

TIME SERIES ANALYSIS FOR THE ADOPTION OF ELECTRONIC COMMERCE  
IN MANUFACTURING INDUSTRY

By

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## **ABSTRACT**

The first essay of this dissertation explores the determinants of industry-level electronic commerce adoption by U.S. manufacturers using data from various U.S. government programs for the period of 2002 – 2019. Findings from a series of nonlinear mixed effects models reveal that the S-shaped electronic commerce adoption rate is best approximated by a Gompertz curve that assumes nonsymmetrical adoption, as opposed to the more conventional logistics curve that assumes symmetrical adoption. I further find that industries with a higher firm death rate exhibit greater adoption of electronic commerce. Third, I find that average firm size positively affects adoption more in concentrated industries. These findings shed new light on understanding industry-level patterns of technological adoption.

The second essay of this dissertation examines how electronic commerce adoption affects manufacturing firms' labor productivity as well as selling, general, and administrative expenses (SG&A) utilizing a multimethod design. Specifically, labor productivity is examined using industry-level data on labor productivity from the Bureau of Labor Statistics, whereas effects on SG&A are examined using firm-level data from WRDS. The industry-level analysis reveals industries with higher rates of electronic commerce adoption see more pronounced increases in labor productivity, holding constant other inputs including capital and purchased inputs. The firm-level analyses show that firms in industries seeing higher rates of electronic commerce adoption experience lower SG&A expenses, holding constant an array of potential confounds. This essay responds to the call from productivity paradox literature for empirical research on the consequences of technology investments and provides insights for policy decision-makers and practitioners for their decision-making on new technology investment.

This dissertation is dedicated to my Lord.  
Psalm 100:4  
Enter his gates with thanksgiving, and his courts with praise!  
Give thanks to him; bless his name!

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## INTRODUCTION

I joined the SAP Enterprise Resource Planning (ERP) setup task force team while working for Hyundai, a Korean manufacturing firm and witnessed the substantial financial and operational investment a company makes when implementing new technology. This led me to ponder the long-standing question: "Is it worthwhile for firms to invest in new technologies such as ERP and Electronic Data Interchange (EDI) network? Do these investments enhance a company's competitiveness, and do the benefits grow over time?" To explore these questions, I turned to the E-commerce Statistics (E-STATS) data provided by the U.S. Census Bureau, specifically focusing on the manufacturing industry. The data reveals a significant increase in electronic commerce from 2002 to 2019, making it a valuable source to address my research interests. Consequently, my dissertation aims to examine the factors and outcomes associated with electronic transaction of orders in manufacturing supply chains. For the purpose of this dissertation, I adopt the formal definition of electronic commerce as defined by the U.S. Census Bureau, which states that it refers to "the value of goods and services sold over computer-mediated networks" (Mesenbourg, 2001, p. 4).

The Industry 4.0 Global Expert Survey by McKinsey & Company (2016) indicates that most companies across industries have recognized the need for digitalization and implementation of Industry 4.0 applications. According to the survey, over 80% of industry experts believe that new technologies will positively impact firms' operations and business models. McDonald's digitalization efforts have also been successful in providing the company with a competitive advantage over its fast-food competitors (Jakab, 2023). With the globalization of supply chains and advancements in technologies like Bitcoin, Blockchain, and Financial Technology, it is expected that more companies will adopt electronic transactions as a crucial component of their

supply chain management (Shih, 2020; Fosso Wamba et al., 2020). Electronic transactions significantly affect how organizations interact and communicate with each other and with their supply chain partners (Johnson & Whang, 2002).

However, despite high expectations, the literature reveals the existence of the "productivity paradox" (e.g., Brynjolfsson et al., 2020; Brynjolfsson, 1993; Solow, 1987). This paradox refers to the phenomenon where increased investments in information technology (IT) may not always lead to a proportional increase in worker productivity and, in some cases, can even lead to a decrease. Solow's (1987) quote, "You can see the computer age everywhere but in the productivity statistics" (p. 36), initiated extensive research and discussions on this topic. Studies have shown that the output per employee did not significantly increase despite substantial IT investments (Roach, 1987), and the return on investment for IT initiatives may take several years to materialize (Brynjolfsson & Hitt, 2003). The productivity paradox challenges our assumptions about the benefits of new technology investments and calls for further research and recommendations (Brynjolfsson et al., 2020). Beyond the productivity paradox, the academic literature has extensively explored various topics related to new technology investment, including EDI network, Logistics Information Technology, and Enterprise Resource Planning. However, Narayanan et al. (2009) suggest that many new technology-related studies (e.g., Ahmad & Schroeder, 2001; Lim & Palvia, 2001) relied on conceptual or single-informant, cross-sectional surveys, leading to ambiguous and inconclusive findings. Scholars, such as Skare and Soriano (2021) and Foster and Rosenzweig (2010), have also pointed out the lack of empirical testing of technology adoption models.

To address this research gap, this dissertation aims to answer two specific research questions. In the first essay (Chapter 1), I investigate the determinants of industry-level



electronic commerce adoption in U.S. manufacturing sectors using panel data from the U.S. Census Bureau spanning from 2002 to 2019. I focus on two factors that influence the adoption process. First, based on Alchian's (1950) theory, I explore how industry-level dynamics can evolve based on the exit of firms, especially given evidence that exiting firms tend to be less productive (Syverson, 2011), and less extensive users of technology are less likely to survive (Bernard et al., 2006). Second, drawing on the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990), I investigate the influence of firm size and industry concentration on electronic commerce adoption. I hypothesize that industries with higher firm death rates exhibit higher adoption of electronic commerce, and sectors with larger average firm size and higher industry concentration adopt electronic commerce at a faster rate. Also, Raguseo et al. (2020) indicate that industry dominance affects the average firm size. The TOE framework suggests that larger firms have more available technologies than smaller firms. Therefore, I expect that manufacturing sectors characterized by larger firms and higher industry concentration will exhibit greater adoption of electronic commerce. To test these hypotheses, I employ a panel data research design using yearly data at the 3-digit NAICS code level for manufacturing. The U.S. Census Bureau and Business Dynamics Statistics serve as the primary data sources due to their consistent definition of electronic commerce over the past two decades.

In the second essay (Chapter 2) of this research, a series of empirical tests are presented to examine the impact of electronic commerce adoption on labor productivity and selling, general & administrative (SG&A) expenses in manufacturing firms. The research questions guiding this study are as follows: RQ1) How does the growth of electronic commerce over time affect manufacturing firms' labor productivity, which is associated with direct costs? RQ2) How does the growth of electronic commerce over time affect manufacturing firms' indirect costs,

such as SG&A expenses? The data used in this essay encompasses all electronic commerce activities involving negotiations of shipment prices and sales terms through internet, extranet, EDI network, electronic mail, or other online systems, including cases with and without online payment. To address these research questions, the essay employs information processing theory (IPT: Galbraith, 1977; Tushman & Nadler, 1978) to explore how the implementation of electronic commerce enhances information processing capabilities, leading to improved labor productivity and reduced SG&A costs. These dependent variables meet a call from Richey et al. (2022) that emphasize the need for specific and clearly-defined dependent variables and expected results that are logical, quantifiable, and applicable in real-world scenarios within the field of logistics and supply chain management (SCM) literature. The two dependent variables used in second essay, namely labor productivity and SG&A expenses, are practical and significant indicators for numerous SCM companies. To test the hypotheses, panel data research is conducted using multiple studies. For Hypothesis 1, an aggregate industry-level study is conducted using yearly data spanning 18 years. The data is collected at the 3-digit NAICS code level, covering 21 sectors within manufacturing (NAICS 31-33). The data sources for this study are the U.S. Census Bureau and the U.S. Bureau of Labor Statistics. For Hypothesis 2, a firm-level study is conducted using yearly data at the 3-digit NAICS code level, focusing on the manufacturing sector (NAICS 31-33). The essay includes 30,900 firms, resulting in a total of 224,439 records. The data sources for the second essay are the U.S. Census Bureau and Compustat. I summarize the aggregate implications of these findings for this dissertation in the Conclusion chapter.

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# **1 CHAPTER ONE:**

## **FACTORS AFFECTING ELECTRONIC COMMERCE ADOPTION:**

### **TIME SERIES ANALYSIS**

#### **1.1 Introduction**

For several decades, there has been a consistent trend toward the use of electronic transactions for order placement and information exchange among firms, their suppliers, and customers in supply chain management (U.S. Census Bureau, 2021). The Industry 4.0 Global Expert Survey conducted by McKinsey & Company (2016) reveals that a significant number of companies across different sectors have been driven to embrace enhanced digitalization and Industry 4.0 applications. The survey findings also highlight that over 80% of industry experts hold an optimistic view regarding the positive impact of new technologies on the operational effectiveness and business models of these firms. Moreover, as supply chains become increasingly globalized (Shih, 2020) and relevant technologies such as Bitcoin, Blockchain, and Financial Technology advance (Fosso Wamba et al., 2020), more and more companies are adopting electronic transactions as a pivotal element of their supply chain management strategy. It is anticipated that this pattern will persist over the coming years. Notably, electronic transactions play a significant role in shaping communication dynamics between organizations and their supply chain members (Johnson & Whang, 2002).

Not surprisingly, this has stimulated research examining adoption processes of innovative technologies in supply chain management across different levels of organizations. In particular, theories have been postulated that new technology adoption more broadly follows an S-shaped curve (e.g., Rogers, 1995; Vargo et al. 2020). However, there are multiple forms of S-shaped curves that imply different dynamics such as symmetric and non-symmetric growth before and

after the 50th percentile of adoption (Grimm & Ram, 2009). Meanwhile, Foster and Rosenzweig (2010) call for more empirical testing of models of technology adoption. Therefore, in this paper, I explore two types of S-shaped curves, the Gompertz curve and the Logistic curve to estimate the fit in the electronic commerce adoption growth curve using panel data sets. I specifically select these two types of sigmoidal curves because of their widespread usage in growth curve modeling studies and their easily interpretable parameters, especially when dealing with a limited number of industries.

Also, given the importance of new technology investment, literature has explored the following topics: Electronic Data Interchange (EDI) network (e.g., Narayanan et al., 2009; Ahmad & Schroeder, 2001; Lim & Palvia, 2001; Bowersox & Daugherty, 1995; Teo et al., 1995), Logistics Information Technology (e.g., Sabherwal & Jeyaraj, 2015; Sanders, 2007), and Enterprise Resource Planning (e.g., Tenhiälä, & Helkiö, 2015; Ghani et al., 2009; Yang & Su, 2009). However, Narayanan et al. (2009) suggest that many of these papers were conducted by using either conceptual or single-informant, cross-sectional surveys, showing some ambiguity and inclusive findings. Furthermore, Skare and Soriano (2021), and Foster and Rosenzweig (2010) argue that empirically testing models of technology adoption process are lacking. Therefore, in this essay, I explore determinants of electronic commerce adoption by examining various panel data from U.S. Census Bureau between 2002 and 2019 in U.S. manufacturing sectors.

In particular, I focus on two factors that affect the electronic commerce adoption process. Per Alchian (1950), I examine how industry-level dynamics can evolve based on the exit of firms, especially given evidence that exiters tend to be less productive (Syverson, 2011), and less extensive users of technology are less likely to survive (Bernard et al., 2006). Also, the

Technology-Organization-Environment framework (Tornatzky & Fleischer, 1990) indicates that organizations are likely to be pressured to adopt new technologies in order to adapt to their business environment. Therefore, I first hypothesize that industries with higher firm death rate have higher adoption of electronic commerce. With the second hypothesis, I suggest that sectors with larger average firm size and higher industry concentration would adopt electronic commerce faster than smaller average firm size and lower industry concentration. For example, Raguseo et al. (2020) indicate that the average size of firms in an industry may differ depending on the number of players dominating that industry. That is, if Industry A has fewer dominant players compared to Industry B, then the average firm size in Industry A is likely to be larger than that of Industry B. Also, Holmes and Stevens (2014) state with an example of North Carolina wood product shops that larger firms tend to have larger market areas, while smaller firms have local markets. In particular, the Technology-Organization-Environment (TOE) framework's organizational context indicates that the scope and size of a firm can affect the firm's technology adoption-related decisions, and the TOE framework's organizational context suggests that larger firms tend to have more available technologies than smaller firms (Tornatzky & Fleischer, 1990). Thus, I expect that manufacturing sectors with larger firms and more concentrated sectors lead to more adoption of electronic commerce.

To test my hypotheses, I rely on a panel data research design by collecting yearly data at the level of 3-digit NAICS codes for manufacturing (NAICS 31-33). For data sources, I use U.S. Census Bureau NBER-CES Manufacturing Industry Database and Business Dynamics Statistics from U.S. Census Bureau. The key reason I use the U.S. Census Bureau as my data source is that the Census Bureau has collected data with a consistent definition of electronic commerce for over 20 years. In order to measure focal variables in a consistent manner for an overall panel data

period, the data should be collected in that way. The formal definition of electronic commerce I use in this essay is defined by the U.S. Census Bureau as “the value of goods and services sold over computer mediated networks” (Mesenbourg, 2001, p. 4), and data in this essay catch all electronic commerce activities from, “the price and terms of sale for shipments are negotiated over an internet, extranet, EDI network, electronic mail, or other online system” (census.gov manufacturing report, 2016, p. 6), whether or not the payment is made online.

The data range from 2002 through 2019 and I choose this specific time window despite the availability of data since 1999 for several reasons. Firstly, there was a significant decline in U.S. manufacturing employment that began in late 2000 (Fort et al., 2018), which was a result of U.S. manufacturing relocating production offshore after the trade liberalization with China in October 2000 (Pierce & Schott, 2016). Given that this event is unrelated to the traditional business cycle dynamics, I decided not to include it in the data analysis. Secondly, there was a modification to the NAICS code in 2002, and including the data from 1999, 2000, and 2001 may have a detrimental impact on the overall data quality. Therefore, to ensure the reliability and consistency of the dataset, I decide to exclude these earlier years. Also, I choose the industry-level data from government agencies over firm-level data because data on some of the key variables, such as firm deaths and industry concentration, are not available from firm-level reports.

This essay contributes to the supply chain management (SCM) literature in several ways. Firstly, it expands the knowledge of the processes of adopting new technologies by empirically examining the determinants of electronic commerce technology adoption. Existing research (e.g., Brynjolfsson, 1993; Sabherwal & Jeyaraj, 2015) has highlighted that ambiguity and inconsistent findings in new technology research may stem from inadequate sample sizes and methodological



errors in previous studies. Therefore, conducting an analysis using population-level data from the U.S. manufacturing industry spanning over 20 years would enhance the generalizability of the findings. Additionally, to the best of my knowledge, this essay is the first to investigate the impact of firm closures on aggregate technology adoption, filling a significant gap in the literature.

Secondly, this essay provides a better specification of boundary conditions. To the best of my knowledge, it is the first empirical study to compare different functional forms for an S-shaped curve, which contributes to a refined understanding of the shape of growth curves in the technology adoption process. By examining various functional forms, this study enhances our understanding of the factors influencing the growth trajectory of technology adoption and provides valuable insights into the adoption patterns of electronic commerce technology. This essay compares the Logistic curve, where 50% of the growth occurs at the inflection point, and the Gompertz curve, where about 37% of the total growth comes before the inflection point with the remainder occurring after the inflection point, to figure out which curve explains better about the electronic commerce adoption growth curve.

Finally, I contribute to practice by providing public policymakers with significant factors affecting new technology adoption in manufacturing industries to help create policies related to new technology adoption. To the extent that information technology adoption at the industry level affects aggregate productivity, policymakers have a huge interest. A key finding of the essay is that firm death contributes to more gains in productivity, and this raises an issue that policies designed to preserve jobs at low-productivity manufacturers may inadvertently stifle aggregate technology adoption. This meets Tokar and Swink's (2019) and Richey and Davis-

Sramek's (2022) calls for Supply Chain Management (SCM) research to provide policy-making contributions.

The essay is organized as follows. The next section provides a literature review and theoretical development, followed by hypotheses development. The subsequent section covers the study design, methodological approach, and results. Finally, theoretical and managerial implications are discussed, along with the limitations.

## **1.2 Literature Review**

I am interested in exploring determinants of electronic commerce adoption, following the call of Ketokivi et al. (2021) for researchers to utilize panel datasets to clearly articulate the nature of their research inquiries. To achieve this, I draw from two theoretical frameworks including the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990), and Diffusion of innovations (DOI) theory (Rogers, 1995).

