middle (UM), and high (H). Workplace lockdown (LD) categories are Recommend (R), Require All (RA), and Require Some (RS). Border lockdown (LD) categories are Ban All (BA) and Ban Some (BS). School lockdown (LD) category is Require All (RA). Stay at Home categories are Recommend (R), Require Most (RM), and Require Some (RS). Mask categories are Full Country (FC) and Not Full (NF). Finally, Mask Type is Not Everywhere (NE), and Everywhere in Public (EIP).

Table 3 Digital Strategies and Sales Growth: IPTW Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	SG	SG	SG	SG	SG	SG	SG	SG
Treatment arms	4.467*** (0.782)	-0.385 (1.772)	11.830*** (2.005)	3.175*** (1.16)	4.817*** (2.437)	12.378*** (3.466)	0.047 (2.271)	4.711*** (1.911)
Treatment	Any Digitization	O	D	R	O+D	D+R	O+R	O+D+R
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,511	4,797	4,890	5,805	4,736	4,590	4,818	4,981

Note:*p<0.1; **p<0.05; ***p<0.01}; SG = Sales Growth; O = Online; D = Delivery; R = Remote

Table 4 Digital Strategies and Sales Growth: Linear Regression Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	SG	SG	SG	SG	SG	SG	SG	SG
Treatment arms	4.819*** (0.648)	1.108 (1.439)	9.148*** (1.35)	3.687*** (0.889)	5.200*** (1.578)	11.041*** (1.974)	4.764*** (1.467)	5.503*** (1.393)
Treatment	Any Digitization	O	D	R	O+D	D+R	O+R	O+D+R
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,511	4,797	4,890	5,805	4,736	4,590	4,818	4,981

Note:*p<0.1; **p<0.05; ***p<0.01}; SG = Sales Growth; O = Online; D = Delivery; R = Remote

Table 5 Digital Strategies and Sales Growth: Doubly Robust Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	SG	SG	SG	SG	SG	SG	SG	SG
Treatment arms	4.647*** (0.683)	-0.094 (1.629)	12.293*** (1.815)	4.252*** (0.918)	3.826 (3.783)	14.556*** (2.449)	0.795 (2.213)	9.868*** (2.949)

Treatment	Any Digitization	O	D	R	O+D	D+R	O+R	O+D+R
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,511	4,797	4,890	5,805	4,736	4,590	4,818	4,981

*Note***:***p<0.1; **p<0.05; ***p<0.01}; SG = Sales Growth; O = Online; D = Delivery; R = Remote

Table 6 Digital Strategies and Sales Growth: Lasso with Firm-level Fixed Effects Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	SG	SG	SG	SG	SG	SG	SG	SG
Treatment arms	4.819*** (0.664)	1.093 (1.389)	9.147*** (1.46)	3.711*** (0.849)	5.206*** (1.539)	11.042*** (2.173)	4.763*** (1.543)	5.526*** (1.44)
Treatment	Any Digitization	O	D	R	O+D	D+R	O+R	O+D+R
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,511	4,797	4,890	5,805	4,736	4,590	4,818	4,981

Note:*p<0.1; **p<0.05; ***p<0.01}; SG = Sales Growth; O = Online; D = Delivery; R = Remote

Table 7 Variables Description

Source	**Variables**	**Description**	**Type**
2019 ES	Business Organization	Is this firm part of a business membership organization, trade association, guild, chamber of commerce, or other business support group?	Binary (0: no; 1: yes)
2019 ES	Secondary School	What percentage of the full-time permanent workers employed completed secondary school?	Continuous
2019 ES	Female Owner	Amongst the owners of the firm, are there any females?	Binary (0: no; 1: yes)
2019 ES	Female Top Manager	Is the Top Manager female?	Binary (0: no; 1: yes)
2019 ES	Firm Age	How many years since the establishment started operation?	Continuous
2019 ES	Government Ownership	What percentage of this firm is owned by government or state?	Continuous
2019 ES	Innovation Index	Index represents firm's innovation ability. Queastion1: During the last three years, has this establishment introduced new or improved products or services? Queastion2: Were any of the new or improved products or services also new for the establishment's main market? Queastion3: During the last three years, has this establishment introduced any new or improved process? 0=No for all three questions; 1=Yes for one of the questions; 2=Yes for two of the questions; 3=Yes for all of the questions	0/1/2/3
2019 ES	Manager Experience	How many years of experience working in this sector does the Top Manager have?	Continuous
2019 ES	Political Position	Has the owner, CEO, top manager, or any of the board members of this firm ever been elected or appointed to a political position in this country?	Binary (0: no; 1: yes)
2019 ES	Power Outage	Over last complete fiscal year, did this establishment experience power outages?	Binary (0: no; 1: yes)
2019 ES	Sales Adjusted Before COVID	In last complete fiscal year, what were this establishment's total annual sales for all products and services? (Adjusted by exchange rate)	Continuous
2019 ES	Sales Expectation	Considering the next year, are this establishment's total sales expected to increase, decrease, or stay the same?	1/0/-1

2019 ES	Training Program	Over last complete fiscal year, did this establishment have formal training programs for its permanent, full-time employees?	Binary (0: no; 1: yes)
2019 ES	University Degree	What percentage of this establishment's permanent full-time employees employed at the end of last complete fiscal year had a university degree?	Continuous
2020 FS	National Support	Since the outbreak of COVID-19, has this establishment received any national or local government support in response to the crisis?	Binary (0: no; 1: yes)
2020 FS	Self Adjustment	Has this establishment adjusted or converted, partially or fully, its production or the services it offers in response to the COVID-19 outbreak? 0=No; 1=Yes	Binary (0: no; 1: yes)
2020 FS	Employee Before COVID	At the end of December 2019, how many permanent, full-time employees did this establishment employ?	Continuous
2020 FS	Sales Growth	Comparing sales with the same month last year, by what percentage did the sales increase, decrease or remain the same? (if decrease, Sales Growth is negative)	Continuous
2020 FS	Remote	Did this establishment start or increase remote work arrangement for its workforce in response to the COVID-19 outbreak? 0=No; 1=Yes	Binary (0: no; 1: yes)
2020 FS	Industry Number	industry mark	Categorical
2020 FS	Country Number	country mark	Categorical

Note: Data sources are World Bank Enterprise Survey 2019 (ES) and World Bank Follow-up Survey 2020 (FS).

Table 8 Mean Comparisons by Groups

	(1) All mean/sd	(2) Control mean/sd	(3) Start 1 mean/sd	(4) Start 2 mean/sd	(5) Increase 2 mean/sd	(6) Same 2 mean/sd	(7) Decrease 2 mean/sd	(8) Quit 2 mean/sd
Sales Growth Wave 1 (percent)	-22.3	-23.2	-20.2	-21.2	-18.1	-17.8	-19.9	-21.7
	(30.4)	(30.1)	(31.2)	(30.5)	(30.5)	(31.7)	(31.3)	(31.5)
Sales Growth Wave 2 (percent)	-18.2	-19.4	-13.8	-20	-9.64	-9.37	-13.3	-16.8
	(29.4)	(29.8)	(27.8)	(29.4)	(24.5)	(28.2)	(26.6)	(29.3)
Sales Growth Wave 3 (percent)	-3.03	-4.49	1.86	-4.25	5.91	2.08	6.11	-1.96
	(32.8)	(33.3)	(32.9)	(28.3)	(30.6)	(23.8)	(33.5)	(34.6)
Female Top Manager	.172	.188	.133	.154	.148	.111	.114	.139
	(.377)	(.39)	(.34)	(.362)	(.356)	(.317)	(.319)	(.346)
Female Owner	.37	.392	.31	.357	.321	.317	.283	.317
	(.483)	(.488)	(.463)	(.48)	(.468)	(.469)	(.452)	(.466)
National Support	.4	.37	.455	.477	.512	.397	.524	.408
	(.49)	(.483)	(.498)	(.5)	(.501)	(.493)	(.501)	(.492)
Self Adjustment	.291	.265	.365	.294	.309	.365	.44	.356
	(.454)	(.442)	(.482)	(.456)	(.463)	(.485)	(.498)	(.479)
Employee Before COVID	57.8	38.9	104	77.6	154	82.4	107	84.9
	(104)	(75.9)	(144)	(122)	(183)	(97)	(137)	(129)
Firm Age	23.8	23.1	25.7	23.5	29.1	24.3	24.8	24.9
	(14.8)	(13.2)	(18.6)	(14.3)	(21.7)	(20.2)	(18.3)	(16.7)
Sales Before COVID (thousands)	5,974	3,134	13,680	7,522	23,453	9,921	15,089	9,290
	(15,421)	(9,089)	(24,513)	(16,356)	(32,984)	(17,757)	(26,469)	(18,032)
Training Program	.356	.307	.475	.411	.519	.492	.506	.439
	(.479)	(.461)	(.5)	(.493)	(.501)	(.504)	(.501)	(.497)
Secondary School	69.7	68.6	74	67.8	75.2	69.4	73	74.7
	(30.4)	(30.9)	(27.8)	(31.9)	(25.3)	(29.3)	(28.2)	(28.5)
University Degree	19.1	16.3	27.7	18.9	29.5	32.5	28.5	25.7
	(22.1)	(19.5)	(27)	(21.8)	(28.3)	(27)	(28.1)	(25.9)
Innovation Index	.623	.539	.84	.697	.914	.889	.886	.778
	(.944)	(.893)	(1.04)	(.957)	(1.07)	(1.11)	(1.11)	(.985)
Power Outage	.32	.315	.31	.374	.327	.349	.313	.294
	(.467)	(.465)	(.463)	(.485)	(.471)	(.481)	(.465)	(.456)
Manager Experience	24.1	24.4	23.1	23.9	24.1	21.6	22.9	23
	(12)	(11.9)	(12.3)	(11.5)	(13.4)	(12.8)	(11.6)	(12)
Political Position	.049	.0462	.0573	.0486	.0556	.0635	.0482	.0611
	(.216)	(.21)	(.232)	(.215)	(.23)	(.246)	(.215)	(.24)
Business Organization	.448	.446	.459	.434	.494	.413	.428	.467
	(.497)	(.497)	(.499)	(.496)	(.502)	(.496)	(.496)	(.5)
Government Ownership	.182	.088	.499	.1	0	0	0	1.04
	(3.33)	(1.65)	(6.35)	(1.22)	(0)	(0)	(0)	(9.14)
Sales Expectation	.394	.387	.438	.34	.426	.556	.422	.431
	(.696)	(.691)	(.686)	(.743)	(.703)	(.616)	(.707)	(.681)
Number of Firms	3,329	2,228	751	350	162	63	166	360

Table 9 Remote Work Adoption Logit Regression

	(1) Wave 1 b/(se)	(2) Wave 1 b/(se)	(3) All b/(se)	(4) All b/(se)
Female Top Manager	-.111	-.144	-.133	-.166
	(.156)	(.155)	(.136)	(.135)
Female Owner	-.115	-.118	-.13	-.13
	(.117)	(.116)	(.104)	(.103)
National Support	.183*	.2*	.22**	.231**
	(.107)	(.106)	(.0954)	(.0945)
Self Adjustment	.721***	.686***	.549***	.522***
	(.114)	(.113)	(.102)	(.102)
Employee Before COVID	.00303***	.00482***	.00374***	.00578***
	(.000569)	(.000479)	(.000611)	(.000524)
Firm Age	.00947***	.0118***	.0063*	.00856***
	(.00365)	(.00355)	(.00341)	(.00332)
Sales Before COVID	2.22e-08***		2.64e-08***	
	(4.07e-09)		(4.73e-09)	
Training Program	.342***	.381***	.314***	.353***
	(.107)	(.106)	(.0955)	(.0944)
Secondary School	.0027	.00238	.00232	.00202
	(.00203)	(.00201)	(.00173)	(.00171)
University Degree	.0143***	.0145***	.0116***	.012***
	(.00239)	(.00238)	(.00224)	(.00223)
Innovation Index	.213***	.21***	.197***	.198***
	(.0547)	(.0543)	(.05)	(.0497)
Sales Expectation	.115	.108	.021	.0186
	(.0738)	(.0731)	(.0651)	(.0646)
Power Outage	-.234**	-.25**	-.0657	-.0805
	(.114)	(.114)	(.0998)	(.0994)
Manager Experience	-.0149***	-.0146***	-.0131***	-.0127***
	(.00469)	(.00464)	(.00419)	(.00414)
Political Position	-.123	-.106	-.258	-.236
	(.217)	(.215)	(.199)	(.196)
Business Organization	.0906	.107	.219**	.226**
	(.123)	(.121)	(.109)	(.108)
Government Ownership	.0219	.0213	.0188	.018
	(.0159)	(.0158)	(.017)	(.0168)
Industry FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	3,304	3,304	3,285	3,285

Note:*p<0.1; **p<0.05; ***p<0.01

Table 10 Remote Work and Sales Growth: IPTW Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	P 2	P 3	P 3	P 3	P 3	P 3	P 3	P 3
Treatment arms	3.337** (1.442)	3.934** (1.741)	1.288 (2.489)	14.202*** (4.184)	7.180** (3.617)	10.333** (4.614)	-0.077 (1.928)	7.020*** (2.499)
Treatment	Start 1	Start 1	Start 2	Increase 2	Same 2	Decrease 2	Quit 2	Quit 2 or not

Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2979	2979	2578	2390	2291	2394	2588	751

Note:*p<0.1; **p<0.05; ***p<0.01

Table 11 Remote Work and Sales Growth: Doubly Robust Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	P 2	P 3	P 3	P 3	P 3	P 3	P 3	P 3
Treatment arms	2.479* (1.476)	5.650*** (1.888)	0.954 (2.726)	9.851*** (1.547)	14.743*** (3.488)	8.938*** (3.257)	2.555 (2.129)	7.663*** (2.498)
Treatment	Start 1	Start 1	Start 2	Increase 2	Same 2	Decrease 2	Quit 2	Quit 2 or not
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2979	2979	2578	2390	2291	2394	2588	751

Note:*p<0.1; **p<0.05; ***p<0.01

Table 12 Variables, Data Source, and Measurement

Variable	**Source**	**Availability**	**Description**	**Type**
Computer use	WBES	2006	Does this store use its own/hired computer for running its business?	Binary (0: no; 1: yes)
Website ownership	WBES	2014,2022	Does the firm have its own website?	Binary (0: no; 1: yes)
Computerized Land Records	ICS	2005	Incidence of corruption in state-wise computerization of land records	High/Low
Electricity	ICS	2005	State-wise Performance Rating Scores based on bribes paid by the common citizens to avail services of Electricity Department	High/Medium/Low
Public Distribution System	ICS	2005	Bribes paid by common citizens to avail services of Public Distribution Department, Classification of States according to Poverty Incidence	High/Medium/Low
Internet Subscription Rank	DOT	2014,2020	Rank states based on total Internet subscription rate	Ordinal value
Ease of Doing Business Rank	RBI DPIIT	2015,2019	Rank states based on state-wise Ease of Doing Business Index	Ordinal value
Poverty	NSSO NITI Aayog NFHS	2012,2016	State-wise percentage of population below poverty line	Continuous (0: minimum; 1: maximum)
Human Development Index	HDR	2007-2008	a composite index, consisting of three indicators – consumption expenditure (as a proxy for income), education and health	Continuous (0: minimum; 1: maximum)
City Corruption	WBES	2005	Establishments are sometimes required to make gifts or informal payments to public officials to “get things done” with regard to customs, taxes, licenses, regulations. Does this occur for establishments in your sector (not necessarily yours)?	Continuous. The mean bribe payments of all firms located in the city.
Perceived Informality	WBES	2006	What percent of total annual sales would you estimate the typical firm in your line of business declares for tax purposes?	Continuous (0-100%)
Bribe (Percent Sales)	WBES	2006, 2014,2022	On average, what percent of total annual sales, do firms like this one pay in informal payments/gifts to public officials to “get things done” with regard to customs, taxes, licenses, regulations, services etc.?	Continuous (0-100%)
Bribe value‡	WBES	2006, 2014,2022	What is the total annual informal payment for the purpose listed above? (Note: the establishment will provide either 'Bribe Percent Sales' or 'Bribe Estimated Value')	Continuous

Regulatory Inspections	WBES	2006	How many times was this store either inspected by all the following agencies or required to meet with officials from these agencies? (Tax Inspectorate, Labor, Fire and Building Safety, Others)	Continuous
Auditor	WBES	2006, 2014,2022	did this establishment have its annual financial statements checked and certified by an external auditor?	Binary (0: no; 1: yes)
Regulatory Consistency	WBES	2006	Government officials' interpretations of the laws and regulations affecting this store are consistent and predictable.	Continuous (1:strongly disagree – 6:strongly agree)
Power Cuts	WBES	2006, 2014,2022	Over the last fiscal year, did this firm experience power outages/power cuts?	Binary (0: no; 1: yes)
Power Supply Problem	WBES	2006, 2014,2022	Is electricity No Obstacle, a Minor Obstacle, a Major Obstacle, or a Very Severe Obstacle to the current operations of this establishment?	Continuous (0:no;1:minor, 2: major, 3: severe, 4: very severe)
Generator	WBES	2006, 2014,2022	Over the last fiscal year, did this establishment own or share a generator?	Binary (0: no; 1: yes)
Store Size	WBES	2006	What is the total selling area in this store?	Continuous (square feet)
Employee	WBES	2006, 2014,2022	Permanent, full-time employees end of last fiscal year	Continuous (head count)
Firm Age	WBES	2006, 2014,2022	In what year did this establishment begin operations in this country?	Continuous
Top Manager Experience	WBES	2006, 2014,2022	How many years of experience working in the industry does the top manager have?	Continuous
Ownership Concentration	WBES	2006, 2014,2022	What percent of this establishment does the largest (individual/company) shareholder(s) own?	Continuous (1-100%)
Government Ownership	WBES	2006, 2014,2022	Owned by government or not (ownership >= 50%)	Binary (0: no; 1: yes)
National Sales	WBES	2006, 2014,2022	What percentage of this establishment's sales were national sales?	Continuous (0-100%)
Sales	WBES	2006, 2014,2022	In the last fiscal year, what were this establishment's total annual sales?	Continuous
Sales 3 Years Ago	WBES	2006, 2014,2022	Three fiscal years ago, what were total annual sales for this establishment?	Continuous

Note: WBES: World Bank Enterprise Survey; ICS: India Corruption Study by Transparency International, HDR: Human development report by the Planning Commission of India, DOT: Department of Telecommunications in India, RBI: Reserve Bank of India, DPIIT: Department for Promotion of Industry and Internal Trade, NSSO: National Sample Survey Organization, NITI Aayog: National Institution for Transforming India, NFHS: National Family Health Survey.
‡ Currency values in datasets are in Indian Rupees.