### **1.2.1 Technology-Organization-Environment (TOE) Framework**

The first theoretical framework in this essay is the Technology-Organization-Environment (TOE) framework, which describes why organizations adopt new technology and examines how the process that organizations use to implement technological innovations could be influenced by three contexts: the technological context, organizational context, and environmental context (Tornatzky & Fleischer, 1990). First, the technological context comprises both technologies which are already in use by firms and technologies that are available in the technology market firms but not in use yet by firms (Baker, 2011). Some examples of the technological context include organizations' technology competence and availability. Also, Chau and Tam (1997) describe that these technologies encompass all three types of technological innovations which

Tushman and Nadler (1986) and Hage (1980) describe, incremental, synthetic, or discontinuous changes; thus, including covering small technological changes to disruptive technological innovations. Therefore, this broad coverage of the technological context would include the topic of this research, electronic commerce adoption.

Second, the organizational context refers to the resources and characteristics of the organization including firm size, scope, intra-firm communication processes, the amount of slack resources, linking structures between employees (Baker, 2011), and so on. For examples of how the organizational context influences the firm's technology innovations, research suggests that cross-functional teams or formal and informal linking agents would promote the organization's technological innovations (e.g., Galbraith, 1973; Tushman & Nadler, 1986). Additionally, Zaltman et al. (1973) state that decentralized organizational structures, which promote teamwork and lateral communication, are conducive to the adoption phase of a firm's technological innovations. In contrast, centralized organizational structures, characterized by centralized decision-making and clearly defined roles, offer advantages during the implementation phase of a firm's technology innovations.

Lastly, the environmental context considers how external factors impact organizations such as government regulation, industries, global competitors, and external shocks including recessions and COVID-19 pandemic (Chau & Tam, 1997; Baker, 2011). For example, Mansfield (1968) and Mansfield et al. (1977) argue that intense competition facilitates firms' technology adoption process and firms experiencing a high level of market uncertainty are more likely to adopt technological innovations. Also, Kamath and Liker (1994) argue that organizations holding a dominant position within an industry have the ability to exert pressure on their supply chain members to adopt technological innovations. From the labor market perspective, when wages for

skilled labor are high, firms are motivated to invest in new technologies to lower labor costs (Levin et al., 1987). Finally, significant regulations could increase firms' technology adoption costs, delaying firms' innovations (Baker, 2011).

The TOE framework has been used to help understand the process of technological innovation adoption, demonstrating the framework's broad applicability and explanatory power (Baker, 2011). Some examples of technology adoption topics are electronic data interchange (EDI) (e.g., Kuan & Chau, 2001), interorganizational systems (e.g., Grover, 1993; Mishra et al., 2007), open systems (e.g., Chau & Tam, 1997), enterprise systems (e.g., Ramdani et al., 2009), and e-business e.g., (Zhu et al., 2003; Zhu & Kraemer, 2005; Zhu et al., 2004). The framework covered various industries such as manufacturing (e.g., Mishra et al., 2007; Zhu et al., 2006), health care (e.g., Lee & Shim, 2007), retail, wholesale, and financial services (e.g., Zhu et al., 2006). Nevertheless, it is noteworthy that several of the aforementioned studies were conducted using either conceptual or single-informant, cross-sectional surveys. In an effort to contribute new insights to the existing literature, this study employs the TOE framework to empirically examine the determinants of electronic commerce adoption, leveraging diverse panel data sources.

The direction of this research is supported by existing research as well. For example, Zhu and Kraemer (2005, p. 63) argue that the TOE framework is a "generic" theory. Also, Baker (2011) suggests that synthesizing the TOE framework with other theories would strengthen the framework's explanation power on specific technology innovation. Therefore, in this essay, I apply Diffusion of innovations (DOI) theory to explore the adoption process of electronic commerce.

### **1.2.2 Diffusion of Innovations (DOI) Theory**

The second theory is Diffusion of innovation (DOI; Rogers, 1995). DOI theory describes the mechanisms, reasons, and speed at which technological innovations spread across industries (Rogers, 1995). Oliveira and Martins (2011) and Rogers (1995) describe that technological innovations are communicated through channels within certain social systems over time. Rogers (1995; 2003) suggests three independent variables for DOI theory: individual characteristics, internal characteristics of the firm structure, and external characteristics of the firm.

Firstly, individual characteristics refer to the leader's attitude toward change (Oliveira & Martins, 2011). DOI theory examines leaders' degree of willingness to adopt innovations, and categorizes leaders as innovators, early adopters, early majority, late majority, and laggards (Rogers, 1995). Secondly, the internal characteristics of the firm structure encompass various attributes such as centralization, complexity, formalization, interconnectedness, organizational slack, and size (Rogers, 1995). Thirdly, the external characteristics of the firm pertain to the concept of system openness (Rogers, 1995).

Extant papers have used DOI theory to explain the process of innovations adoption, and some examples of technology adoption topics are Material Requirements Planning (MRP) (e.g., Cooper & Zmud, 1990), Intranet (e.g., Eder & Igbaria, 2001), Website (e.g., Beatty et al., 2001), Enterprise resource planning (ERP) (e.g., Bradford & Florin, 2003), and e-business (e.g., Hsu et al., 2006). In particular, DOI theory has been widely used in empirical research. For example, Mustonen-Ollila and Lyytinen (2003) identify potential DOI factors that influence innovation adoption in information system processes, such as innovation factor, task factor, individual factor, environmental factor, and organizational factor. Also, Chigona and Licker (2008) use DOI

to describe the process of adopting new technology facilities by the urban impoverished population in Cape Town, South Africa.

These two theories, the TOE framework and the DOI theory, are primarily theorized to operate at the level of the individual firm. However, considering that firms' behaviors have an impact on the overall industry, when discussing firm-level behavior, we are only examining the decision to adopt technology and not considering the churn of firms in the economy.

Furthermore, these theories have also been applied to other levels. For example, Li (2020) has demonstrated that behavioral models and the TOE framework yield similar results when considering individual perception as a factor.

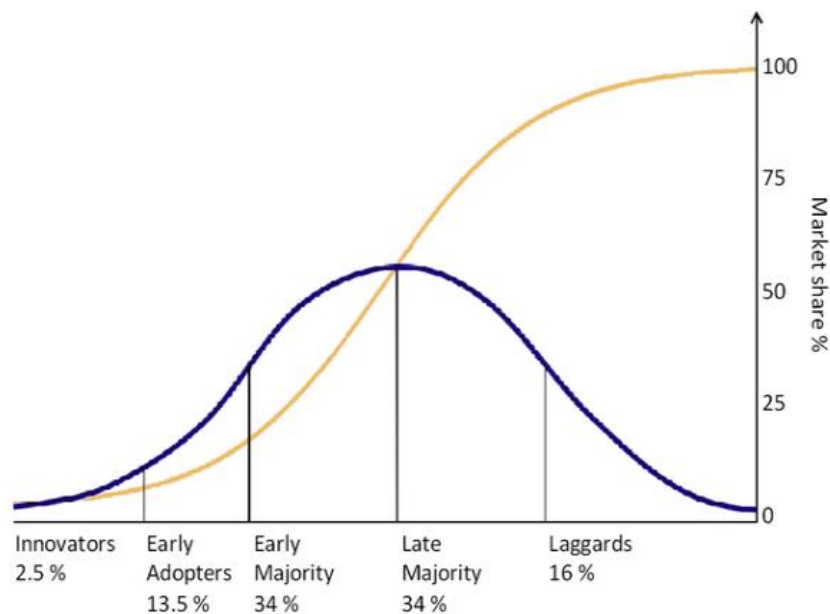
### **1.2.3 Technology Adoption Life Cycle**

Given that the efficient use and adoption of technology innovation is a crucial step of the development process, it is not surprising that literature has been exploring the adoption process (Foster & Rosenzweig, 2010; Karahanna et al., 1999). When it comes to Information Technology (IT) adoption or technology adoption, Rogers's (1995) Diffusion of innovations (DOI) life cycle has been widely accepted. For example, Straub (2009) uses this model to explain how and why individuals accept innovations and argue that innovation adoption for individuals needs to accommodate cognitive, emotional, and contextual concerns. Similarly, Feng (2020), uses this model to describe how customers accept electronic vehicles and hydrogen vehicles in the context of the increase in automotive manufacturers' R&D expenditures.

Figure 1.1. shows the DOI life cycle (Rogers, 1995). Rogers (1995) categorized 5 different technology adopters; innovators, early adopters, early majority, late majority, and laggards. The probability density function (PDF) of the graph, the blue line, is normally distributed. That is, innovators, early adopters, and early majority cover the first 50%, and late

majority and laggards cover the second 50%, showing a symmetric shape. The yellow line shows the cumulative distribution function (CDF), and the line displays an s-curve shape. So, this s-curve can be divided into 3 phases: early, middle, and late phases. The rate of progress in adoption is relatively slow in the adoption's early phase and the adoption rate increases during the middle phase. But the curve change rate tapers down, asymptotically reaching a certain limit. This s-curve graph is also symmetric, where the first half and the second half are identical. This assumption of a symmetric curve in the technology adoption life cycle has not been challenged; rather, it has been widely accepted (e.g., Straub, 2009; Feng, 2020).

**FIGURE 1. 1. DIFFUSION OF INNOVATIONS LIFE CYCLE**



(Adapted from Rogers, 2015)

On the other hand, in terms of the life cycle for technology performance, not technology adoption which this essay tries to research, there are two houses of thought. As shown in Figure 1.2, Christensen (1992)'s technology s-curve describes how new technologies replace old technologies and empirically examines the framework of the disk drive industry's technological

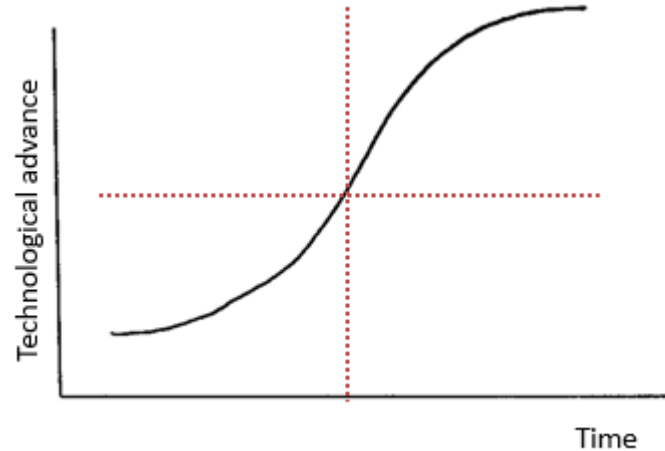
growth<sup>1</sup>. Similarly, Roussel (1984) suggests the technological life cycle curve with the four stages of technological maturity: embryonic or emerging, growth, mature, and aging. Both Christensen's (1992) S-curve and Roussel's (1984) life cycle curve shows an increasing s-curve shape. For example, Sahal (1981) describes that the rate of change in technology performance is somewhat slow in an initial phase, but the rate of acceleration in technology performance increases as the technology becomes better controlled and understood, and the rate of change slows down and asymptotically reaches a natural limit when the technology approaches a mature phase. However, the technology S-Curve (Christensen, 1992) and the technology life cycle curve (Roussel, 1984) have a distinction. Christensen's (1992) technology s-curve shows a symmetric pattern. On the other hand, in the 4 phases in the technology life cycle curve (Roussel, 1984), the lower asymptotes cover the embryonic or emerging phase, the first phase, but the upper asymptotes cover both the mature and the aging phases, the third and fourth phases, showing faster growth and slower tapering than the technology s-curve (Christensen, 1992).

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<sup>1</sup> Utterback and Abernathy (1975) introduced the technology curve as a framework, predating Christensen's (1992) s-curve. However, the curve presented by Utterback and Abernathy in 1975 exhibits a more significant drop than our electronic commerce adoption curve. Therefore, in my essay, I utilize Christensen's (1992) s-curve model. It is worth noting that Dr. James Utterback is acknowledged by Christensen (1992) as a contributor to his s-curve model.

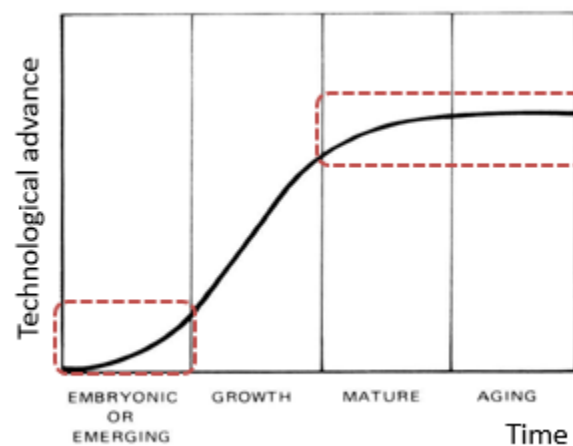


**FIGURE 1. 2. THE TECHNOLOGY S-CURVE (CHRISTENSEN, 1992)**



(Adapted from Christensen, 1992)

**FIGURE 1. 3. THE TECHNOLOGY LIFE CYCLE CURVE (ROUSSEL, 1984)**



(Adapted from Roussel, 1984)

Unlike the technology performance life cycle, the idea of a symmetric curve in the technology adoption life cycle has not been challenged. Understanding the nuance of how firms adopt new technology, such as electronic commerce, would benefit literature and the decision-making for policymakers and manufacturing firms on new technology investment, which covers a significant amount of expenditures (e.g., Purwita & Subriadi, 2019). Therefore, I examine the growth curve for technology adoption empirically with industry-level data for overall

manufacturing industries. Likewise, I question that the growth curve for the adoption of electronic commerce may not symmetric. Therefore, this gets us to be an important topic that has not been discussed in this literature.

### **1.3 Hypothesis Development**

#### **1.3.1 Independent Variables**

In this section, I will describe the key predictors used in this research, such as firm death, the two-way interaction of average firm size and industry concentration for academic research.

##### **1.3.1.1 Firm Death**

The first independent variable focuses on firm death. Daepp et al. (2015) describe that firm death occurs when a company stops sales and stops production. Papers have explored the impact of firm death on industry-level aggregates, especially productivity (Foster et al. 2006, 2008). For instance, Syverson (2011) presents evidence indicating that firms with lower productivity face a higher risk of failure, while Bernard et al. (2006) demonstrate that firms using technology less extensively also face a greater likelihood of failure.

Specifically, Alchian (1950) argues that the death of firms can have a significant impact on industry-level dynamics. Similarly, McKenzie and Paffhausen (2019) study the data on firm death in developing countries and claim that firm death can raise aggregate productivity because when less productive and less profitable firms exit an industry it leads to the subsequent reallocation of resources and customers to more efficient firms. Also, Stewart and Gallagher (1985) researched data during recessions in the United Kingdom between 1974 and 1983, and

argue that the closing of inefficient firms during the recession made the economy more efficient. Therefore, it is expected that a higher firm death rate would winnow less efficient firms.

Also, the environmental context of the TOE framework explains how firms' behaviors in adopting and implementing new technology could be affected by external pressures from competitors as well as the influence exerted by business stakeholders (Tornatzky & Fleischer, 1990). Therefore, I would expect in this context that:

**Hypothesis 1 (H1): *Industries with a higher rate of firm failure, adopt electronic commerce more quickly.***

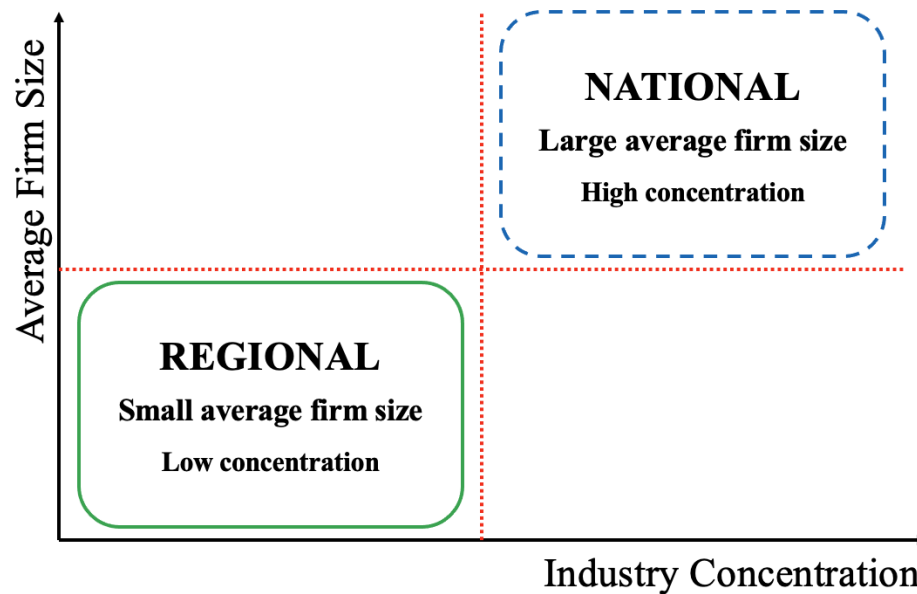
#### **1.3.1.2 Two-Way Interaction of Average Firm Size And Industry Concentration**

Empirical studies show the impact of firm size on new technology investments. For example, Raguseo et al. (2020) argue that bigger companies may have an advantage in utilizing both external resources from the market and their own internal IT assets to create valuable, rare, difficult-to-copy, and long-lasting resources and abilities from new technology investment. Also, Covin et al. (1994) argue that firm size could influence the effectiveness of specific structures, and tactics in improving firm performance. In particular, Oliveira and Martins (2011) state that firm size can impact the decisions of a firm's investment in IT.