Table 13 Summary Statistics—India 2006 Dataset

Variable	Mean	Std. Dev.	Min	Max
Computer use	.177	.382	0	1
Computerized Land Records	.498	.5	0	1
Electricity	2.298	.641	1	3
Public Distribution System	1.844	.723	1	3
Human Development Index	.503	.094	.358	.75
City Corruption	.439	.25	0	.882
Perceived Informality	62.683	36.237	0	100
Bribe Percent Sales	.835	2.283	0	20
Bribe Value	15699.466	73731.749	0	920000
Regulatory Inspections	1.863	3.891	0	45
Auditor	.346	.476	0	1
Regulatory Consistency	3.101	1.526	1	6
Power Cuts	.847	.36	0	1
Power Supply Problem	1.678	1.207	0	4
Generator	.317	.465	0	1
Store Size	475.907	2346.889	10	65000
Employee	3.472	18.098	0	400

Firm Age	15.693	12.543	2	81
Top Manager Experience	13.805	9.846	1	57
Ownership Concentration	96.117	16.366	1	100
Government Ownership	.012	.111	0	1
National Sales	99.982	.422	90	100
Sales	2049000	3450000	10000	20000000
Sales 3 years ago	2277000	5114000	10000	45000000

Note: Number of observations: 1124

Table 14 Summary Statistics—India 2014 Dataset

Variable	Mean	Std. Dev.	Min	Max
Website ownership	.512	.5	0	1
Bribe value	399188.19	6553000	0	3.600e+08
Auditor	.813	.39	0	1
Power Cuts	.65	.477	0	1
Power Supply Problem	1.552	1.236	0	4
Generator	.599	.49	0	1
Employee	109.217	352.682	2	9999
Firm age	20.118	14.318	1	151
Top Manager Experience	13.664	9.228	1	65
Ownership Concentration	77.532	26.045	3	100
Government Ownership	.001	.029	0	1
National Sales	93.357	21.017	0	100
Sales	2.947e+08	1.728e+09	160000	9.000e+10
Sales 3 Years Ago	2.529e+08	1.605e+09	50000	8.680e+10
Poverty	.192	.101	.051	.399
Internet Subscription Rank	10.837	6.282	1	21
Ease of Doing Business Rank	10.942	6.241	1	23

Note: Number of observations: 6932

Table 15 Summary Statistics—India 2022 Dataset

Variable	Mean	Std. Dev.	Min	Max
Website ownership	.602	.489	0	1
Bribe value	9352000	80600000	0	5.000e+09
Auditor	.617	.486	0	1
Power Cuts	.213	.409	0	1
Power Supply Problem	.905	1.122	0	4
Generator	.38	.485	0	1
Employee	92.606	185.7	2	10000
Firm age	22.971	14.975	3	184
Top Manager Experience	18.035	10.224	1	70
Ownership Concentration	87.694	22.281	1	100
Government Ownership	.001	.032	0	1
National Sales	92.312	23.098	0	100
Sales	4.627e+08	1.704e+09	350000	5.072e+10
Sales 3 Years Ago	4.501e+08	1.766e+09	0	7.000e+10
Poverty	.193	.124	.007	.519
Internet Subscription Rank	11.359	6.41	1	21
Ease of Doing Business Rank	11.972	6.615	1	24

Note: Number of observations: 8810

Table 16 Factors impacting IT adoption and use (2006)

	(1) Coefficient	Standard error	(2) Coefficient	Standard error
Computerized Land Records	-0.428***	(0.159)	-0.455***	(0.158)
Electricity	-0.303**	(0.154)	-0.293*	(0.153)
Public Distribution System	-0.337***	(0.117)	-0.344***	(0.115)
Human Development Index	-0.214	(0.959)	-0.417	(0.956)
City Corruption	-0.569**	(0.275)	-0.535**	(0.272)
Perceived Informality	0.00157	(0.00187)	0.00180	(0.00185)
Regulatory Inspections	0.0319**	(0.0162)	0.0321**	(0.0158)
Auditor	0.280**	(0.133)	0.336***	(0.130)
Regulatory Consistency	0.00344	(0.0391)	0.00619	(0.0388)
Power Cuts	0.157	(0.197)	0.150	(0.196)
Power Supply Problem	0.0134	(0.0518)	0.0187	(0.0512)
Generator	0.648***	(0.135)	0.669***	(0.134)
Store Size	0.000596***	(0.000151)	0.000615***	(0.000149)
Employee	0.0619***	(0.0206)	0.0785***	(0.0195)
Firm Age	-0.0116*	(0.00621)	-0.00962	(0.00608)
Top Manager Experience	-0.0128*	(0.00773)	-0.00980	(0.00754)
Ownership Concentration	-0.00420	(0.00344)	-0.00426	(0.00339)
Government Ownership	0.389	(0. 426)	0.471	(0.421)
Sales 3 Years Ago	4.37e-08**	(1.38e-08)		
Log likelihood	-300.2		-305.3	
Chi-squared	449.2***		439.0***	
pseudo R^2	0.428		0.418	
N	1124		1124	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 17 Relating computer adoption with sales performance and bribe payments

	(1) Sales	(2) Bribe Value	(3) Sales	(4) Bribe Value	(5) Sales	(6) Bribe Value	(7) Sales	(8) Bribe Value
IT Adoption and Use	1761488.669*** (254016.234)	37944.754*** (6971.538)	2507891.193*** (265019.077)	44859.455*** (6839.956)	1781506.189*** (250877.307)	38969.565*** (6904.078)	2507305.435*** (262154.469)	45712.143*** (6782.438)
Computerized Land Records					-355725.017* (203961.251)	10209.081* (5612.960)	-435764.115** (218608.474)	9465.528* (5655.820)
Electricity					-562393.557*** (205176.938)	4251.036 (5646.415)	-554172.577** (220012.394)	4327.408 (5692.142)
Public Distribution System					-480196.516*** (161543.471)	7589.715* (4445.634)	-506253.707*** (173211.252)	7347.647 (4481.307)
Human Development Index					-442203.109 (1245827.460)	-61870.910* (34284.844)	-153311.259 (1335698.090)	-59187.143* (34557.068)
City Corruption					-507014.406 (348154.514)	7996.629 (9581.121)	-302307.498 (372941.222)	9898.328 (9648.704)
Perceived Informality	2573.064 (2444.244)	-4.032 (67.083)	3672.806 (2618.491)	6.156 (67.581)	3611.503 (2302.429)	-44.726 (63.362)	4595.668* (2467.561)	-35.583 (63.841)
Regulatory Inspections	43295.482* (22259.184)	-31.528 (610.909)	72355.833*** (23736.287)	237.689 (612.617)	42578.333** (21481.605)	-43.217 (591.168)	74395.791*** (22882.366)	252.363 (592.011)
Auditor	950007.127*** (198696.222)	11361.723** (5453.266)	1238737.369*** (211615.303)	14036.531** (5461.642)	975101.785*** (193238.222)	13127.387** (5317.865)	1234524.398*** (206084.415)	15537.388*** (5331.798)
Regulatory Consistency	-25665.940 (52309.452)	-1866.715 (1435.646)	-15846.436 (56067.150)	-1775.746 (1447.054)	-8892.007 (51542.457)	-1794.930 (1418.435)	-3142.588 (55267.466)	-1741.519 (1429.875)
Power Cuts	-102487.667 (242485.761)	-4967.613 (6655.081)	-241542.588 (259671.845)	-6255.823 (6701.948)	-64745.479 (231050.189)	-5915.211 (6358.441)	-157394.081 (247637.701)	-6775.905 (6406.862)
Power Supply Problem	-46322.793 (70738.596)	2423.202 (1941.438)	-36359.759 (75823.734)	2515.500 (1956.957)	-27889.387 (67494.956)	1849.806 (1857.443)	-11835.100 (72363.249)	1998.948 (1872.176)
Generator	778628.292*** (207407.326)	-6414.439 (5692.345)	969263.413*** (221756.438)	-4648.388 (5723.378)	704652.489*** (201982.202)	-7260.882 (5558.497)	906170.945*** (215937.881)	-5388.802 (5586.727)
Store Size	203.540*** (66.704)	1.252 (1.831)	199.730*** (71.503)	1.217 (1.845)	206.188*** (66.407)	1.463 (1.827)	200.455*** (71.207)	1.409 (1.842)
Employee	-19981.236** (8674.327)	-367.195 (238.069)	-9705.788 (9258.540)	-272.003 (238.956)	-19988.358** (8623.483)	-324.941 (237.316)	-9854.090 (9208.538)	-230.795 (238.243)
Firm Age	-18075.651**	-215.462	-11114.526	-150.974	-17701.605**	-242.789	-10508.521	-175.966

	(8016.591)	(220.017)	(8573.592)	(221.278)	(7937.859)	(218.448)	(8490.791)	(219.673)
Top Manager Experience	28693.128***	203.246	31240.685***	226.846	29366.534***	178.703	32155.423***	204.611
	(9923.340)	(272.348)	(10635.196)	(274.487)	(9877.220)	(271.819)	(10588.909)	(273.955)
Ownership Concentration	7675.395	25.249	2215.497	-25.332	8785.794*	-4.708	3276.526	-55.888
	(5387.664)	(147.866)	(5757.179)	(148.589)	(5332.499)	(146.749)	(5699.698)	(147.462)
Government Ownership	144366.931	-36775.948*	1236383.992	-26659.461	111471.196	-38142.791*	1225486.194	-27793.742
	(725287.408)	(19905.690)	(772073.845)	(19926.683)	(716619.342)	(19721.176)	(762829.374)	(19735.857)
sales_3yearsago	0.239***	0.002***			0.239***	0.002***		
	(0.019)	(0.001)			(0.019)	(0.001)		
_cons	-419008.435	33383.939*	16943.766	37422.616*	1961715.261*	12407.360	2183845.234*	14470.918
	(734575.158)	(20160.594)	(786581.675)	(20301.120)	(1051722.582)	(28943.129)	(1127622.118)	(29173.744)
Fixed Effect								
State	Yes	Yes	Yes	Yes	No	No	No	No
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1124	1124	1124	1124	1124	1124	1124	1124
R2	0.469	0.123	0.389	0.108	0.465	0.113	0.385	0.098
adj. R2	0.453	0.098	0.371	0.083	0.455	0.095	0.373	0.081
Log lik.	-18159.729	-14118.317	-18238.340	-14127.849	-18163.251	-14124.886	-18242.234	-14134.467
F	30.066	4.803	22.411	4.287	43.545	6.387	32.793	5.697

Note: Standard errors in parentheses; * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 18 Impact of IT adoption on sales performance and bribe payments (2006)

	(1) Sales	(2) Bribe Value	(3) Sales	(2) Bribe Value
IT Adoption and Use	1,827,331.921***	24,008.174***	1,929,327.412***	23,964.211***
	(412,119.632)	(6,665.576)	(427,877.225)	(6,445.679)
Constant	1,706,879.572***	8,458.372***	1,700,019.210***	8,357.080***
	(186,017.024)	(1,868.042)	(188,577.148)	(1,793.631)
State-Level Controls	No	No	Yes	Yes
Fixed Effects				
State	Yes	Yes	No	No
Industry	Yes	Yes	Yes	Yes
N	1124	1124	1124	1124

Note: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 19 Factors impacting IT adoption and use (2014)

	(1) Coefficient	Standard error	(2) Coefficient	Standard error
Poverty	-1.885***	(0. 256)	-1.863***	(0.255)
Internet Subscription Rank	-0.00855**	(0. 00402)	-0.00765*	(0. 00400)
Ease of Doing Business Rank	-0.0163***	(0. 00312)	-0.0166***	(0. 00311)
Ownership Concentration	-0.00305***	(0. 000701)	-0.00369***	(0. 000692)
Government Ownership	-0.310	(0. 558)	-0.309	(0. 562)
Firm Age	-0.00134	(0. 00134)	-0.00170	(0. 00133)
National Sales	-0.0121***	(0. 00106)	-0.0124***	(0. 00106)
Employee	0.00133***	(0. 000134)	0.00198***	(0. 000124)
Top Manager Experience	-0.000378	(0. 00205)	-0. 000289	(0. 00204)
Auditor	0.424***	(0. 0447)	0.427***	(0. 0446)
Generator	0.397***	(0. 0450)	0.408***	(0. 0448)
Power Cuts	-0.178***	(0. 0492)	-0.172**	(0. 0489)
Power Supply Problem	-0.0228	(0. 0176)	-0.0311***	(0.0175)
Sales 3 Years Ago	4.15e-10**	(5.64e-11)		
Log likelihood	-3797.3		-3814.7	
Chi-squared	2010.9***		1976.1***	
pseudo R^2	0.209		0.206	
N	6932		6932	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 20 Factors impacting IT adoption and use (2022)

	(1) Coefficient	Standard error	(2) Coefficient	Standard error
Poverty	0.0953	(0.198)	0.0948	(0.198)
Internet Subscription Rank	-0.0175**	(0. 00377)	-0.0175***	(0. 00377)
Ease of Doing Business Rank	0.00955***	(0. 00256)	0.00956***	(0. 00256)
Ownership Concentration	-0.00487***	(0. 000734)	-0.00497***	(0. 000733)
Government Ownership	0.0455	(0. 560)	0.0863	(0. 551)
Firm Age	0.000725	(0. 00113)	0.000804	(0. 00112)

National Sales	-0.00416***	(0. 000723)	-0.00417***	(0. 000723)
Employee	0.00113***	(0. 000140)	0.00123***	(0. 000133)
Top Manager Experience	0.000242	(0. 00163)	0. 000233	(0. 00163)
Auditor	0.600***	(0. 0313)	0.601***	(0. 0313)
Generator	0.936***	(0. 0372)	0.935***	(0. 0372)
Power Cuts	-0.121**	(0. 0477)	-0.120**	(0. 0477)
Power Supply Problem	0.0467***	(0.0158)	0.0480***	(0.0158)
Sales 3 Years Ago	2.79e-11**	(1.13e-11)		
Log likelihood	-4800.8		-4803.9	
Chi-squared	2239.7***		2233.3***	
pseudo R^2	0.189		0.189	
N	8810		8810	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 21 Impact of IT adoption on sales performance and bribe payments (2014)

	(1) Sales	(2) Bribe Value	(3) Sales	(4) Bribe Value
IT Adoption and Use	142,801,214.406***	288,162.647***	144,245,482.685***	284,209.901***
	(41,045,902.858)	(108,908.944)	(39,444,941.917)	(108,022.113)
Constant	190,619,568.032***	173,560.811***	186,471,335.115***	174,074.963***
	(32,076,664.453)	(35,310.829)	(30,355,193.742)	(34,873.155)
State-Level Controls	No	No	Yes	Yes
Fixed Effects				
State	Yes	Yes	No	No
Industry	Yes	Yes	Yes	Yes
N	6932	6932	6932	6932

Note: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; The coefficients in the table are in Indian Rupees. If we adjust currency values to 2006 with deflators provided by World Bank, the ATE in each column would be 80,325,683.103, 162,091.489, 81,138,084.046, and 159,868.069 respectively.

Table 22 Impact of IT adoption on sales performance and bribe payments (2022)

	(1) Sales	(2) Bribe Value	(3) Sales	(4) Bribe Value
IT Adoption and Use	114,913,252.380**	-1,840,957.132	107,798,765.539*	-2,388,260.521*
	(51,967,206.767)	(1,257,492.808)	(55,687,315.910)	(1,297,669.466)
Constant	354,831,551.817***	7,898,958.955***	365,217,125.977***	8,478,193.289***
	(47,935,262.926)	(1,178,579.402)	(51,994,696.160)	(1,220,839.957)
State-Level Controls	No	No	Yes	Yes
Fixed Effects				
State	Yes	Yes	No	No
Industry	Yes	Yes	Yes	Yes
N	8810	8810	8810	8810

Note: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; The coefficients in the table are in Indian Rupees. If we adjust currency values to 2006 with deflators provided by World Bank, the ATE in each column would be -719,951.527, 44,939,651.255, -933,987.967, and 42,157,356.342 respectively.