Also, papers display the impact of industry concentration on new technology investments. For example, Schryen (2013) shows that the characteristics of the sector in which a company operates have an impact on the company's investments of resources in IT and the resulting effectiveness of such investments. Similarly, Raguseo et al. (2020) explore how firm size and industry concentration influence the connection between big data analytics solutions and firm profitability.

However, when it comes to effective firm size, it is difficult just to focus on firm size by itself, rather firm size needs to be considered in conjunction with the industry to which firms belong. This is because if Industry A is dominated by a smaller number of players than Industry B, the average firm size of Industry A could be bigger than Industry B (Raguseo et al., 2020). For example, Figure 1.4. shows that, in the blue dashed line box, there are industries where the average firm size is large, and the industry concentration is high, whereby firms operate on a national, scale such as Boeing, GM, Ford, and Coca-Cola. In the green solid line box, there are other industries with small average firm size and low industry concentration, whereby firms are on a regional scale, such as local printing shops and wood products shops (Holmes & Stevens 2014). Therefore, as a second predictor, I focus on the two-way interaction between average firm size and industry concentration.

**FIGURE 1. 4. TWO-WAY INTERACTION OF AVERAGE FIRM SIZE & INDUSTRY CONCENTRATION**



Dunne et al. (2009) suggest that firms with national scope have a larger average firm size than firms with regional scope. In general, larger firms would have more technology availability and more interfirm relationships. Smith et al. (1988) argue that firm size affects decision-making behaviors because larger firms have a better level of decision-making on information and rational decision processes. Saito et al. (2007) found that larger firms had more interfirm relationships by studying data from 800,000 Japanese firms. Likewise, the TOE framework's organizational context suggests that organization scope and size would influence firms' technological innovations adoption, and the TOE framework's organizational context indicates that larger firms would have more technology availability (Tornatzky & Fleischer, 1990). Therefore, I posit that:

**Hypothesis 2 (H2):** *Sectors with larger average firm size and higher industry concentration would lead to faster adoption of electronic commerce.*

## 1.4 Methodology

To answer my research questions, I utilize a panel data research design by collecting yearly data at the level of 3-digit NAICS codes for manufacturing (NAICS 31-33). For data sources, I use U.S. Census Bureau NBER-CES Manufacturing Industry Database, and Business Dynamics Statistics from U.S. Census Bureau. The data range from 2002 through 2019.

### 1.4.1 Variables

The dependent variable is electronic commerce adoption for each manufacturing sector, which I denote as electronic commerce adoption. To improve parameter interpretability, electronic commerce adoption is multiplied by 100 from the electronic commerce adoption rate from Electronic Commerce Statistics (E-STATS) in U.S. Census Bureau.

As I rely on nonlinear growth curve modeling (c.f., Ram & Grimm, 2007; Grimm & Ram, 2009), my focal predictors center on variables that represent the passage of time. The first focal predictor is firm death. firm death is calculated from the number of firms that exited during the last 12 months, divided by the total number of firms. Prior to estimation, I grand mean center firm death to make the intercepts meaningful and multiply the rate of firm death by 100 to improve parameter interpretability. The data source for the first independent variable, firm death, is from Business Dynamics Statistics from U.S. Census Bureau in U.S. Census Bureau, and I calculate firm death as the number of firms that exited during the last 12 months, which is the way my data from Business Dynamics Statistics in U.S. Census Bureau have been collected.

The second independent variable is average firm size  $\times$  industry concentration. For average firm size, I grand mean center average firm size to make the intercepts meaningful. The data source for the second independent variable, average firm size, is from National Bureau of

Economic Research (NBER) and Center for Economic Studies (CES) from U.S. Census Bureau. For industry concentration, I use  $\ln(\text{concentration}_4)$  as the natural logarithm of  $\text{concentration}_4$  and is calculated as the percentage of the total value of shipments of the 4 largest companies for each manufacturing industry factor. I used the natural logarithm of the variable because the data were skewed, and, after the natural log transformation, the distribution is close to normal. Also, I grand mean center  $\ln(\text{concentration}_4)$  to make the intercepts meaningful. The data source for the variable, industry concentration, is from the Economic Census.

In this essay, the use of control variables is restricted because the factors, firm death and average firm size  $\times$  industry concentration, I focus on are reasonably exogenous, including too many control variables could negatively impact interpretations (c.f., Connelly et al., 2023; Miller & Kulpa, 2022).

### 1.4.2 Sigmoid Curve

Thieme (2018) describes the sigmoid curve, as the curve that looks like an elongated S and shows the growth patterns that an initial adjustment phase characterized by minimal growth, followed by a phase of rapid growth, and finally, a slowdown as the capacity or population approaches its limits within a given task or environment. While there are various types of nonlinear growth models, I focus on two sigmoid curves, Logistic and Gompertz, because they are well-known curves that have a lot of use in the growth curve modeling literature, and they have easily interpretable parameters and do not have too many parameters such that estimation becomes difficult with an inherently limited number of industries<sup>2</sup>.

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<sup>2</sup> There are other types of sigmoidal curves, including the Richards curve (Richards, 1959). The Richards curve, also referred to as the generalized logistic function, provides flexibility in terms of asymmetry by incorporating an additional parameter,  $\tau$ , that determines the distance between the inflection point and a particular asymptote (Grimm & Ram, 2009).

#### **1.4.2.1 Logistic Curve**

The Logistic curve exhibits the slowest rates of acceleration near its lower and upper asymptotes, while the fastest rates are observed at the inflection point in the middle (Grimm & Ram, 2009). Additionally, the Logistic curve assumes a symmetric growth pattern where half of the total change occurs at the inflection point. Therefore, when measured by time, it takes the exact amount of time to get to the 50th percentile as it does from the 50th to the 100th percentile (Grimm & Ram, 2009). That would be consistent with the patterns of the Rogers' (1995) technology s-curve curve and the Christiansen's (1992) technology life cycle curve.

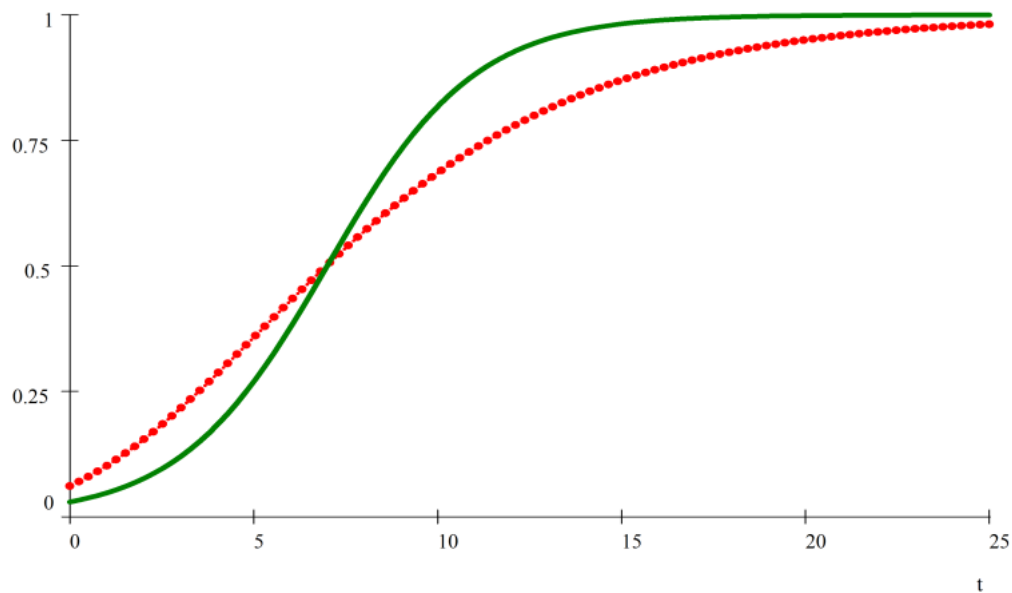
#### **1.4.2.2 Gompertz Curve**

The Gompertz curve shares similarities with the Logistic curve, as it exhibits slow lower and upper asymptotes and a fast inflection point. However, unlike the Logistic curve, the Gompertz curve is not symmetric such that the inflection point indicates about 37% (i.e.,  $1/e$ ) of the total change (Grimm & Ram, 2009). The Gompertz curve is more consistent with the shape of the Roussel (1984) curve with the longer upper asymptotes than the lower asymptotes. Therefore, this essay tests and statistically compares which of these functions works better because it helps refine the understanding of these adoption processes.

Figure 1.5 shows the cumulative distribution for the Logistic curve (green-solid line) and the Gompertz curve (red-dotted line). This graph highlights the characteristics of both curves: the Logistic curve is symmetric, while the Gompertz curve is asymmetric. The data source for this graph is Harvey and Kattuman (2020, p. 27).



**FIGURE 1. 5. CUMULATIVE DISTRIBUTION FOR LOGISTIC (GREEN - SOLID) AND GOMPERTZ (RED - DOTTED) CURVE**



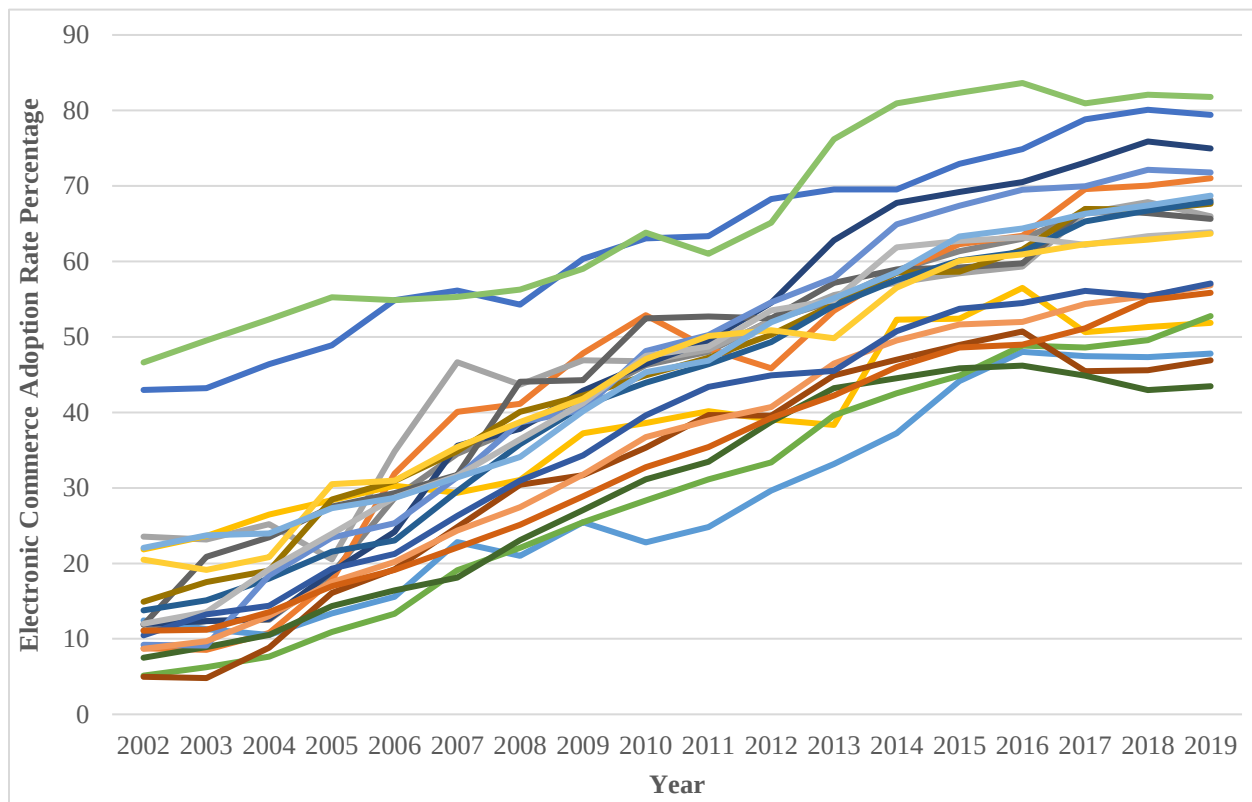
\*Logistic curve  $\gamma = 0.5$ , Gompertz curve  $\gamma = 0.2$ .  
(Source: Harvey & Kattuman, 2020, p. 27)

## 1.5 Analysis and Results

### 1.5.1 Model-Free Evidence

As suggested by Davis-Sramek et al. (2023), I display model-free evidence to visualize relationships between variables and the variation in my dataset. Figure 1.6. shows a spaghetti plot showing the adoption of electronic commerce across the different three-digit NAICS codes for manufacturing. This plot shows that every sector has a consistent pattern with an S-shaped curve over time, at the same time, there is also some heterogeneity amongst sectors.

**FIGURE 1. 6. SPAGHETTI PLOT FOR THE LEVEL OF ELECTRONIC COMMERCE ADOPTION FOR THE U.S. MANUFACTURING SECTORS (NAICS 311-339)**

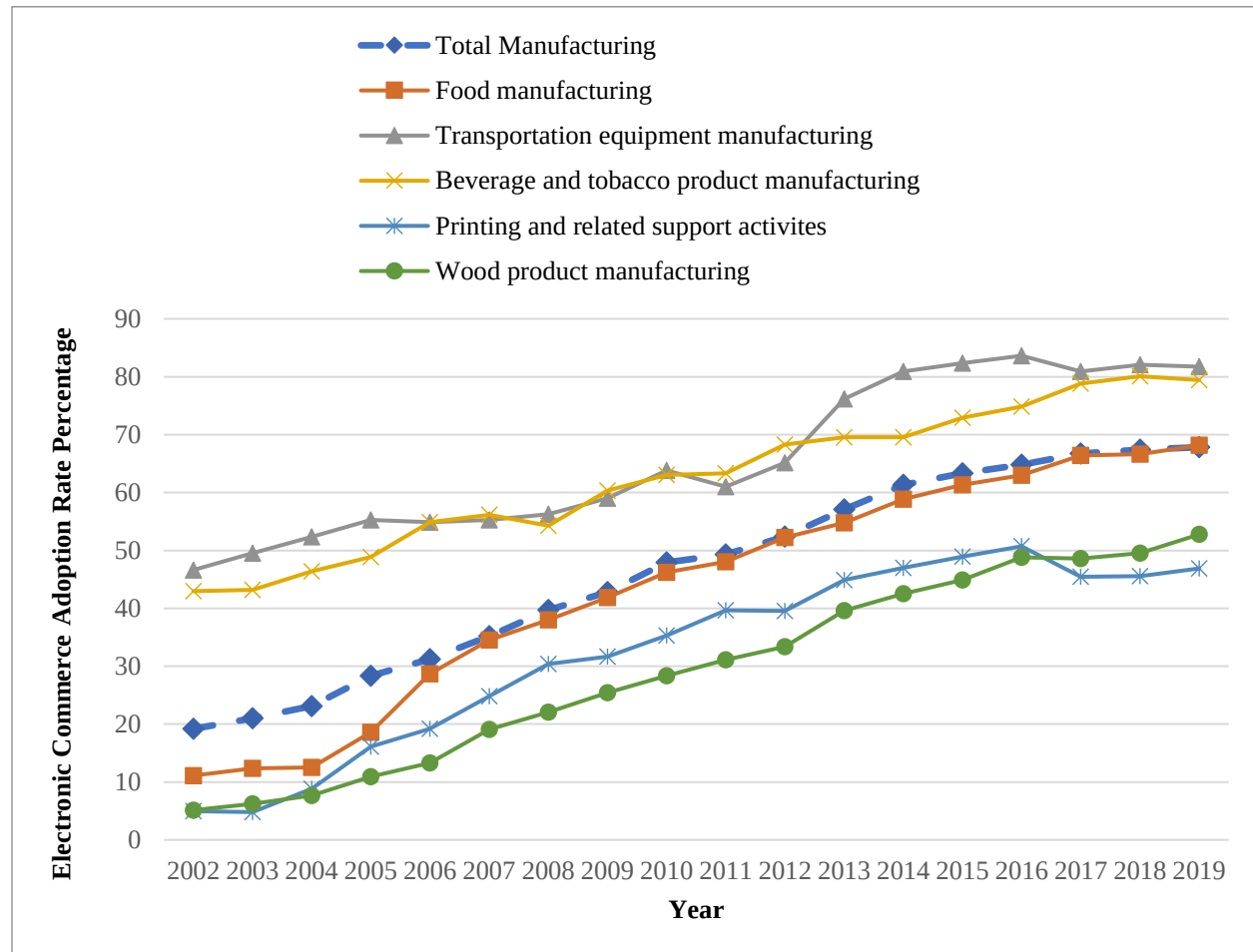


(Source: U.S. Census Bureau)

Figure 1.7. displays a few sectors at the top and bottom graphs among all industries to visually illustrate the range of industries as opposed to seeing all 21 industries at once. This plot shows transportation equipment manufacturing and beverage and tobacco product manufacturing at the top as these two industries' electronic commerce start at around 35 - 40%, ending at around 80% of the electronic commerce adoption rate. These two sectors are dominated by very large national firms like, Boeing, GM, Ford, and Bosch for Transportation equipment and Coca-Cola, Anheuser Busch, Philip Morris, and British American Tobacco for beverage and tobacco products. On the other hand, printing and related support activities and wood product manufacturing are at the bottom among all sectors. These two sectors are at the other end of the spectrum because the printing sector has a very small average firm size with regional

competition and the wood products sector is similar because of expensive transportation costs for wood products.