6.2 Figures

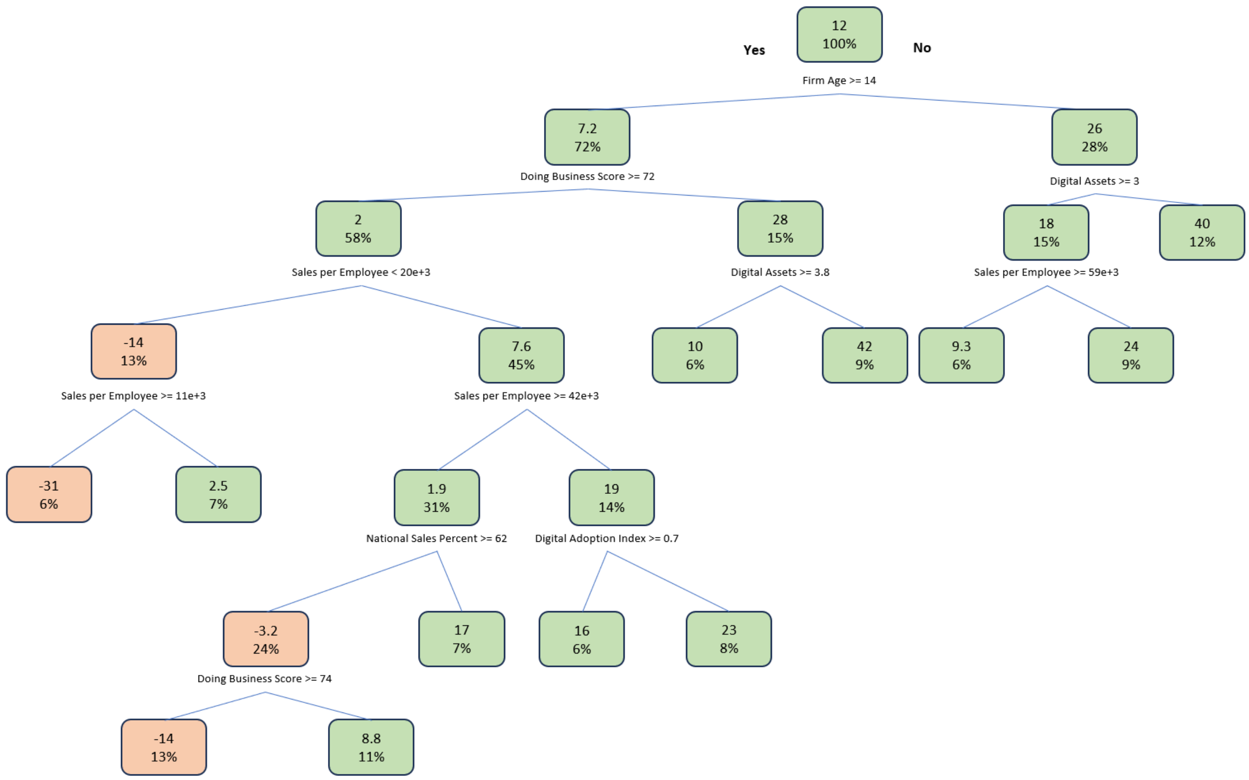

Figure 1 Causal Tree for the Delivery+Remote Configuration

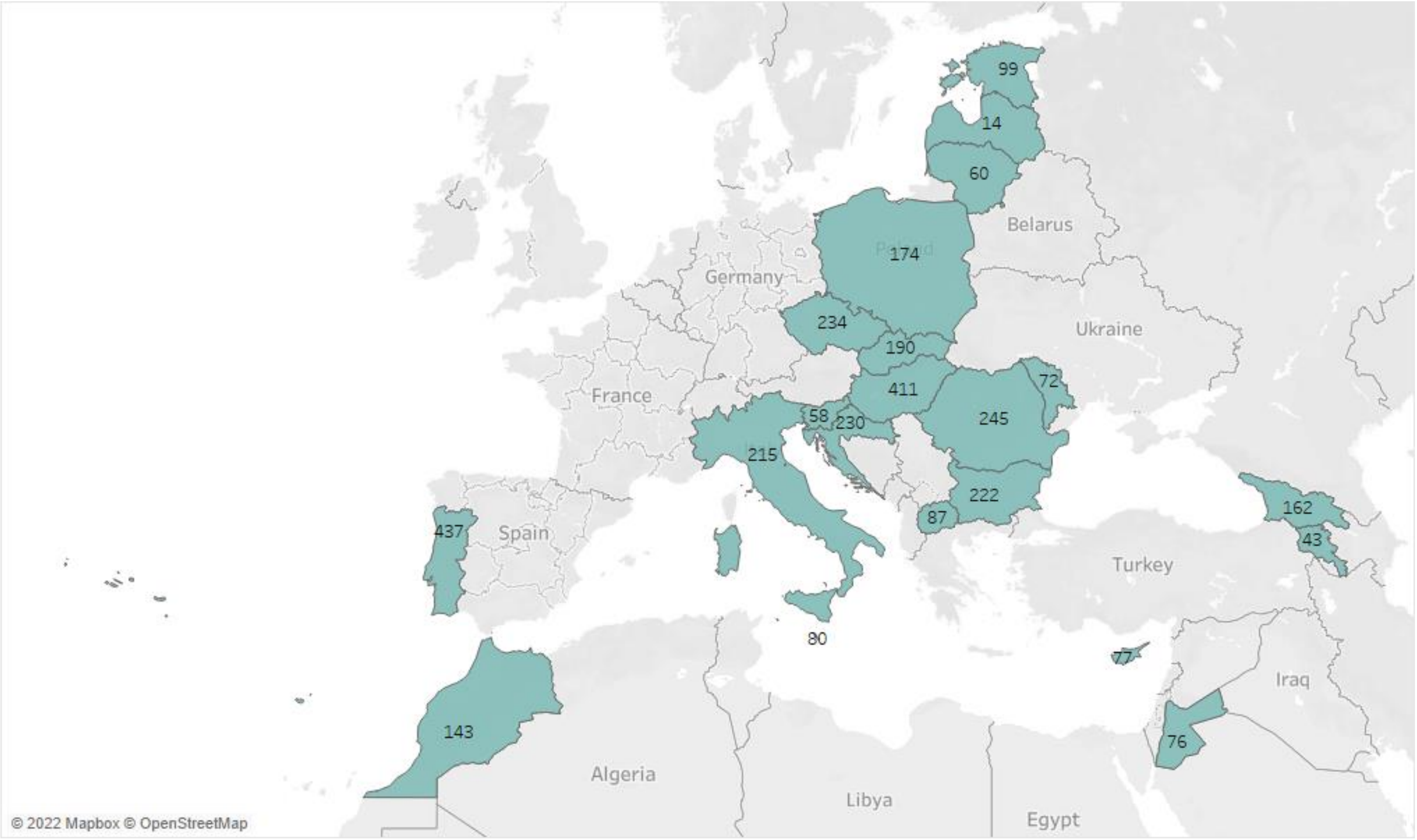

Figure 2 Sample Size by Countries

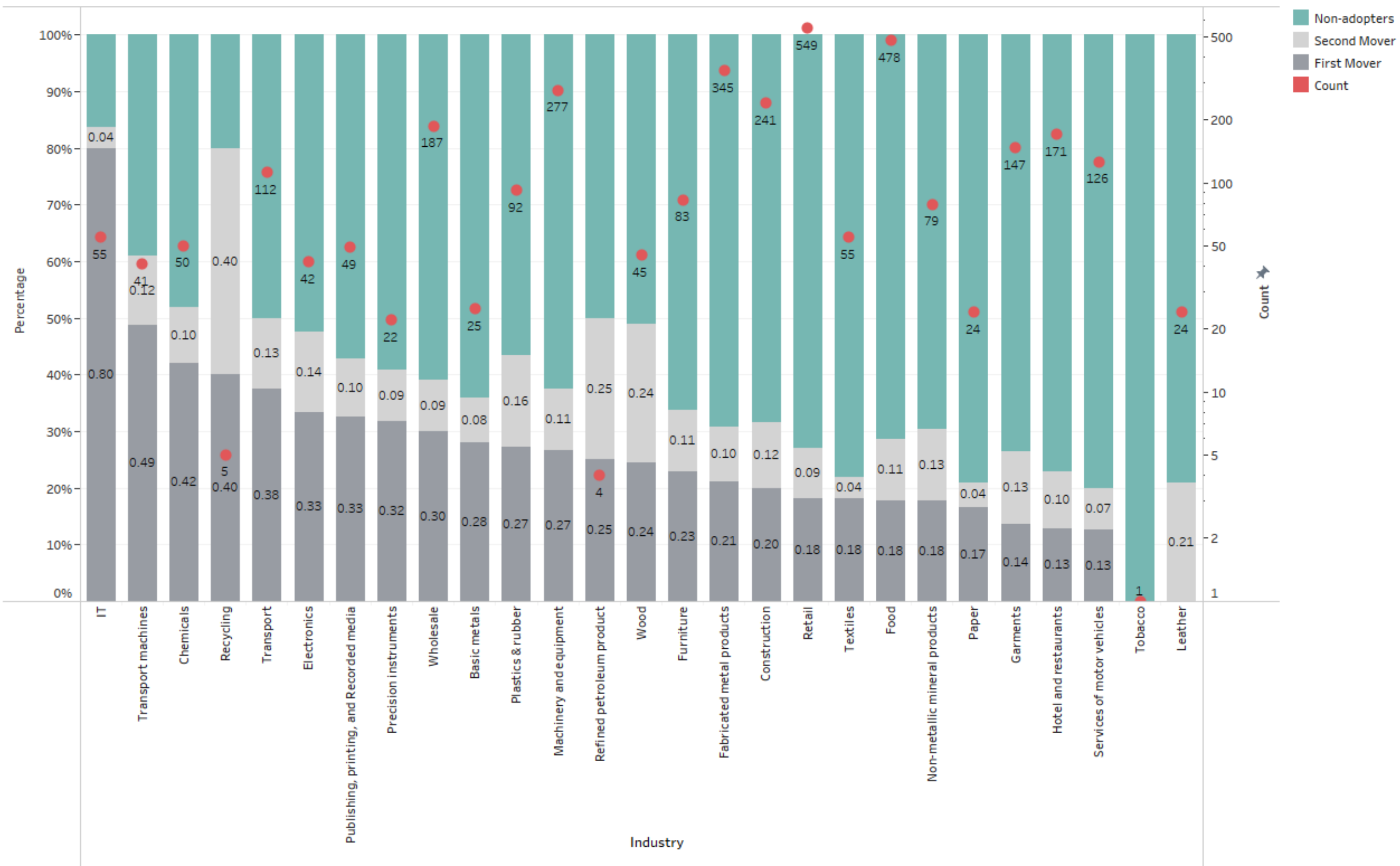

Figure 3 Remote Work Choices by Industries

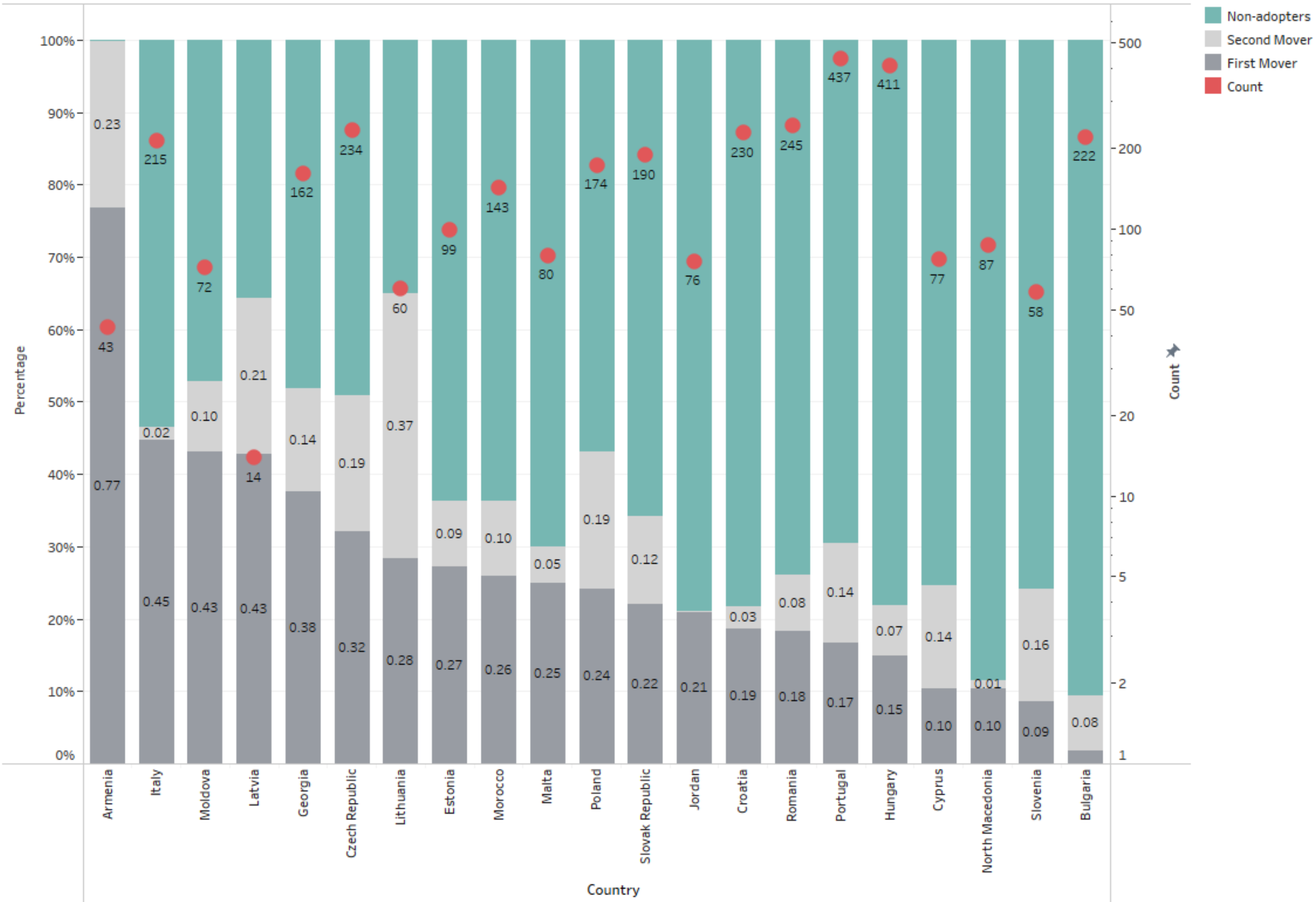

Figure 4 Remote Work Choices by Countries

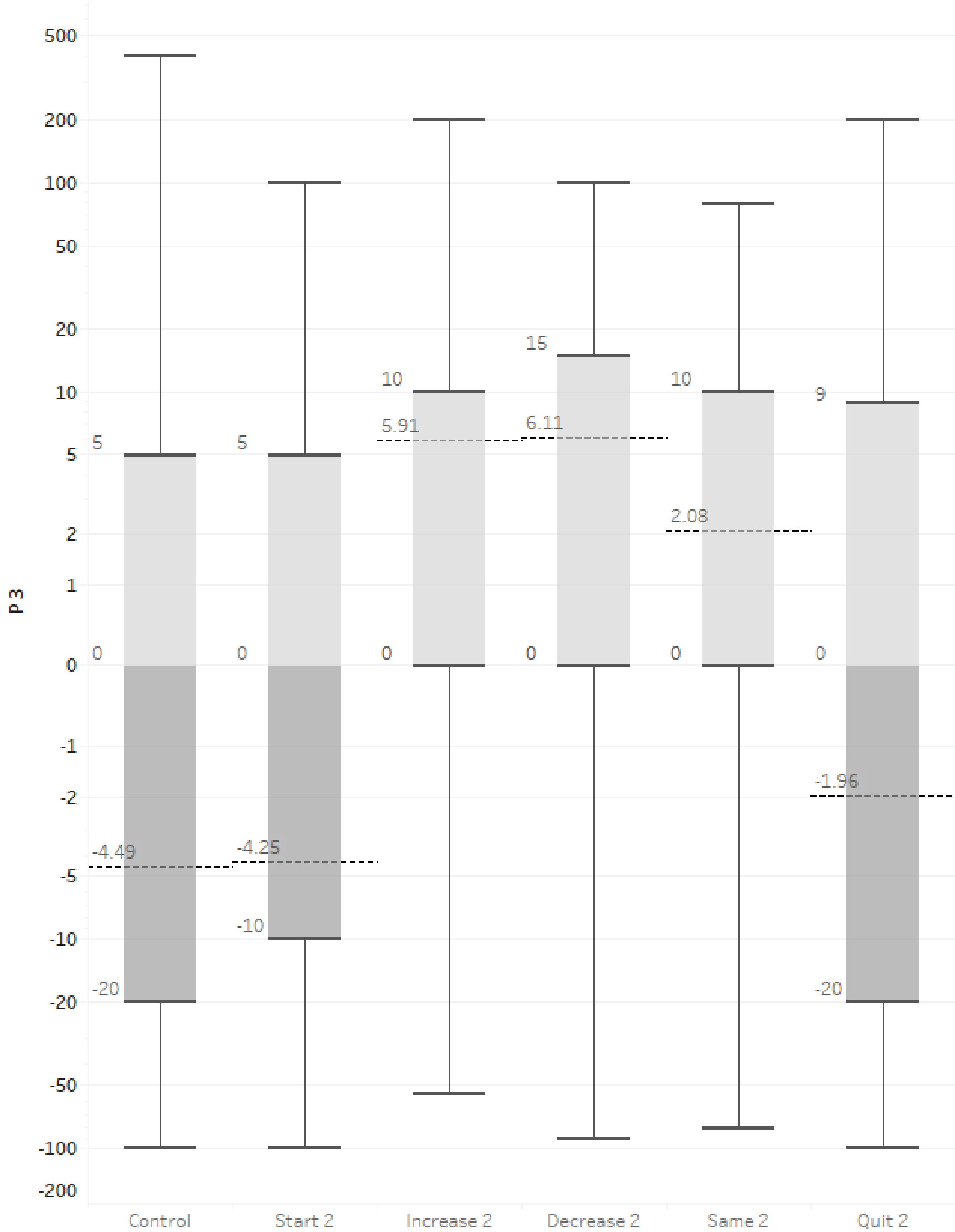

Figure 5 Sales Growth In Survey Wave 3

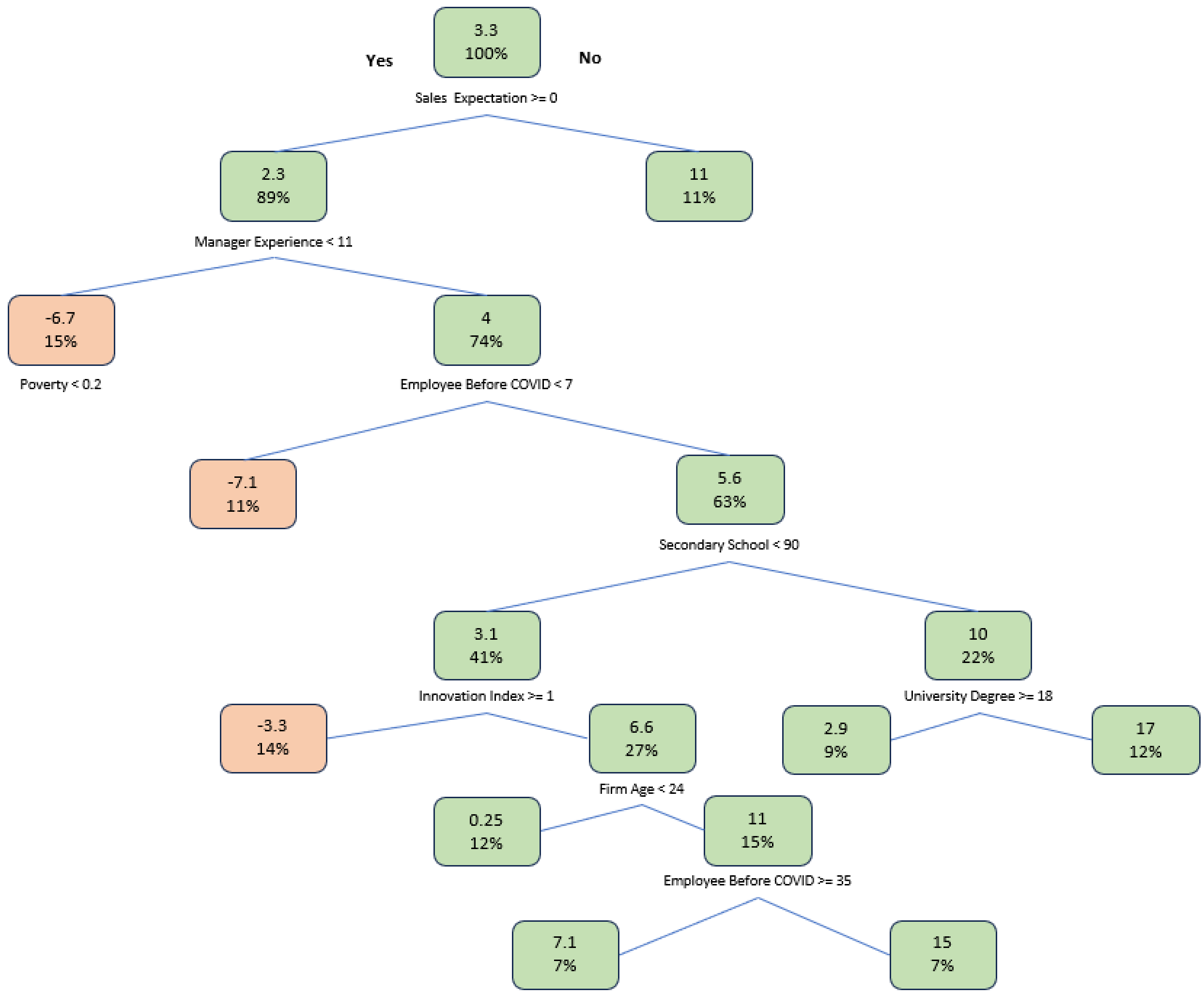

Figure 6 First Mover Causal Tree in Survey Wave 2

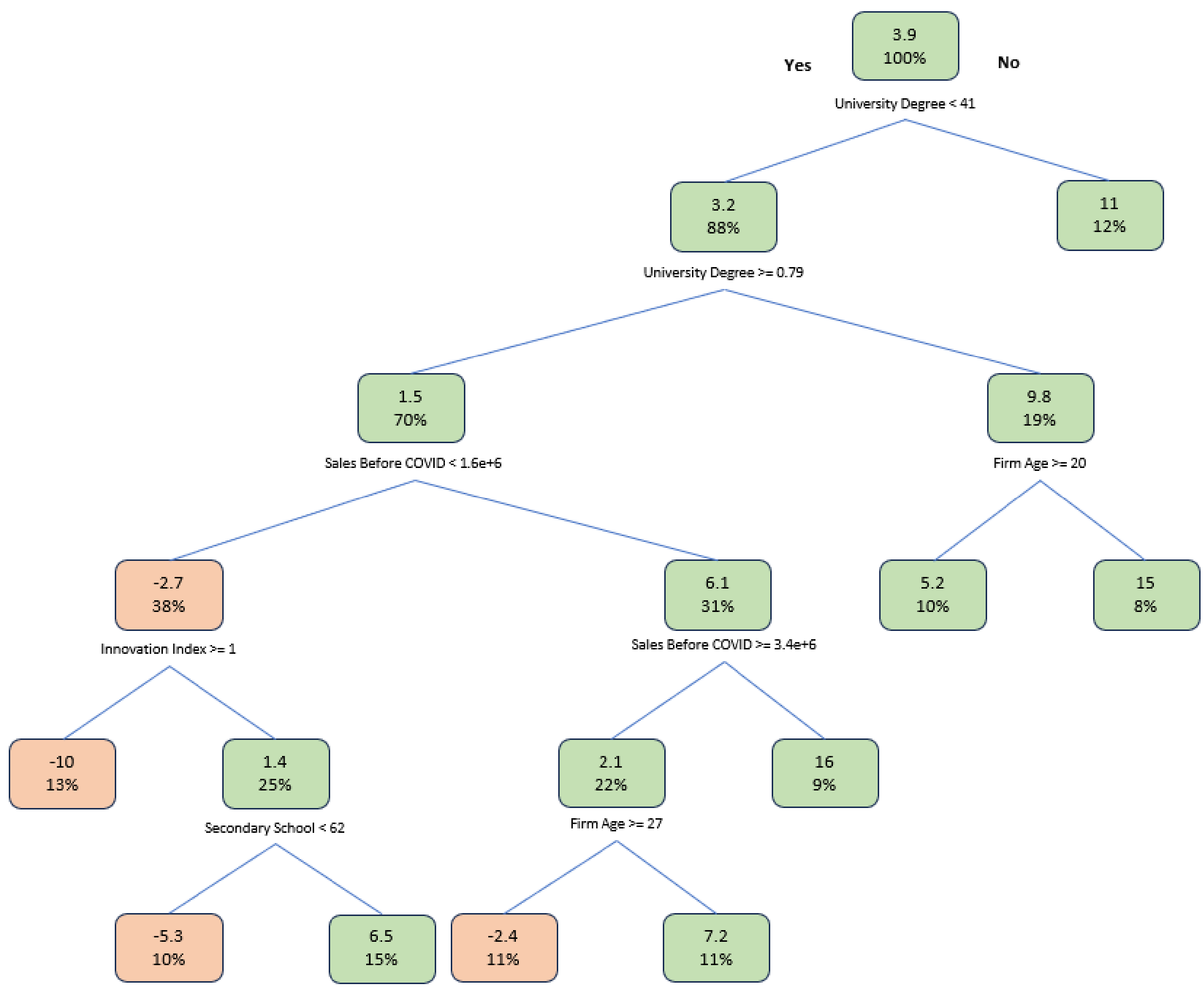

Figure 7 First Mover Causal Tree in Survey Wave 3