**FIGURE 1. 7. SPAGHETTI PLOT FOR THE LEVEL OF ELECTRONIC COMMERCE ADOPTION FOR THE U.S. MANUFACTURING SECTORS (ONLY TOP & BOTTOM)**



(Source: U.S. Census Bureau)

### 1.5.2 Econometric Approach

To examine the hypotheses, I employed a series of mixed-effects models on the panel data (Fitzmaurice et al., 2011; Ployhart et al., 2002). The reason I selected this method is the mixed effects modeling framework assumes each subject's pattern of change is s-shaped, coupled with the covariance structure modeling approach not working with small number settings (Harring &

Blozis, 2016). Following the recommendations of Grimm and Ram (2009), I developed a mixed-effects model with the Gompertz curves. The models are designed by PROC NLMIXED when using SAS 9.4 (SAS/STAT(R) 14.1 User's Guide: The NLMIXED Procedure). I use I use the multilevel modeling framework (e.g., Level 1 & Level 2). Table 1.1 contains descriptive statistics and correlations.

**TABLE 1. 1. CORRELATION MATRIX, MEANS, AND STANDARD DEVIATIONS OF MEASURES**

| <i>Variables</i>                    | <i>Mean</i> | <i>SD</i> | <i>1</i> | <i>2</i> | <i>3</i> | <i>4</i> | <i>5</i> | <i>6</i> | <i>7</i> | <i>8</i> |
|-------------------------------------|-------------|-----------|----------|----------|----------|----------|----------|----------|----------|----------|
| NAICS                               | 325.05      | 8.84      | 1.00     |          |          |          |          |          |          |          |
| <i>electronic commerce adoption</i> | 0.42        | 0.19      | −0.02    | 1.00     |          |          |          |          |          |          |
| <i>year</i>                         | 2011        | 5.20      | 0.00     | 0.84     | 1.00     |          |          |          |          |          |
| Logistic                            | 42.48       | 18.58     | −0.02    | 0.99     | 0.84     | 1.00     |          |          |          |          |
| Gompertz                            | 42.42       | 18.73     | −0.02    | 0.99     | 0.84     | 0.99     | 1.00     |          |          |          |
| <i>industry concentration</i>       | 0           | 0.61      | −0.23    | 0.30     | 0.01     | 0.31     | 0.31     | 1.00     |          |          |
| <i>firm death</i>                   | 0           | 2.54      | −0.34    | −0.30    | −0.22    | −0.31    | −0.30    | −0.11    | 1.00     |          |
| <i>average firm size</i>            | 0           | 39.80     | 0.21     | 0.28     | −0.03    | 0.28     | 0.28     | 0.41     | −0.37    | 1.00     |

\*N = 378 records, from 2002 to 2019.

### 1.5.3 Sigmoid Growth Functions

I use two types of sigmoid growth functions: the Logistic model and the Gompertz model. I chose these two sigmoid functions because they are the most widely used symmetric and asymmetric growth functions. The Logistic process assumes that symmetrical rates change around the 50th percentile (Jarne et al., 2005; Franses, 1994; Dhar & Bhattacharya, 2018) while the Gompertz process is asymmetric (Franses, 1994).

#### 1.5.3.1 Logistic

The Logistic model is calculated as follows:

$$(1) \quad Y[t]_n = g_{0n} + g_{1n} \cdot A_1[t] + e[t]_n$$

$$(2) \quad A_1[t] = \frac{1}{1 + e^{-(t-\lambda) \cdot \alpha}}$$

where  $g_{0n}$  denotes the lower asymptote value of the function,  $g_{0n} + g_{1n}$  equals the upper asymptotic;  $\lambda$  denotes the inflection point, which is the time when the rate of change reaches its peak, that is around the 50th percentile, and  $\alpha$  represents the rate of change.

#### 1.5.3.2 Gompertz

The Gompertz model is calculated as follows:

$$(3) \quad Y[t]_n = g_{0n} + g_{1n} \cdot A_1[t] + e[t]_n$$

$$(4) \quad A_1[t] = e^{-e^{-\alpha(t-\lambda)}}$$

where  $g_{0n}$  equals the lower asymptote value of the function,  $g_{0n} + g_{1n}$  is the upper asymptotic;  $\lambda$  is the inflection point, which is the time when the rate of change reaches its peak, that is  $1/e$ , around the 37th percentile; and  $\alpha$  represents the rate of change.

#### 1.5.4 Logistic versus Gompertz Fit

I fit both the Logistic and the Gompertz using electronic commerce adoption data from the U.S. Census Bureau. First, I will compare the Logistic and Gompertz curves based on their correlation to electronic commerce adoption and model fits. As shown in Table 1.2, both models fit almost equally well, with similar AIC and BIC values. Specifically, the correlation to electronic commerce adoption is 0.98869 for the Logistic curve and 0.98932 for the Gompertz curve, indicating that the Gompertz curve fits slightly better. The fit of the Logistic model (AIC = 2030.4, BIC = 2038.7) and the fit of the Gompertz model (AIC = 2027.7, BIC = 2036.1) are similar. Therefore, it is difficult to determine which curve is superior based on the information presented in Table 1.2.

**TABLE 1. 2. COMPARISON BETWEEN LOGISTIC AND GOMPERTZ BASED ON CORRELATION AND MODEL FIT**

| <b>Correlation</b>                  | <b>Logistic</b> | <b>Gompertz</b> |
|-------------------------------------|-----------------|-----------------|
| <i>electronic commerce adoption</i> | 0.9890          | 0.9899          |
| <i>Model Fit</i>                    |                 |                 |
| –2 Log Likelihood                   | 2014.4          | 2011.7          |
| AIC                                 | 2030.4          | 2027.7          |
| AICC                                | 2030.7          | 2028.1          |
| BIC                                 | 2038.7          | 2036.1          |

Second, I compare the Logistic and the Gompertz curves with the observed data of *electronic commerce adoption* and see how two curves emulate the observed data. As shown in Table 1.3, the observed *electronic commerce adoption* was 11% in 2002 and increased to 68% in 2019. In contrast, the Gompertz curve starts with an individual-specific lower asymptote  $g_{0n}$  of 2.44% and grows by 70.82%, reaching an upper asymptote  $g_{0n} + g_{1n}$  of 73.26%. On the other hand, the Logistic curve has a negative lower asymptote of -17.45% and then experiences a change in asymptote of 90.39%, reaching approximately 72.95%. Despite both models fitting well with similar AIC and BIC values, the Logistic curve fails to capture the initial stages of *electronic commerce adoption* in each manufacturing sector, although the upper asymptotes are similar. This disparity arises because the Logistic curve assumes symmetrical rate changes around the 50th percentile (Jarne et al., 2005; Franses, 1994; Dhar & Bhattacharya, 2018), whereas the Gompertz process is asymmetric (Franses, 1994). Therefore, in this essay, I will choose the Gompertz curve for my analysis.

**TABLE 1. 3. COMPARISON BETWEEN LOGISTIC AND GOMPERTZ BASED ON EMULATION TO OBSERVED DATA (FOOD MANUFACTURING, NAICS: 311)**

| Type                                                 | Lower asymptote, $g_{0n}$ | Upper asymptote, $g_{0n} + g_{1n}$ |
|------------------------------------------------------|---------------------------|------------------------------------|
|                                                      | Year 2002                 | Year 2019                          |
| Observed Data<br><i>electronic commerce adoption</i> | 11.11%                    | 68.15%                             |
| Logistic                                             | -17.45%                   | 72.95%                             |
| Gompertz                                             | 2.44%                     | 73.26%                             |

\*Data source: the U.S. Census Bureau



### 1.5.5 Hypotheses Analysis

Using notation from Grimm and Ram (2009), I specified the following model to test Hypothesis 1, and Hypothesis 2:

$$(5) \quad g_{0n} = \gamma_0 + u_0 + \beta_1 \cdot DeathsMC100 + \beta_2 \cdot Lnconcentration4MC + \beta_3 \cdot FirmSizeMC + \beta_4 \cdot Lnconcentration4MC \cdot FirmSizeMC$$

$$(6) \quad g_{1n} = \gamma_1 + u_1 + \delta_1 \cdot DeathsMC100 + \delta_2 \cdot Lnconcentration4MC + \delta_3 \cdot FirmSizeMC + \delta_4 \cdot Lnconcentration4MC \cdot FirmSizeMC$$

$$(4) \quad A_1[t] = e^{-e^{-\alpha(t-\lambda)}}$$

$$(7) \quad electronic\ commerce\ adoption = g_{0n} + g_{1n} \cdot A_1[t]$$

These are Level 2 equations of the nonlinear growth model. The variable,  $g_{0n}$ , is set equal to the equation (5)'s intercept ( $\gamma_0$ ) plus the random effect ( $u_0$ ) plus the factor loadings ( $\beta_1$ ,  $\beta_2$ , etc.) of the independent variables. A similar Level 2 equation is used for  $g_{1n}$  with equation (6). Next, the basis vectors of slope loadings,  $A_1[t]$ , are defined.  $A_1[t]$  describes the equation for the Gompertz curves, the (4) equation. Following this, the Level 1 equation (7) is introduced for *electronic commerce adoption*, which is the sum of the random intercept,  $g_{0n}$ , and the random slope,  $g_{1n}$ , multiplied by the slope loadings,  $A_1[t]$ . The outcome variable, *electronic commerce adoption*, is defined based on the Level 1 equation, assuming a normal distribution with a mean equal to the expected value derived from the Level 1 equation for *electronic commerce adoption*, and a Level 1 residual variance. Furthermore, the Level 2 variances and covariances, representing the random effects, are also specified using a multivariate normal distribution with means set to 0. Starting values for fixed effect parameters were calculated using Microsoft Excel solver.

In Table 1.4, the results are shown from PROC NLMIXED estimated to test Hypothesis 1 and Hypothesis 2. For Hypothesis 1, in Table 1.3 it is observed that for the Gompertz model,  $\beta_1$  is positive and statistically significant ( $p < 0.01$ ) and  $\delta_1$  is negative and also statistically significant ( $p < 0.05$ ). As such, in the Gompertz model, the results indicate that an industry with a higher rate of firm death experienced a higher intercept but a less pronounced slope on electronic commerce adoption between 2002 and 2019. Taken together, the support may be more mixed for Hypothesis 1.

I now examine Hypothesis 2. In Table 1.4, it is observed that the Gompertz model shows that  $\beta_4$  is positive and statistically significant ( $p < 0.01$ ) and  $\delta_4$  is negative and also statistically significant ( $p < 0.01$ ). The results from the Gompertz model indicate that sectors with larger firms and concentrated sectors experienced a statistically significant higher intercept but a less pronounced slope on the adoption of electronic commerce between 2002 and 2019. Taken together, these results provide mixed support for Hypothesis 2.

**TABLE 1. 4. RESULTS FROM THE GOMPERTZ MODELS FOR HYPOTHESES**

| Parameter                                         | Label                                                   | Gompertz Model     |
|---------------------------------------------------|---------------------------------------------------------|--------------------|
| Intercept for $g_{0n}$ ( <i>Intercept</i> )       | $\gamma_0$                                              | 9.0996*** (3.99)   |
| Intercept for $g_{1n}$ ( <i>Slope</i> )           | $\gamma_1$                                              | 59.5803*** (21.87) |
| Inflection point                                  | $\lambda$                                               | 5.0960*** (23.01)  |
| Rate of change                                    | $\alpha$                                                | 0.1966*** (17.39)  |
|                                                   | $g_{0n}$ ( <i>Intercept</i> ) $g_{1n}$ ( <i>Slope</i> ) |                    |
| <i>firm death</i>                                 | $\beta_1$                                               | 0.8067*** (3.00)   |
|                                                   | $\delta_1$                                              | -0.9709** (-2.12)  |
| <i>industry concentration</i>                     | $\beta_2$                                               | 6.8821*** (4.48)   |
|                                                   | $\delta_2$                                              | -7.7275*** (-3.37) |
| <i>average firm size</i>                          | $\beta_3$                                               | -0.00932 (-0.26)   |
|                                                   | $\delta_3$                                              | 0.1566*** (3.90)   |
| <i>industry concentration × average firm size</i> | $\beta_4$                                               | 0.1827*** (5.01)   |
|                                                   | $\delta_4$                                              | -0.1819*** (-3.40) |
| <i>Model Fit</i>                                  |                                                         |                    |
| -2 Log Likelihood                                 |                                                         | 1962.6             |
| AIC                                               |                                                         | 1994.6             |
| BIC                                               |                                                         | 2011.3             |

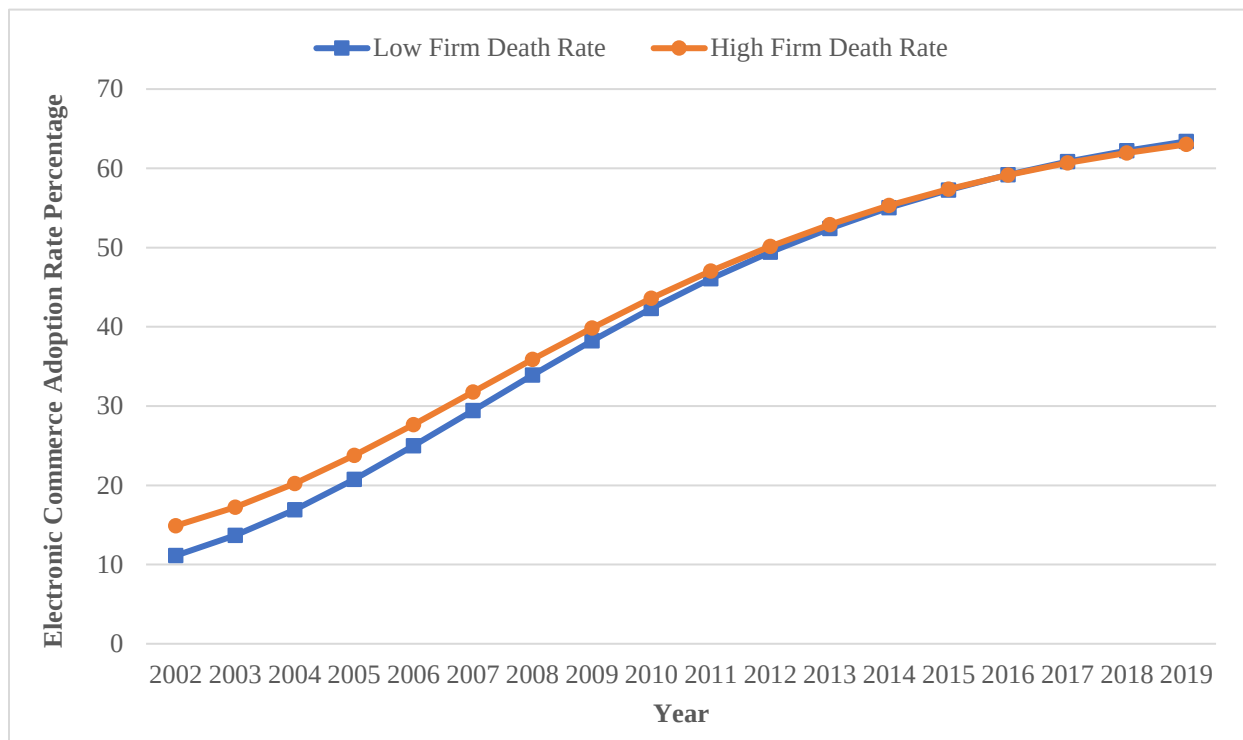
\* =  $p < 0.10$ ; \*\* =  $p < 0.05$ ; \*\*\* =  $p < 0.01$   
z-statistics in parentheses.