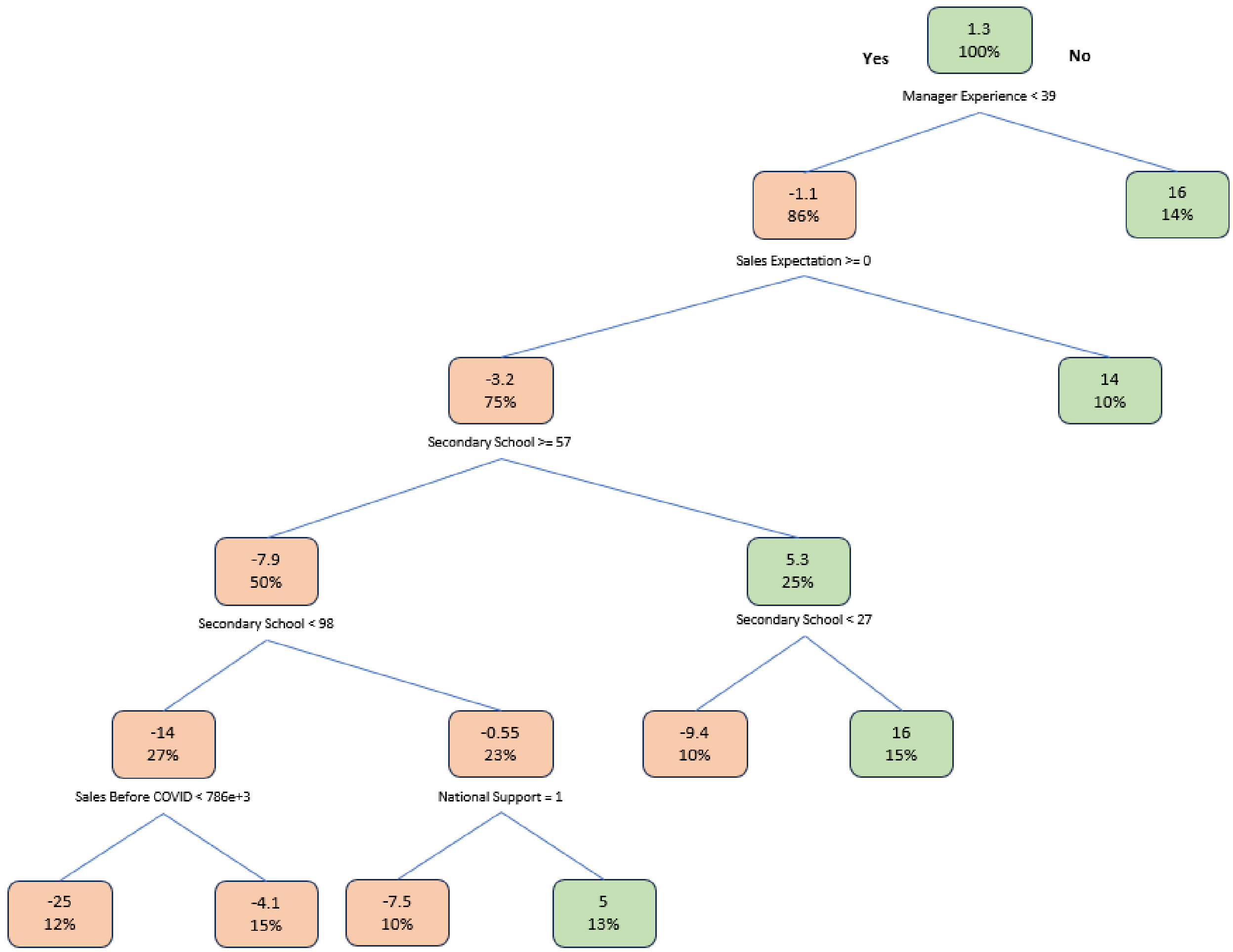

Figure 8 Second Mover Causal Tree in Survey Wave 3

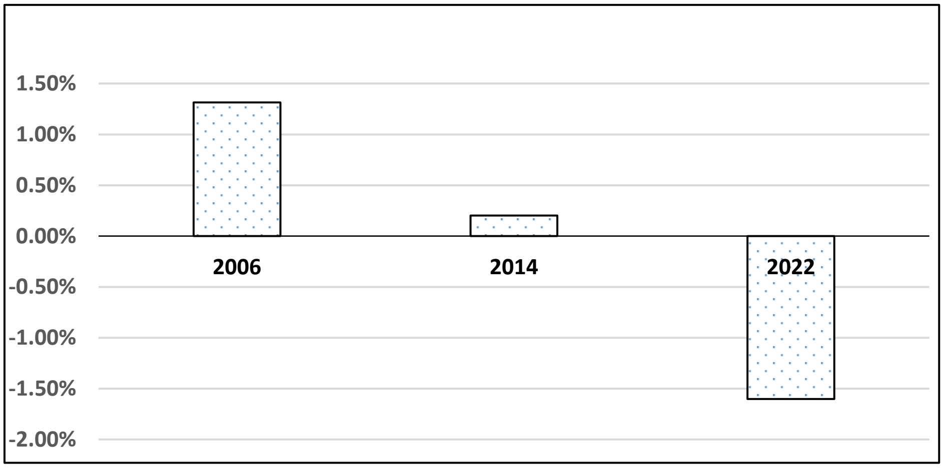

Figure 9 Ratio of Bribe payments to additional sales by year

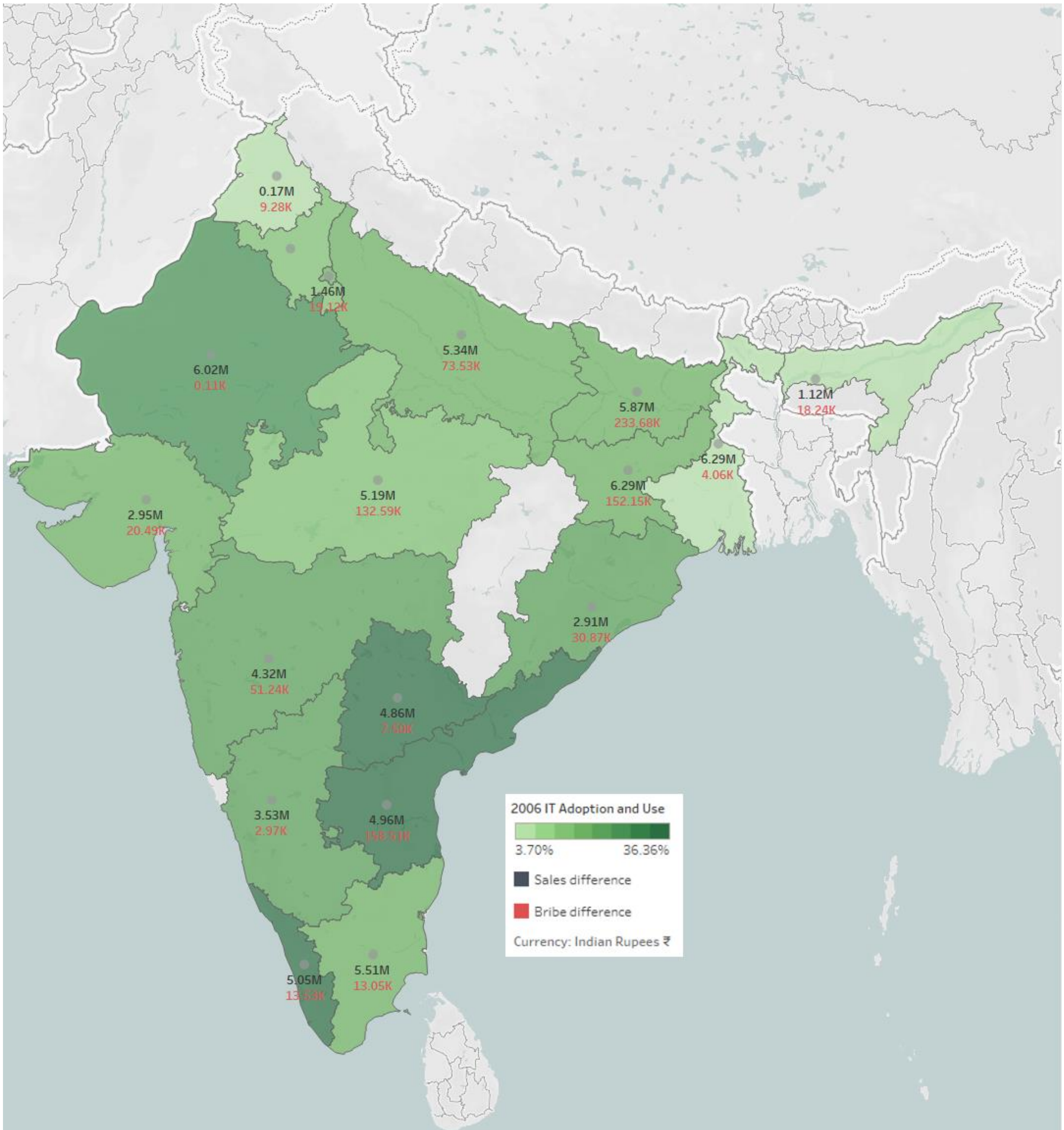

Figure 10 IT adoption and use, Sales difference, and Bribe differentce in 2006