To visualize the relationship between *firm death* in *electronic commerce adoption* (Hypothesis 1) and the interaction of *average firm size* and *industry concentration* in electronic commerce (Hypothesis 2), I plotted the model-implied trajectories for *firm death* in *electronic commerce adoption* and the interaction of *average firm size* and *industry concentration* on

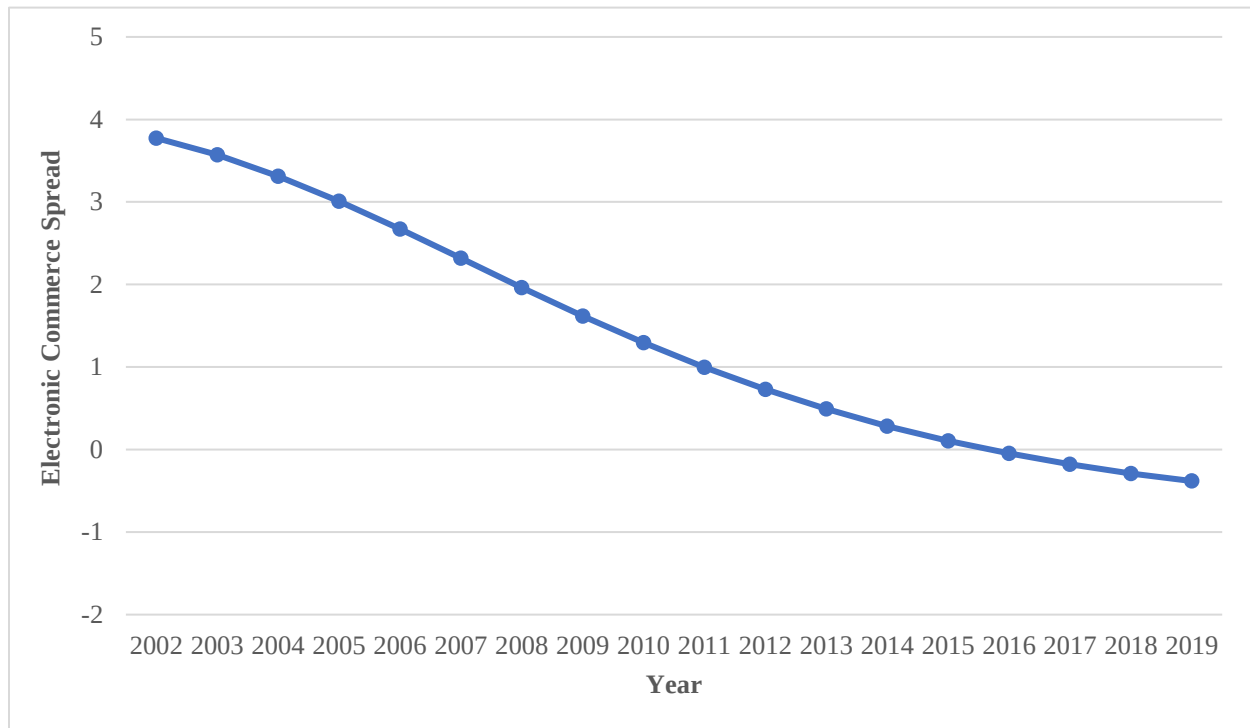
*electronic commerce adoption* in Figures 1.8A and 1.9A, respectively. For both figures, I assigned the low *firm death* (Hypothesis 1) and the small *firm size* and low *industry concentration* (Hypothesis 2) to -1 standard deviation from the mean, and the high *firm death* (Hypothesis 1) and the small *average firm size* and low *industry concentration* (Hypothesis 2) to +1 standard deviation from the mean. I also plotted the spread in *electronic commerce adoption* between the low *firm death* and high *firm death* in Figure 1.8B and the spread in *electronic commerce adoption* between small *average firm size* and low *industry concentration* and large *average firm size* and high *industry concentration* in Figure 1.9B.

These figures provide interesting findings. In Figure 1.8A, the high *firm death* graph starts significantly higher than the low *firm death* graph, but the spread between the two graphs becomes narrower, and the graphs cross between 2015 and 2016. Looking at the spread between the graphs of Figure 1.8A in Figure 1.8B, the effect of *firm death* is more pronounced at the beginning of the overall period. That is, the industries with higher rates of *firm death* had higher rates of initial *electronic commerce adoption*. But interestingly, manufacturing sectors with higher *firm death* did not have *electronic commerce adoption* any more quickly than sectors with lower *firm death* since 2016. Turning our attention to Hypothesis 2, in Figure 1.9A and Figure 1.9B, the size of the implied effect on *electronic commerce adoption* between small *average firm size* and low *industry concentration* and large *average firm size* and high *industry concentration* becomes even stronger as time goes by. As Hypothesis 2 expected, an inspection of these figures displays that sectors with larger *average firm size* and higher *industry concentration* have shown a more rapid rate of *electronic commerce adoption* than manufacturing sectors with smaller *average firm size* and lower *industry concentration*.

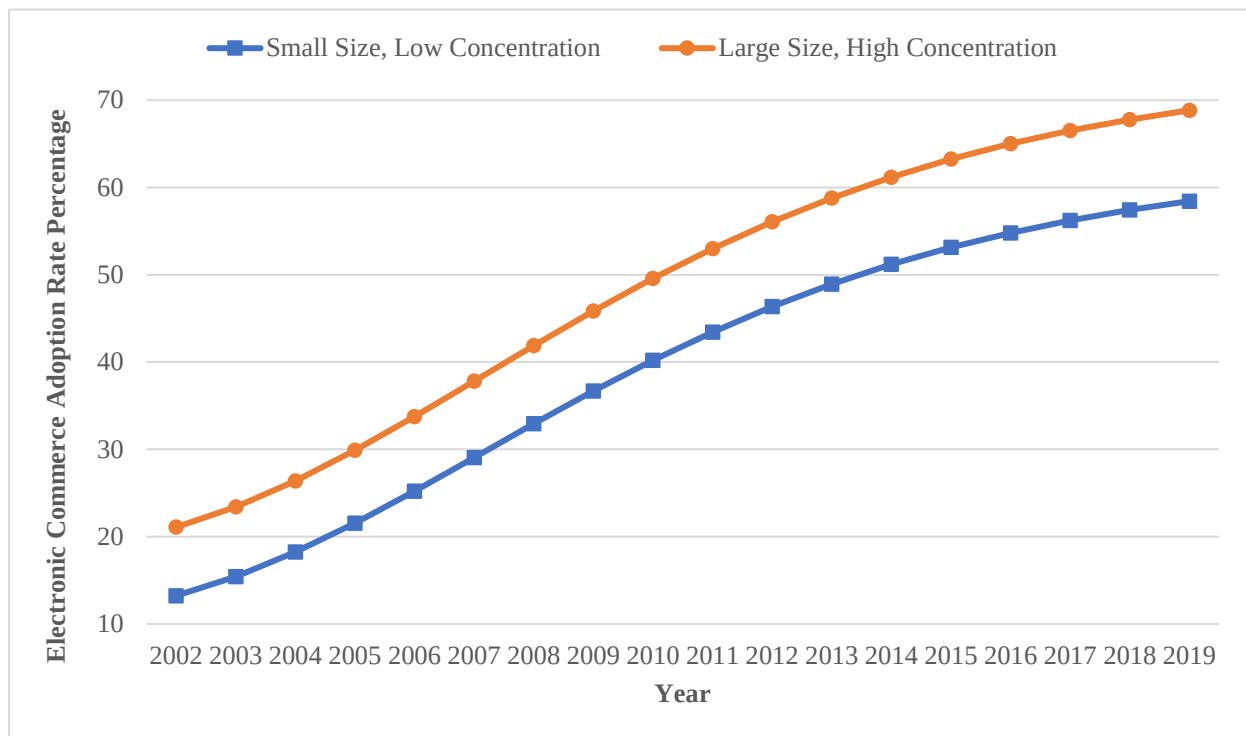
**FIGURE 1.8 A. IMPLIED EFFECT OF FIRM DEATH RATE ON ELECTRONIC COMMERCE**



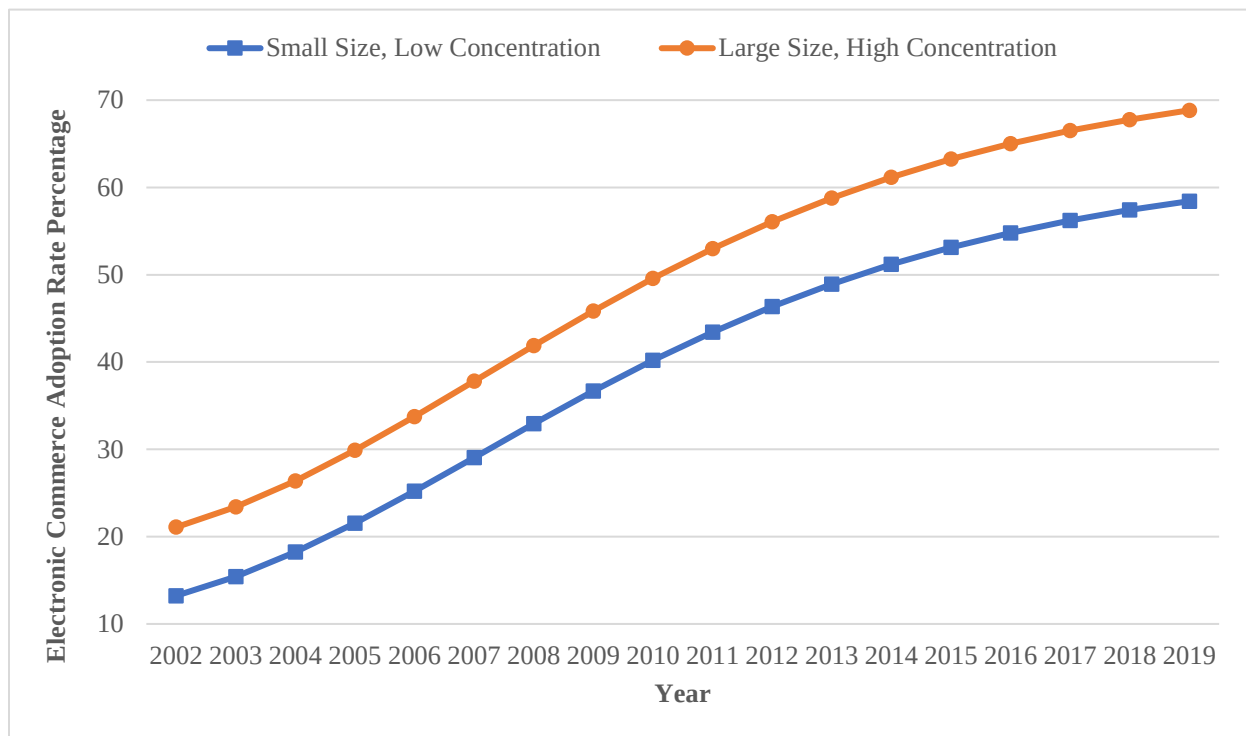
**FIGURE 1.8 B. SPREAD IN ELECTRONIC COMMERCE BETWEEN LOW FIRM DEATH RATE VS HIGH FIRM DEATH RATE**



**FIGURE 1.9 A. IMPLIED EFFECT OF AVERAGE FIRM SIZE × INDUSTRY CONCENTRATION ON ELECTRONIC COMMERCE**



**FIGURE 1.9 B. SPREAD IN ELECTRONIC COMMERCE BETWEEN SMALL SIZE & LOW CONCENTRATION VS LARGE SIZE & HIGH CONCENTRATION**



## 1.6 DISCUSSION

### 1.6.1 Theoretical Contributions

My research contributes to the existing theoretical knowledge regarding which factors have affected the differential adoption of electronic commerce by manufacturing industries. To organize my theoretical contributions, I utilize the framework suggested by Makadok, Burton, and Barney (2018).

The first theoretical contribution is about better-specifying boundary conditions. To the best of my knowledge, this is the first empirical study comparing different functional forms for an S-shaped curve, which helps refine the understanding of technology adoption. The technology performance growth curves have two theories of growth: 1. Symmetrical growth (E.g.,



Christensen, 1992). 2. Slower tapering growth (E.g., Roussel, 1984). However, the technology adoption growth curve model has a dominant theory, which is the DOI life cycle (Rogers, 1995). This DOI life cycle with a symmetric growth cycle has been widely accepted and not challenged. My essay compares the Gompertz curve, which experiences approximately 37% of total growth before the inflection point and the remaining growth after it, and the Logistic curve, where 50% of the growth takes place at the inflection point, to figure out which curve explains better about the new technology adoption growth curve.

The second theoretical contribution is adding generalizability. Swanson et al. (2016) indicate that industry-level studies tend to have more generalizability than firm-level studies. Also, papers such as Brynjolfsson (1993), Kohli and Devaraj (2003), and Sabherwal and Jeyaraj (2015) point out that some of the potential reasons for the inconsistent results from extant papers on new technology adoption are sample bias, inadequate sample size, inappropriate measures.

The third theoretical contribution, which falls under Makadok, Burton, and Barney's (2018) framework is the use of the precise variable of electronic commerce. Another potential reason for inconsistent findings from papers on new technology adoption is the fact that I have different surveys measuring things differently as Sabherwal and Jeyaraj (2015) suggest. The U.S. Census Bureau is using a consistent definition of this variable of electronic commerce while collecting over 20 years of data.

Last but not least, the fourth theoretical contribution is about mechanisms. First of all, the TOE framework has been often used as a firm-level framework. However, when I utilize this framework from the industry level, one of the new mechanisms was suggested, which is the rate of firm death in an industry. In particular, Baker (2011) states that the TOE framework has shown limited theoretical development since the framework's introduction, and Zhu and Kraemer

(2005, p. 63) also argue that the TOE framework is a “generic” theory. However, as firm death rate is identified as a significant factor affecting the adoption of new technology adoption, this essay broadens the use of the TOE framework. Second, another contribution in mechanism is that this essay introduces new environmental factors such as import competition for the technology adoption of a firm. To the best of my knowledge, none of the supply chain literature has recognized the role of competition from imports triggering organizations' need for the adoption of new technology. Third, I argue that the interaction in firm size and industry concentration, which can be used as a good proxy for firms that are likely national or regional in scope, is one of the significant factors leading firms to invest in new technology.

### **1.6.2 Managerial Contributions**

This essay has implications for public policymakers and managers. Turning first to public policymakers, the first implication of my findings is that understanding factors affecting new technology adoption in manufacturing industries would help policymakers to respond to changes. In particular, by understanding the characteristics of the technology adoption growth curve such as nonlinear, and asymptotic aspects better, policymakers can utilize their resources and investments more efficiently. Also, policymakers would have a better expectation of industry-level phenomena in firms' new technology adoption, and they can utilize this information on making better government policies, such as tax incentives or subsidies, in promoting technology investment. In particular, there have been calls for SCM increasing making policymaking contributions (e.g., Tokar & Swink, 2019; Richey & Davis-Sramek, 2022).

For managers, this study highlights the importance of industry-level characteristics such as firm death rate, and the interaction of average firm size and industry concentration. For example, firms in the apparel manufacturing sector where there is high import competition would

feel more pressured to adopt electronic commerce, compared to firms in food manufacturing where there is low import competition. Similarly, organizations on a national scale such as Ford, GM, Chrysler, and Tesla may need to consider more investment in technological innovation than organizations on a regional scale such as local wood products and printing firms.

### **1.6.3 Limitations**

This study has a few limitations. First, the analysis in this essay is limited to the industry level, which is bound to the essay's data sources. Therefore, my analysis focuses on between industries. This limitation may raise concerns regarding the generalizability of the findings to individual firms. This is because my essay does not explore the heterogeneity within a manufacturing sector. For example, exploring the impact of the size between firms within an industry toward the adoption of new technology would broaden the understanding of the new technology adoption process in firms.

Second, this study examines the antecedents of electronic commerce adoption process, but all data in this essay are from the U.S. and may not represent all the technology adoption processes in organizations out of the U.S. It would be interesting to examine data from firms in other countries. Third, given that my data sources from the U.S. Census Bureau, NBER-CES Manufacturing industry database, and Business Dynamics Statistics use yearly data; however, quarterly data (e.g., Compustat) or monthly data may provide a more detailed explanation of the processes of technology adoption. For example, firm-level data from Compustat and company financial reports offer quarterly data, and if there are some sources that have monthly data, they would offer greater temporal granularity.

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## **2 CHAPTER TWO:**

### **CONSEQUENCES OF MANUFACTURING INDUSTRIES ADOPTING ELECTRONIC COMMERCE: TIME SERIES ANALYSIS**

#### **2.1 Introduction**

The Industry 4.0 Global Expert Survey from McKinsey & Company (2016) indicates that the majority of firms across industries have felt compelled to implement more digitalization and Industry 4.0 applications. The survey also revealed that over 80% of industry experts believe that new technologies will have a positive impact on firms' operational effectiveness and business models. Additionally, Jakab (2023) reports that McDonald's digitalization efforts have helped the company gain a greater advantage over its fast-food competitors and that McDonald's daunting digital edge would create loyalty and enable value promotions, leading to competitive advantages. Consequently, with more globalized supply chains (Shih, 2020), and the advancement of relevant technologies, including Bitcoin, Blockchain, and Financial Technology (Fosso Wamba et al., 2020), it is expected that more companies will adopt new technologies, including electronic transactions, as a key component of their supply chain management strategy. This trend is expected to continue in the years to come. Specifically, the way organizations interact and communicate with each other as well as with their supply chain members is greatly impacted by electronic transactions (Johnson & Whang, 2002).

Yet, in spite of many people's expectations, literature reveals the "productivity paradox" (e.g., Brynjolfsson et al. 2020; Brynjolfsson 1993; Solow 1987), which refers to the phenomenon observed in business process analysis that despite increased investment in information technology (IT), there may be a lack of corresponding increase in worker productivity, and in some cases, productivity may even decrease. Solow's (1987) famous quote "You can see the

computer age everywhere but in the productivity statistics" (p. 36) initiated decades of research and discussions on this topic. Roach (1987) found that output per employee did not significantly increase between 1977 and 1989 despite substantial investment in IT, and Brynjolfsson and Hitt (2003) demonstrated that ROI for IT may take at least 5-7 years to realize. The productivity paradox questions our assumptions on new technology investments, instigate novel avenues of research, and leads to recommendations (Brynjolfsson et al. 2020).

In this essay, I present a series of empirical tests on independent variables that are strongly linked to a specific type of information technology, namely, electronic commerce adoption. As such, I conduct the investigation of the impact of electronic commerce adoption on manufacturing firms' labor productivity and selling, general & administrative (SG&A) expenses. The research questions that guide this study are as follows: RQ1) How does electronic commerce growth over time affect manufacturing firms' performances such as labor productivity, which is related to direct costs? RQ2) How does electronic commerce growth over time affect manufacturing firms' indirect costs such as SG&A expenses? In particular, the formal definition of electronic commerce used in this essay is defined by the U.S. Census Bureau, which is "the value of goods and services sold over computer-mediated networks" (Mesenbourg, 2001, p. 4). The essay's data covers all electronic commerce activities in which the price and sales terms for shipments are negotiated using internet, extranet, EDI network, electronic mail, or other online systems, encompassing both cases where online payment is made and cases where payment is not made online.

To test my research questions, I use information processing theory (IPT: Galbraith 1977; Tushman & Nadler, 1978) to explore the increase in information processing capabilities with the implementation of electronic commerce can enhance the match with information processing

needs, leading to increases in labor productivity and decreases in SG&A costs. In particular, Richey et al. (2022) call for more specific and clearly-defined dependent variables and expected results which are logical, quantifiable, and applicable in real-world scenarios in the Logistics and supply chain management (SCM) literature. The two dependent variables of this essay, namely Labor Productivity and SG&A expenses, can be easily understood in practical terms and are significant indicators for numerous SCM companies.

I test my hypotheses by conducting panel data research using multiple studies. For Hypothesis 1, I utilized an aggregate industry-level study by collecting yearly data for 18 years. The data were obtained at the 3-digit NAICS code level and covered 21 sectors within manufacturing (NAICS 31-33). The sources of data were the U.S. Census Bureau and the U.S. Bureau of Labor Statistics. For Hypothesis 2, I conducted a firm-level study by collecting yearly data at the 3-digit NAICS code level. The study focused on the manufacturing sector (NAICS 31-33) and involved 30,900 firms, resulting in a total of 224,439 records. The data sources for this study were the U.S. Census Bureau and Compustat. The key reason I use the U.S. Census Bureau as my data source is that the Census Bureau has collected data with a consistent definition of electronic commerce for over 20 years. To measure the focal variables consistently for an overall panel data period, data must be collected in this way.

This essay makes a significant contribution to the SCM literature in various ways. Firstly, Secondly, this essay enhances the generalizability of the results by utilizing data spanning over 20 years from the U.S. Census Bureau, which surveys a stratified random sample of companies covering the entire U.S. manufacturing industry population. Existing studies, such as Brynjolfsson (1993), Kohli and Devaraj (2003), and Sabherwal and Jeyaraj (2015), have highlighted that inconsistent findings in previous literature on new technology adoption could be

due to sample bias, inadequate sample size, or inappropriate measures. Thirdly, this essay uses the precise variable of electronic commerce, that does not change in measurement method over 20 years drawing from the Census Bureau. Sabherwal and Jeyaraj (2015) suggest that one of the reasons for inconsistent findings in previous literature on new technology adoption is the fact that different surveys measure things differently.

This essay also provides implications for practitioners. Firstly, the findings offer additional evidence of the positive relationship between new technology adoption and efficiency gains in both direct and indirect cost aspects. Policymakers can utilize this information in creating better government policies, such as tax incentives or subsidies, to promote technology investment. For managers, the essay suggests that the outcomes of electronic commerce adoption cover not only direct costs, such as labor productivity, but also indirect costs, such as selling, general, and administrative expenses (SG&A).

The remainder of this essay is organized as follows. The first section contains the pertinent literature streams. The second describes the theoretical development and the logic for hypotheses development. The third section explains the research design, defines the measured variable, and describes data transformations. The fourth section sketches the econometric methodological approach, describes results, and details robustness tests. The fifth section explains the theoretical and managerial implications and discusses limitations.

## **2.2 Literature Review**

### **2.2.1 Productivity Paradox**

Many papers have witnessed the "productivity paradox" (e.g., Brynjolfsson et al. 2020; Brynjolfsson, 1993; Solow, 1987), which highlights the phenomenon observed in the analysis of

business processes. It suggests that despite increased investment in IT, worker productivity may experience a decline rather than an improvement. Additionally, Brynjolfsson (1993) points out that there is a noted inverse relationship between economy-wide productivity and the introduction of computers in the data of manufacturing industries. Similarly, Roach (1991) cites statistics demonstrating that from the mid-1970s to 1986, while production worker output increased by 16.9%, IT worker output dropped by 6.6%.

Other papers in the literature on the productivity paradox suggest possible reasons for this phenomenon. The first potential reason is measurement errors and incorrect use of methods (Diewert & Fox, 1999; Polak, 2017; Brynjolfsson et al., 2018). For example, Brynjolfsson (1993) argues that the lack of IT productivity improvement could be caused by deficiencies in measurement and the methodological tool kit. The second reason could be new technologies' high adjustment costs, which refers to the expenses and difficulties associated with adopting or implementing new information technology systems or upgrading existing ones within an organization (Brynjolfsson et al., 2018). Greer and Hare (1997) suggest that the presence of inadequate software design, insufficient computer skills among employees, and ineffective administrative management may result in significant costs associated with adjustment. The literature also suggests false hopes for new technologies and the wrong intention on technology investment for another reason causing the productivity paradox. For example, Polak (2017) asserts that managers receive more favorable evaluations when they actively pursue the latest technology. Consequently, they are strongly motivated to invest in such technologies, even if the potential benefits are relatively minor.



Therefore, in this essay, I empirically revisit the productivity paradox with panel data sets including the consistent measurement of electronic commerce from the Economic Census from 2002 to 2019.

### **2.2.2 Business Value of New Technologies**

Much research about the value of new technologies written between the late 1980s and early 2000s was done using either conceptual or single-informant, cross-sectional surveys (Narayanan et al. 2009). However, research in this field, including multiple meta-analysis papers such as Narayanan et al. (2009) and Sabherwal and Jeyaraj (2015), shows some ambiguity and inclusive findings. For example, different papers have contradictory results on the benefits of EDI for inventory level decrease and delivery performance improvement. Lim and Palvia (2001) conduct cross-sectional surveys with 114 managers from the U.S. automobile and pharmaceutical industries and show statistically significant results that firms that have integrated Electronic Data Interchange (EDI) systems tend to have better performance outcomes in product availability and delivery from their vendors when compared to those without EDI. On the other hand, Teo et al. (1995) conduct surveys from 210 managers in Singapore using an EDI software, Tradenet and display that the relationship between EDI integration and inventory levels is not statistically significant. As another example, Ahmad and Schroeder (2001) conduct a survey with representatives from 85 plants in the electronic, machinery, and automobile industries of Germany, Italy, Japan, and the U.S. and suggest that firms that use EDI to connect with their suppliers and customers improve their on-time delivery performance. On the other hand, Walton and Marucheck's (1997) results from a survey of 30 companies using EDI find that having access to EDI technology is not enough to increase supplier reliability.

As such, extant papers explore possible reasons for mixed results in the outcomes of investments in new technologies. Kohli and Devaraj (2003) state that inadequate sample size and analysis methods may be the cause of this inconsistency in previous research. In particular, Sabherwal and Jeyaraj (2015) call for further research on the topic of new technologies' outcomes with larger sample size and secondary data sources. Therefore, I will explore the consequences of an investment in electronic commerce with the U.S. manufacturing industry's population-level data for over 20 years.

## **2.3 Theory and Hypotheses Development**

### **2.3.1 Information Processing Theory**

In information processing theory (IPT: Galbraith 1977; Tushman & Nadler, 1978), organizations are conceptualized as systems responsible for processing information. IPT comprises three fundamental theoretical components, namely, information processing needs, information process capability, and the congruence between information processing requirements and capabilities (Tushman & Nadler, 1978). Firstly, information processing needs refers to the quantum of information necessary for organizations to make decisions pertaining to specific objectives (Zhu et al., 2018). Secondly, information processing capability denotes the organizational capacity to effectively acquire, comprehend, and synthesize information to facilitate decision-making processes (Tushman & Nadler, 1978).

IPT theorizes that decision-makers' main task in a firm's design is to identify information processing requirements and to match the requirements with the firm's information processing capabilities. As such, IPT suggests that firms experience diminished efficiency when there is a misalignment between their information processing requirements and capabilities. Specifically,

when the information processing demands placed on firms surpass or lag behind their corresponding processing capacities, a decline in overall efficiency is anticipated (Tushman & Nadler, 1978). That is, when a firm possesses the appropriate capabilities that align effectively with its requirement needs, it has the potential to achieve enhanced performance. Moreover, information processing theory (IPT) asserts that uncertainty gives rise to the information processing needs of firms (Bensaou & Venkatraman, 1995). Notably, organizations are particularly susceptible to heightened levels of uncertainty within the context of supply chain operations (Zhu et al., 2018). Busse et al. (2017) highlight that inadequate information regarding supply chain activities poses a significant obstacle to the implementation of sustainable supply chain management practices among various stakeholders within the supply chain network.

Extant research has explored the benefits of new technology investments in increasing information processing capabilities. For example, the development of information systems has facilitated information processing capability (e.g., Gunasekaran & Ngai, 2004). Muir et al. (2019) indicate that firms' investment in resources such as information technology to process information better can create information processing capabilities. Harris and Davenport (2006) posit that information technology (IT) plays a crucial role in facilitating access to dependable information for effective decision-making. Furthermore, Tenhiala et al. (2018) emphasize that information systems possess the capability to alleviate uncertainties encountered in organizational contexts. Therefore, in this essay, I use IPT as an overarching theory to explain the impact of electronic commerce adoption.

### **2.3.2 Labor productivity**

Labor productivity has been a research topic of particular interest, and exploring the elements affecting productivity has yielded significant findings across many fields (Syverson, 2011).

Specifically, papers have explored the relationship between IT and productivity (e.g., Brynjolfsson & Hitt, 2003; Aral et al., 2006; Aral et al., 2012; Brynjolfsson & Syverson, 2018). For example, Brynjolfsson and Hitt (2003) states that IT is the biggest single factor driving productivity resurgence. Similarly, Aral et al. (2012) suggest that electronic communication networks increase information workers' ability to multitask more productively. Additionally, Aral et al. (2006) provide evidence indicating that investments in enterprise systems, such as Enterprise Resource Planning (ERP), result in enhancements in both overall productivity and operational performance. This generates a "virtuous cycle" (p. 27) wherein the initial investments prompt performance gains, subsequently fostering a climate conducive to further investment.

Investments in new technologies not only benefit overall organizational productivity but also labor productivity. Electronic commerce enables companies to manage larger volumes of information and create structures to help information processing leverage relations between supply chain members (Srinivasan & Swink, 2015). In addition, information systems can enhance decision-making quality by decreasing information delays and providing decision-makers with greater access to more and better-quality information gathered from suppliers and customers (Srinivasan & Swink, 2015). In particular, IPT theorizes that this improved information processing capability can lead to lead time reduction in communication and decision-making (Galbraith, 1977). Subramani (2004) further asserts that information systems have the potential to lower the resource costs associated with acquiring, storing, and processing information. Especially when different supply chain parties are in conflicts due to priority differences or plans need to be changed due to various supply chain problems, information processing structures in electronic commerce can help reduce ambiguities and equivocality and find solutions (Srinivasan & Swink, 2015).

Also, Chen and Kamal (2016) suggest that information and communication technology adoption can lower search and communication costs, leading to increases in intra-firm trade shares. Therefore, the increase in information processing capabilities with electronic commerce implementation can enhance the match for cases when information processing needs are increased, such as priority conflicts between supply chain parties and changed plans due to various supply chain problems. This match will lead to a reduction in production-related problem-solving time and expedited communication, resulting in an increase in labor productivity. Furthermore, electronic commerce assists in automating manual tasks, leading to a potential reduction in the number of hours worked, the denominator in the labor productivity calculation. Therefore, I expect in this context that:

**Hypothesis 1 (H1): *As the adoption of electronic commerce increases, labor productivity increases.***

### **2.3.3 Selling, General & Administrative (SG&A) Expenses**

Selling, general, and administrative (SG&A) expenses encompass all non-production expenditures accrued by a company within a specified timeframe. These expenses consist of various categories, including but not limited to rent, advertising, marketing, accounting, litigation, travel, meals, management salaries, and bonuses (Zarzycki, 2021; Anderson et al., 2003). In essence, SG&A costs encompass a wide range of indirect costs that contribute to the overall operational expenses of a company (Banker et al., 2018).

Extant papers have explored SG&A expenses as proxies of other activities. For example, Patatoukas (2012) take reduced SG&A expenses as a form of efficiency gains. Also, Cooper and Kaplan (1998) states that the behavior of SG&A costs can be examined in relation to sales revenue given that many SG&A expenses components are driven by sales volume, and Anderson

et al. (2003) and Banker et al. (2014) also related SG&A expenses changes to net sales revenue changes as SG&A expenses cover around 26 to 29% of sales revenue on average in their panel data.