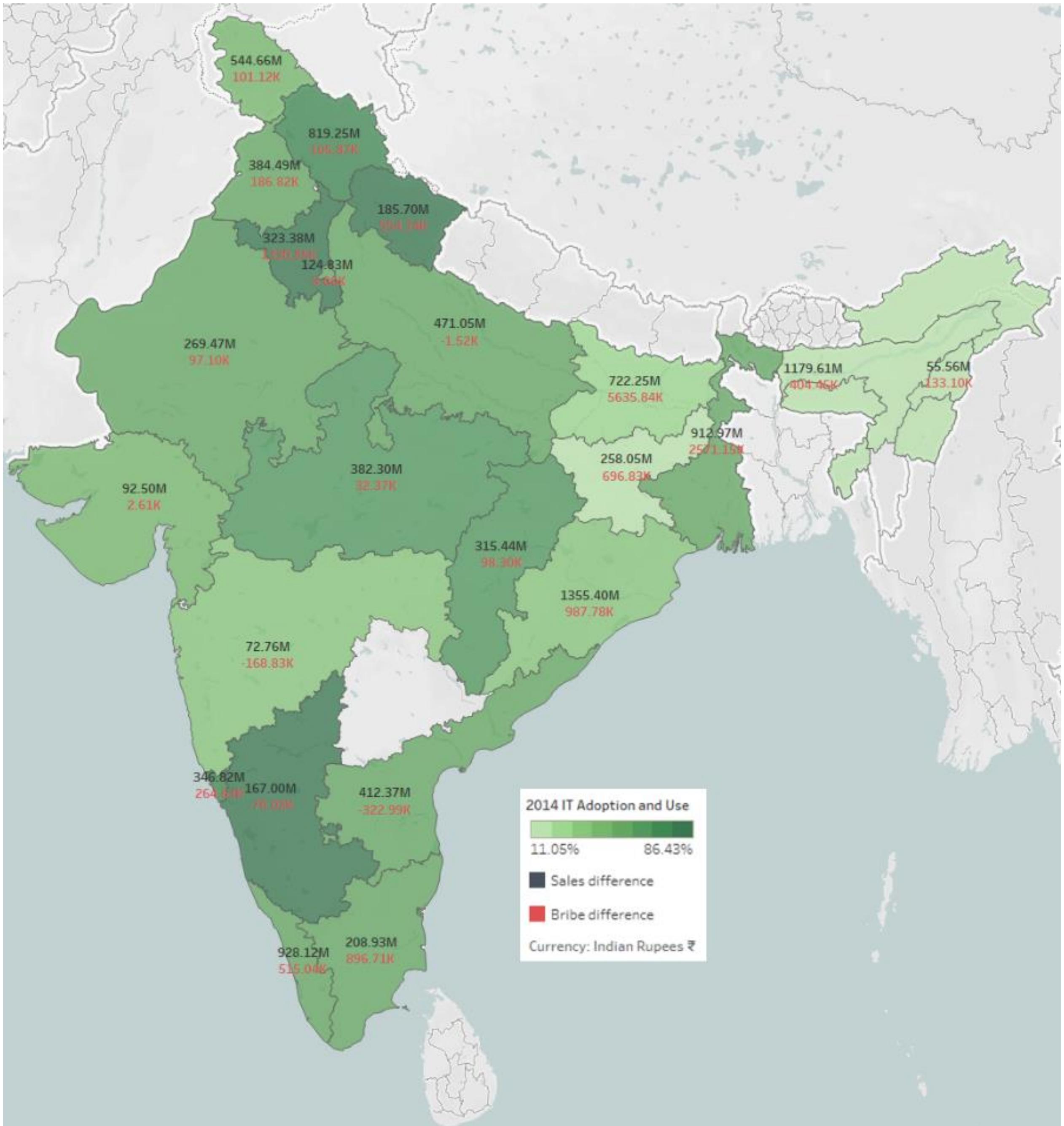

Figure 11 IT adoption and use, Sales difference, and Bribe differentce in 2014

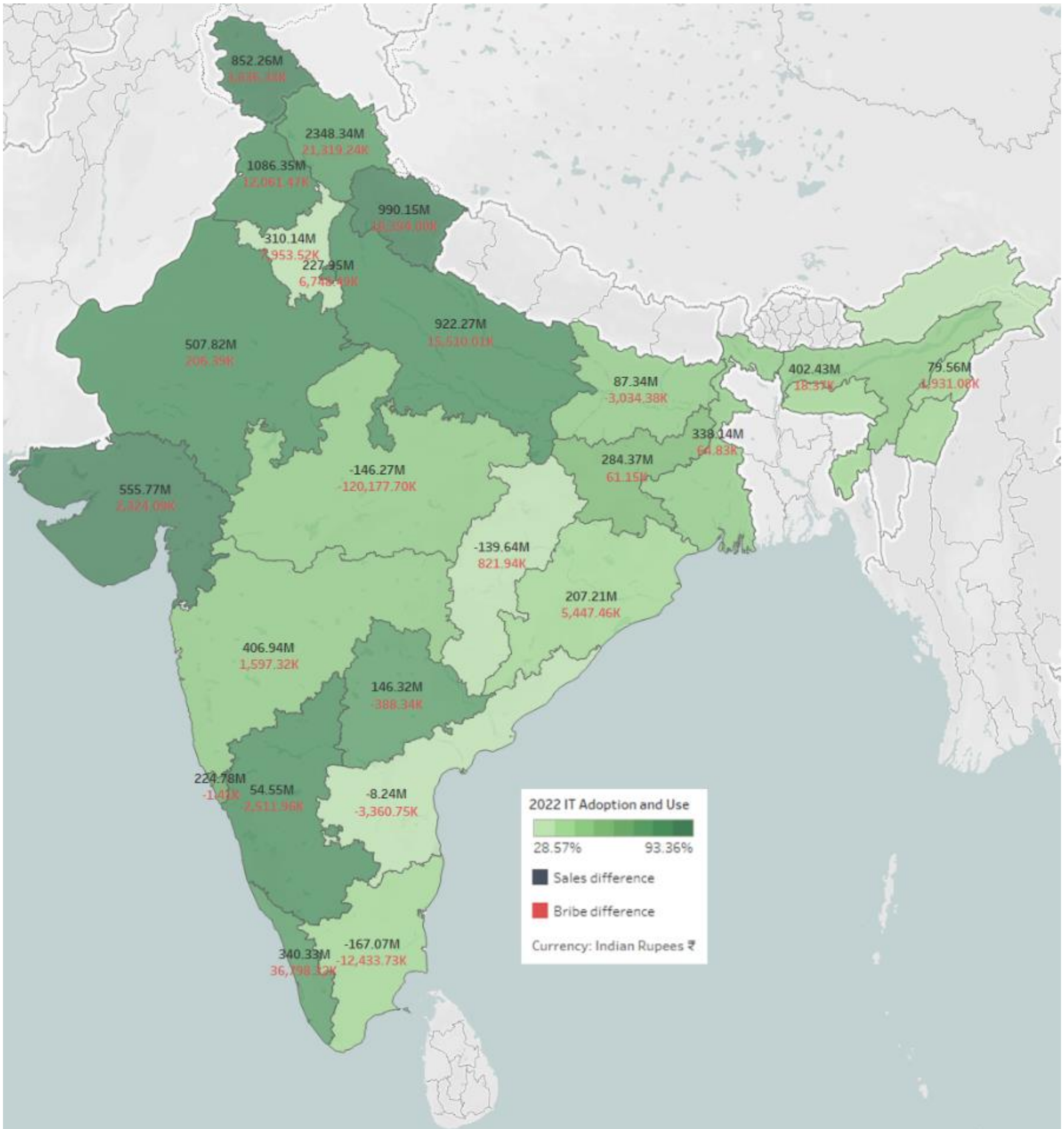

Figure 12 IT adoption and use, Sales difference, and Bribe differentce in 2022

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