IPT suggests that increased information processing capabilities of a focal firm through electronic commerce can meet the information processing needs of the firm's suppliers and customers better, thereby improving the firm's relationship with members of its supply chain. Additionally, Kalwani and Narayandas (1995) suggest that an improved relationship between a manufacturing firm and its suppliers can decrease the manufacturer's selling expenses by minimizing service costs, fostering repeat sales and cross-selling opportunities, and overall improving the efficiency of selling expenditures. Furthermore, electronic commerce can lower general and administrative expenses. Firstly, electronic commerce would reduce the need for administrative personnel to process orders, which would reduce overall personnel hours and lower the firm's administrative expenses (Piris et al., 2004). Secondly, electronic transactions can reduce paperwork and increase accuracy, resulting in savings in general expenses (Downing, 2006). Therefore, I posit that:

**Hypothesis 2 (H2):** *As the adoption of electronic commerce increases, SG&A costs decrease.*

## **2.4 Methodology**

To test my hypotheses, I conduct panel data research using a multimethod approach. I use Study 1 to test the first hypothesis and Study 2 to test the second hypothesis. The data range from 2002 through 2019 and I selected this time window despite the availability of data since 1999 for several reasons. First, there was a sharp drop in U.S. manufacturing employment that started in late 2000 (Fort et al., 2018) that stemmed from U.S. manufacturing offshoring production

following trade liberalization with China in October 2000 (Pierce & Schott, 2016). As such, I did not want to include this unique event in the data. Additionally, a change was made to the NAICS code in 2002, and incorporating data from 1999, 2000, and 2001 may have a negative effect on the overall quality of the data. As a result, in order to maintain the dataset's reliability and consistency, I have made the decision to exclude these earlier years.

## **2.4.1 Study 1**

### **2.4.1.1 Data descriptions**

To test the first hypothesis in Study 1, I utilize an aggregate industry-level study by collecting yearly data at the level of 3-digit NAICS codes for manufacturing (NAICS 31-33). For the electronic commerce statistics data source, I use E-Commerce Statistics data from the U.S. Census Bureau. This dataset spans over 20 years and captures the value of goods and services sold online, encompassing transactions conducted over open networks like the internet or proprietary networks employing systems such as EDI. Each year's data are collected from over 50,000 manufacturing plants through Annual Survey of Manufactures. Productivity-related variables are sourced from the U.S. Bureau of Labor Statistics, which gathers various measures of efficiency in converting inputs into goods and services outputs. Specifically, for the period between 2002 and 2019, data is collected for aggregated codes pertaining to NAICS sectors 311 and 312, 313 and 314, as well as 315 and 316. Therefore, an aggregated code is used to compute the results of Study 1 for sectors 311 and 312, 313 and 314, as well as 315 and 316.

I merge the U.S. Census Bureau and the U.S. Bureau of Labor Statistics data using manufacturing sectors' NAICS codes. In order to enhance clarity regarding the datasets

employed in Study 1, Table 2.1 presents a comprehensive list of the datasets, the variables, and respective data sources.



**TABLE 2. 1. DATASETS AND THEIR SOURCES FOR STUDY 1**

| <b>Data</b>              | <b>Using Variables</b>                                                                                                                                                                                               | <b>Source</b>                                 |
|--------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------|
| Electronic Commerce data | Electronic Commerce Adoption                                                                                                                                                                                         | The U.S. Census Bureau 2002-2019              |
| Productivity data        | Labor Productivity, Capital Inputs, Materials Inputs, Energy Inputs, Purchased Business Services Inputs, Capital Productivity, Energy Productivity, Materials Productivity, Purchased Business Services Productivity | The U.S. Bureau of Labor Statistics 2002-2019 |

### 2.4.1.2 Variables

#### 2.4.1.2.1 Dependent Variable

The dependent variable for Study 1 is labor productivity for each manufacturing sector, which I denote as *Labor Productivity*. The data source for the dependent variable, *Labor Productivity*, is the U.S. Bureau of Labor Statistics. The U.S. Bureau of Labor Statistics (2023) describes that *Labor productivity* is an economic performance metric that assesses the connection between the volume of output in terms of goods and services produced and the amount of labor hours required to generate that output. That is, *Labor Productivity* is calculated as follows:

$$(1) \quad \text{Labor Productivity} = \frac{\text{Output index}}{\text{Hours worked}}$$

*Labor Productivity* data is calculated into indexes, where the 2012 annual labor productivity indexes are set to 100. To measure the labor productivity of manufacturing sectors, the U.S. Bureau of Labor Statistics uses sectoral output, which refers to the current dollar value

of, that is, inflation-adjusted goods and services produced by industry for delivery to consumers outside that industry (The U.S. Bureau of Labor Statistics, 2023).

#### **2.4.1.2.2 Independent Variable**

The key measure of interest for Study 1 is the electronic commerce adoption rate for each manufacturing sector (NAICS 311 – 339), denoted *Electronic Commerce Adoption*.

Specifically, *Electronic Commerce Adoption* is scaled up by 100 To enhance the precision of covariance parameter estimation and to enable the estimated regression coefficients to indicate semielasticities (Hand and Crowder 1996; Wooldridge 2009). *Electronic Commerce Adoption* is defined as "the value of goods and services sold over computer-mediated networks" (Mesenbourg, 2001, p. 4), and the data in this essay covers all electronic commerce activities where "the price and terms of sale for shipments are negotiated over an internet, extranet, EDI network, electronic mail, or other online system" (Census.gov manufacturing report, 2016, p. 6), regardless of whether payment is made online. The data source for the focal predictor, *Electronic Commerce Adoption*, is the Electronic Commerce Statistics (E-STATS) in the U.S. Census Bureau.

#### **2.4.1.2.3 Control Variables**

I incorporate control variables for two reasons. Firstly, control variables help to rule out potential alternative causes, more consistent with traditional endogeneity due to omitted variables Secondly incorporating these control variables helps to reduce the standard errors of my analysis estimations (Cohen et al., 2003), thereby enhancing the interpretation of the parameters. To account for two dependent variables, I have used separate control variables. For labor

productivity, which consists of Hypothesis 1, I have chosen *Capital Inputs*, *Materials Inputs*, *Energy Inputs*, *Purchased Business Services Inputs*, and *Recession* as control variables.

The first control variable for labor productivity is *Capital Inputs*, also referred to as capital services. This term encompasses the flow of services generated by diverse capital assets, including equipment, structures, inventories, land, and intellectual property, all of which are utilized in the production of goods and services (Eldridge et al., 2018). The measurement of *Capital Inputs* is derived from data obtained from the U.S. Bureau of Economic Analysis' fixed asset accounts by detailed asset, as well as GDP by industry. The U.S. Bureau of Labor Statistics (2023) assumes that the growth in *Capital Inputs* is approximately proportional to the growth of the capital stock. This growth is computed as a Törnqvist index, which captures the expansion of the productive capital stock for each asset, with the weights representing the assets' respective shares of capital costs. The impact of capital composition on output growth can be determined by subtracting the growth in the share-weighted capital stock from the share-weighted growth in capital input.

The second control variable, *Materials Inputs*, refers to goods employed in the production of other goods and services, encompassing both raw materials and manufactured products (Harper, 1999). The measurement of *Materials Inputs* is adjusted to exclude transactions between establishments operating within the same sector (The U.S. Bureau of Labor Statistics, 2023). The third control variable, *Energy Inputs*, is defined as the fuels and electricity used in manufacturing goods and services (Eldridge et al., 2018). The fourth control variable, *Purchased Business Services Inputs*, entails services that companies purchase from other businesses to execute their business operations or the production of goods and services. Examples of such services include accounting, legal services, automotive repair and maintenance, and laboratory analysis of

products (Eldridge et al., 2018; Harper, 1999). *Purchased Business Services Inputs* are adjusted to exclude transactions occurring between establishments operating within the same sector. Price and quantity indexes of *Materials Inputs*, *Energy Inputs*, and *Purchased Business Services Inputs* are obtained from the U.S. Bureau of Economic Analysis's annual industry accounts (The U.S. Bureau of Labor Statistics, 2023).

I chose these control variables because the U.S. Bureau of Labor Statistics (2022) indicates that labor productivity could be increased or decreased over time by factors such as *Materials Inputs*, *Energy Inputs*, and *Purchased Business Services Inputs*. The data source for *Capital Inputs*, *Materials Inputs*, *Energy Inputs*, and *Purchased Business Services Inputs* is the U.S. Bureau of Labor Statistics. I included a categorical variable, *Recession*, which refers to the Great Recession, a period of marked general decline observed globally from December 2007 to June 2009 (Bureau of Economic Affairs, 2009), and I controlled for the years 2008 and 2009 when the Great Recession influenced the behaviors of organizations and customers (Reed & Crawford, 2014). In addition, I include industry-fixed effects to control for time-invariant industry-specific characteristics. Standard errors are also clustered at the sector level as each sector is affected by the adoption of electronic commerce.

## **2.4.2 Study 2**

### **2.4.2.1 Data descriptions**

To test the second hypothesis, I utilize a firm-level study by collecting yearly data at the level of 3-digit NAICS codes for manufacturing (NAICS 31-33). For the electronic commerce statistics data source, I use E-Commerce Statistics data from the U.S. Census Bureau. A detailed description of the data for the adoption rate of electronic commerce is provided above in Study 1.

For the data source of financial variables, I use Standard & Poor's Compustat (Compustat). Compustat is a database of financial, market, and statistical data that encompasses publicly traded corporations in the United States and Canada (Standard & Poor's, 2003). Also, Compustat database encompasses over 10,000 active companies and 9,700 inactive companies, ensuring a substantial coverage of financial data (Standard & Poor's, 2003).

To provide a better view of the datasets used in this essay, Table 2.2 presents a comprehensive list of the datasets, the variables, and respective data sources.

**TABLE 2. 2. DATASETS AND THEIR SOURCES FOR STUDY 2**

| <b>Data</b>              | <b>Using Variables</b>                                                       | <b>Source</b>                         |
|--------------------------|------------------------------------------------------------------------------|---------------------------------------|
| Electronic Commerce data | Electronic Commerce Adoption                                                 | The U.S. Census Bureau 2002-2019      |
| Financial data           | SG&A Expenses, Property, Plant, & Equipment, Sales, Total Operating Expenses | Standard & Poor's Compustat 2002-2019 |

#### **2.4.2.2 Variables**

##### **2.4.2.2.1 Dependent Variable**

The dependent variable for Study 2 is Selling, General, and Administrative (SG&A) expenses, denoted as *SG&A Expenses* and its data source is Compustat. This variable accounts for all non-production related expenses, incurred as part of regular business operations, such as expenses related to generating operating income. That is, SG&A costs cover costs indirectly associated with the operation (Anderson et al., 2003). Also, I use the natural logarithm of the variable because the data were skewed, and after the natural log transformation, the distribution is close to normal.

#### 2.4.2.2.2 Independent Variable

The key measure of interest for Study 2 is the electronic commerce adoption rate for each manufacturing sector (NAICS 311 – 339), denoted *Electronic Commerce Adoption*. Specifically, *Electronic Commerce Adoption* is scaled up by 100 To enhance the precision of covariance parameter estimation and to enable the estimated regression coefficients to indicate semielasticities (Hand and Crowder 1996; Wooldridge 2009). A detailed description of the data for the adoption rate of electronic commerce is provided above in Study 1.

#### 2.4.2.2.3 Control Variable

The control variables for *SG&A Expenses*, which consist of Study 2, are *Property, Plant, & Equipment, Sales, and Recession*. The first control variable for *SG&A Expenses* is *Property, Plant, & Equipment*, which refers to the overall gross cost or valuation of tangible fixed assets utilized in revenue generation (Standard & Poor's, 2003). *Sales* encompasses the gross sales figure, representing the total amount billed to customers for regular sales transactions completed within the specified period. This value is adjusted to account for cash discounts, trade discounts, and returned sales and allowances for which credit is granted to customers (Standard & Poor's, 2003). The data source for *Property, Plant, & Equipment*, and *Sales* is Compustat. Before estimation, I grand mean center *Property, Plant, & Equipment*, and *Sales* to make the intercepts meaningful. Also, I use the natural logarithm of these three control variables because the data were skewed, and after the natural log transformation, the distribution for all of these three control variables is close to normal. Lastly, I also included a categorical variable, *Recession*, controlling for the years 2008 and 2009. In addition, to control for changes in macroeconomic conditions I include year-fixed effects and firm-fixed effects to control for time-invariant firm-specific characteristics.

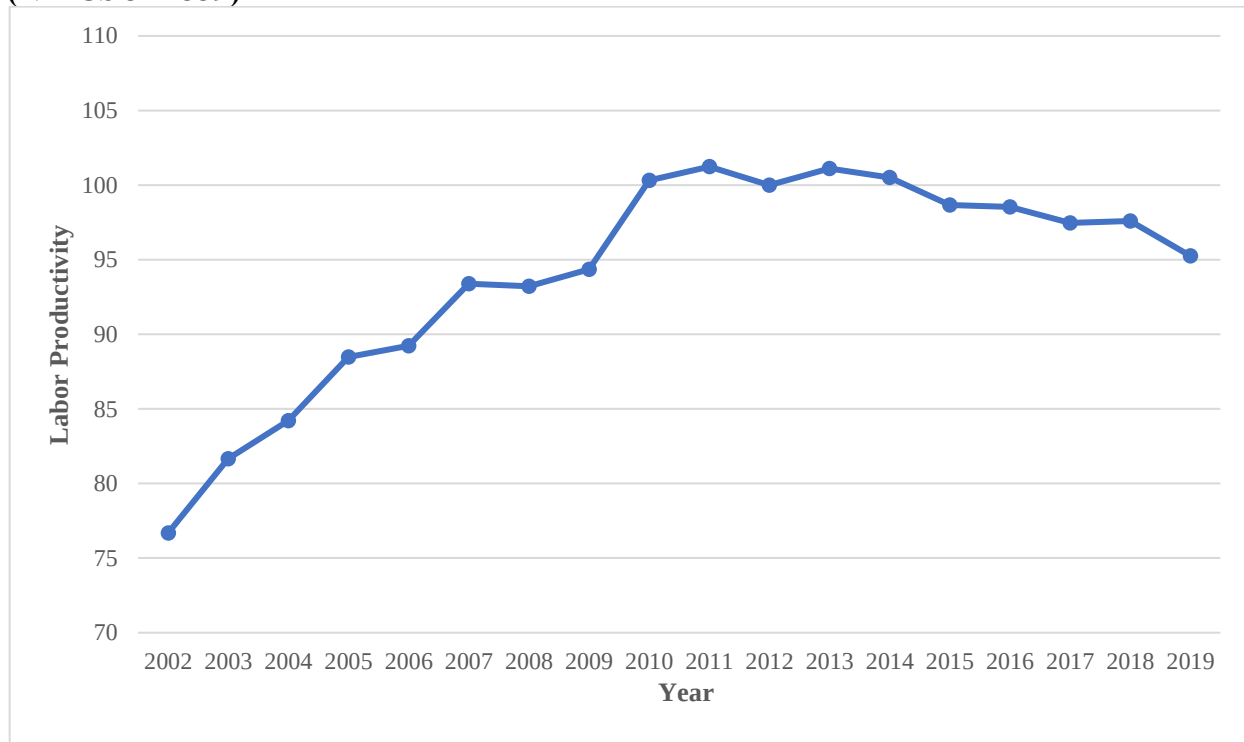
Also, I only included the U.S. manufacturing firms from Compustat given that my focal predictor, *Electronic Commerce Adoption*, which is sourced from the U.S. Census Bureau, is calculated only for the U.S. companies. Standard errors are clustered at the firm level because the granularity of Compustat data is firm-level and each firm could be affected by the adoption of electronic commerce. Following the advice of Miller and Kulpa (2022), I avoid the inclusion of variables that are not relevant to the theory, as they could affect the interpretation of the results.

## **2.5 Analysis and Results**

### **2.5.1 Model-Free Evidence**

Following the recommendation of Davis-Sramek et al. (2023), I present model-free evidence to visually depict the relationships between variables and the variability within my dataset. Figure 2.1 displays the aggregate annual labor productivity indexes for all manufacturing sectors (NAICS 31-39) between 2002 and 2019. The graph shows that labor productivity trended upward from 2002 to 2013 and has been decreasing since 2013. The data source for this figure is the U.S. Bureau of Labor Statistics.

**FIGURE 2. 1. LABOR PRODUCTIVITY FOR MANUFACTURING SECTORS BY YEAR (NAICS 311-339)**

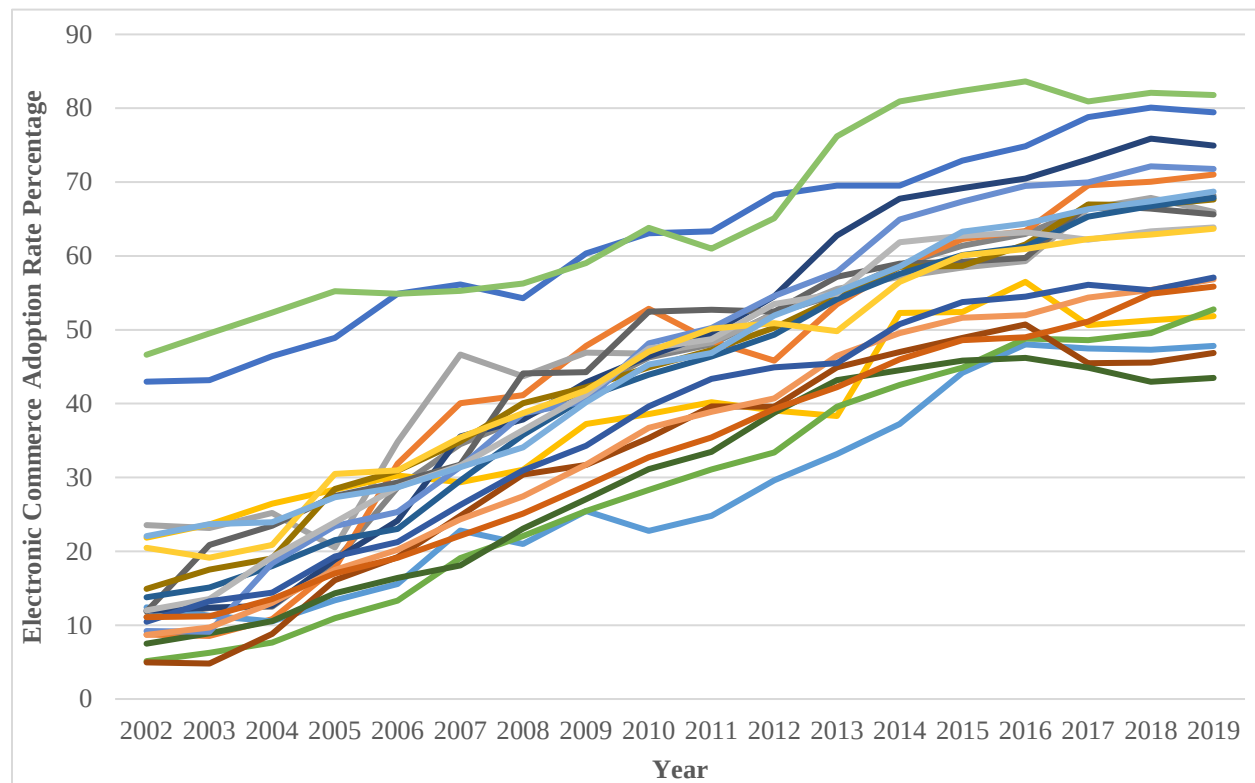


Indexes = 100 in 2012  
(Source: The U.S. Bureau of Labor Statistics)

Figure 2.2 presents a spaghetti plot illustrating the implementation of electronic commerce across various three-digit NAICS codes within the manufacturing sector. The plot reveals a consistent S-shaped pattern over time in each sector, indicating a similar trend. However, there is also some variation or diversity observed among the sectors.



**FIGURE 2. 2. SPAGHETTI PLOT FOR THE LEVEL OF ELECTRONIC COMMERCE ADOPTION FOR THE U.S. MANUFACTURING SECTORS (NAICS 311-339)**

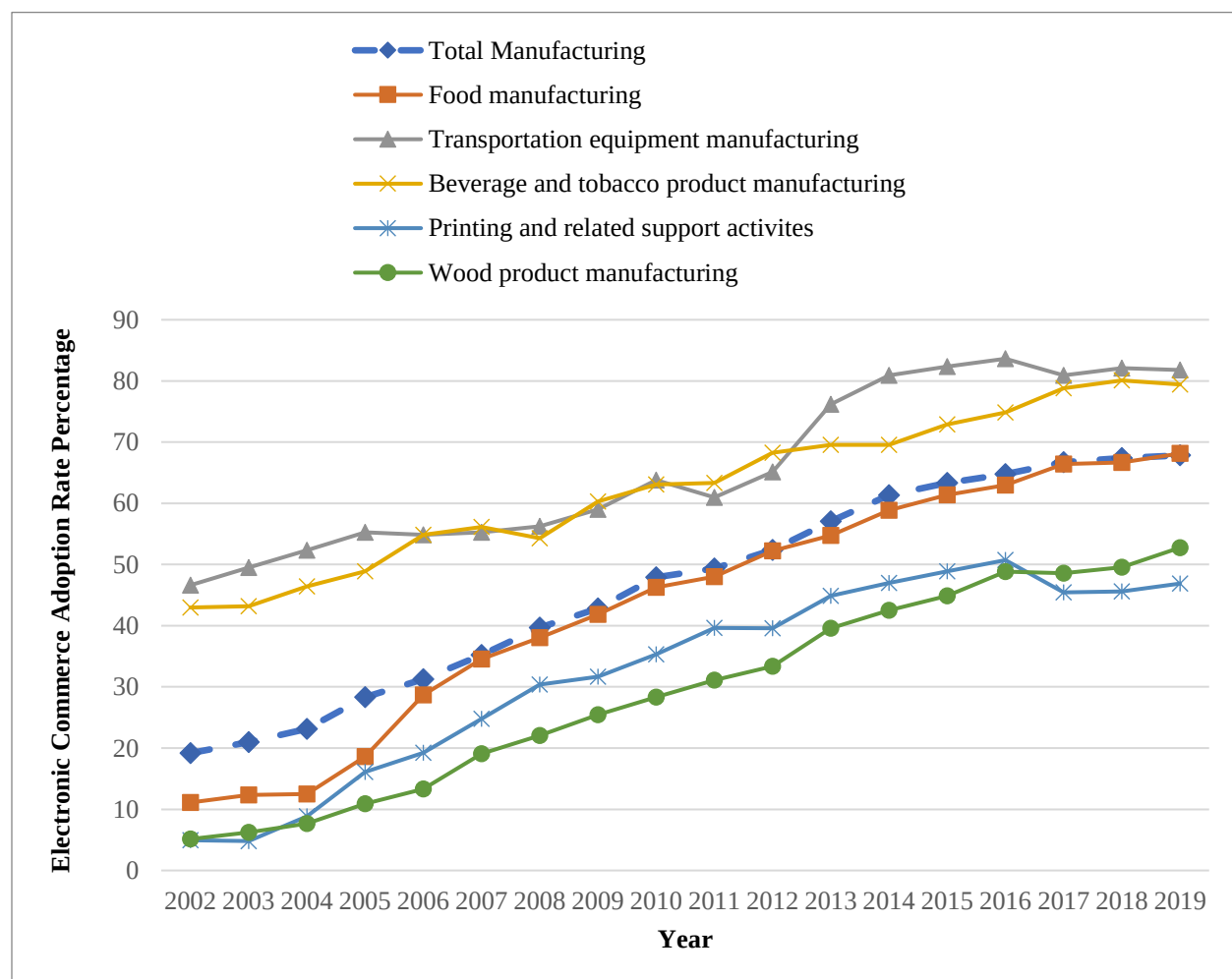


(Source: U.S. Census Bureau)

Figure 2.3 focuses on a select number of sectors in the top and bottom graphs, providing a visual representation of the industry range instead of presenting all 21 industries simultaneously. The plot highlights the adoption of electronic commerce in Transportation equipment manufacturing and Beverage and tobacco product manufacturing. These sectors exhibit a gradual increase in electronic commerce adoption rates, starting around 35-40% and reaching approximately 80%. Notably, these industries are predominantly dominated by major national firms such as Boeing, GM, Ford, and Bosch in transportation equipment, and Coca-Cola, Anheuser Busch, Philip Morris, and British American Tobacco in beverage and tobacco products.

In contrast, Printing and related support activities, as well as Wood product manufacturing, are situated at the lower end among all sectors. These two sectors differ significantly from others in terms of firm size and market dynamics. Printing and related support activities sector comprises relatively smaller firms with regional competition, while Wood product manufacturing sector faces high transportation costs for its products.

**FIGURE 2. 3. SPAGHETTI PLOT FOR THE LEVEL OF ELECTRONIC COMMERCE ADOPTION FOR THE U.S. MANUFACTURING SECTORS (ONLY TOP & BOTTOM)**



(Source: U.S. Census Bureau)

### **2.5.2 Econometric Approach**

I estimate a series of panel data regression models to test our hypothesized predictions. The models for Studies 1 and 2 were estimated using STATA version 17. Table 2.3. and Table 2.4. contain descriptive statistics and correlations for Hypothesis 1 (Study 1) and Hypothesis 2 (Study 2), respectively.

**TABLE 2. 3. CORRELATION MATRIX, MEANS, AND STANDARD DEVIATIONS OF MEASURES FOR H1 (STUDY 1)**

| <i>Variables</i>                                | <i>Mean</i> | <i>SD</i> | <i>1</i> | <i>2</i> | <i>3</i> | <i>4</i> | <i>5</i> | <i>6</i> | <i>7</i> | <i>8</i> | <i>9</i> | <i>10</i> | <i>11</i> |
|-------------------------------------------------|-------------|-----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|-----------|-----------|
| <i>Labor Productivity</i>                       | 97.21       | 9.72      | 1.00     |          |          |          |          |          |          |          |          |           |           |
| <i>Electronic Commerce Adoption</i>             | 43.03       | 19.24     | 0.24     | 1.00     |          |          |          |          |          |          |          |           |           |
| <i>Capital Inputs</i>                           | 101.25      | 9.15      | 0.19     | 0.24     | 1.00     |          |          |          |          |          |          |           |           |
| <i>Materials Inputs</i>                         | 114.23      | 50.61     | 0.33     | -0.36    | 0.20     | 1.00     |          |          |          |          |          |           |           |
| <i>Energy Inputs</i>                            | 129.22      | 157.93    | 0.50     | -0.27    | 0.23     | 0.88     | 1.00     |          |          |          |          |           |           |
| <i>Purchased Business Services Inputs</i>       | 114.54      | 47.13     | 0.43     | -0.24    | 0.40     | 0.81     | 0.85     | 1.00     |          |          |          |           |           |
| <i>Recession</i>                                | .11         | .31       | -0.09    | -0.09    | -0.01    | -0.05    | 0.02     | -0.09    | 1.00     |          |          |           |           |
| <i>Capital Productivity</i>                     | 105.50      | 18.29     | 0.45     | -0.50    | -0.02    | 0.77     | 0.73     | 0.73     | -0.11    | 1.00     |          |           |           |
| <i>Energy Productivity</i>                      | 112.42      | 86.22     | 0.08     | 0.12     | -0.04    | -0.25    | -0.28    | -0.33    | -0.07    | -0.14    | 1.00     |           |           |
| <i>Materials Productivity</i>                   | 98.89       | 18.18     | 0.06     | 0.32     | 0.11     | -0.67    | -0.42    | -0.39    | -0.02    | -0.36    | 0.32     | 1.00      |           |
| <i>Purchased Business Services Productivity</i> | 100.50      | 39.78     | 0.07     | -0.03    | -0.15    | -0.22    | -0.22    | -0.44    | 0.02     | -0.08    | 0.87     | 0.28      | 1.00      |

\*N = 324 records, from 2002 to 2019.

\*311,312; 313,314; and 315,316 are in aggregated codes.

**TABLE 2. 4. CORRELATION MATRIX, MEANS, AND STANDARD DEVIATIONS OF MEASURES FOR H2 (STUDY 2)**

| <i>Variables</i>                            | <i>Mean</i> | <i>SD</i> | <i>1</i> | <i>2</i> | <i>3</i> | <i>4</i> | <i>5</i> | <i>6</i> |
|---------------------------------------------|-------------|-----------|----------|----------|----------|----------|----------|----------|
| <i>SG&amp;A</i>                             | 657.96      | 2533.54   | 1.00     |          |          |          |          |          |
| <i>ln(SG&amp;A)</i>                         | 3.83        | 2.47      | 0.53     | 1.00     |          |          |          |          |
| <i>Electronic Commerce Adoption</i>         | 44.16       | 18.28     | 0.09     | 0.15     | 1.00     |          |          |          |
| <i>ln(Property, Plant, &amp; Equipment)</i> | 4.45        | 3.21      | 0.43     | 0.82     | 0.14     | 1.00     |          |          |
| <i>ln(Sales/Turnover)</i>                   | 5.29        | 3.04      | 0.44     | 0.90     | 0.14     | 0.90     | 1.00     |          |
| <i>Recession</i>                            | .11         | .31       | 0.0023   | -0.0013  | -0.041   | 0.0052   | 0.0035   | 1.00     |

\*N = 30,885 records, from 2002 to 2019.

### 2.5.2.1 Analysis in Study 1

To test hypothesis H1, I estimate the following OLS regression as follows:

$$(2) \quad \begin{aligned} \text{Labor Productivity}_{i,t} = & \alpha_0 + \alpha_1 \cdot \text{Electronic Commerce Adoption}_{i,t} + \alpha_2 \cdot \\ & \text{Capital Inputs}_{i,t} + \alpha_3 \cdot \text{Energy Inputs}_{i,t} + \alpha_4 \cdot \text{Materials Inputs}_{i,t} + \alpha_5 \cdot \\ & \text{Purchased Business Services Inputs}_{i,t} + \alpha_6 \cdot \text{Recession}_t + \eta_i + e_{i,t} \end{aligned}$$

In Equation 2 in Study 1,  $i$  indexes each manufacturing sector, and  $t$  indexes each year of measurement. Also,  $\eta_i$  is manufacturing sector fixed effects;  $e_{i,t}$  is the residual of the dependent variable,  $\text{Labor Productivity}_{i,t}$ .

Turning first to H1, in Table 2.5, we see the coefficient of  $\text{Electronic Commerce Adoption}_{i,t}$  is statistically significant and positive, consistent with my expectations. Therefore, H1 is corroborated. The results tell us that a 1 percentage point increase in electronic commerce adoption rate for the manufacturing sector results in an increase of 0.27154 index points in labor productivity for the manufacturing sector. Also, shifting from the 25th percentile to the 75th percentile of  $\text{Labor Productivity}$  would result in a 13.12 change in the labor productivity index.

**TABLE 2. 5. RESULTS FOR HYPOTHESIS 1 (STUDY 1)**

| Dependent Variable                 |            | Labor Productivity |
|------------------------------------|------------|--------------------|
|                                    |            | $\beta(\text{SE})$ |
| <b>Independent Variable</b>        |            |                    |
| Electronic Commerce Adoption       | $\alpha_1$ | 0.27154 (0.045)*** |
| <b>Control Variables</b>           |            |                    |
| Capital Inputs                     | $\alpha_2$ | -0.13093 (0.077)   |
| Energy Inputs                      | $\alpha_3$ | 0.05471 (0.014)*** |
| Materials Inputs                   | $\alpha_4$ | -0.08922 (0.068)   |
| Purchased Business Services Inputs | $\alpha_5$ | 0.04825 (0.047)    |
| Recession                          | $\alpha_6$ | -1.86410 (0.686)** |
| Constant                           | $\alpha_0$ | -1.68722 (6.972)   |
| Sector Fixed Effects               | $\eta_i$   | Yes                |
| Number of Observations             |            | 324                |

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01

311,312; 313,314; and 315,316 are in aggregated codes.

Standard errors cluster-robust

### 2.5.2.2 Analysis in Study 2

To test hypothesis H2, I estimate the following OLS regression as follows:

$$(3) \quad \ln(\text{SG\&A Expenses})_{f,s,t} = \beta_0 + \beta_1 \cdot \text{Electronic Commerce Adoption}_{s,t} + \beta_2 \cdot \ln(\text{Property, Plant, \& Equipment})_{f,s,t} + \beta_3 \cdot \ln(\text{Sales})_{f,s,t} + \chi_f + \sigma_t + u_{f,s,t}$$

In Equation 3 in Study 2,  $f$  indexes each firm and  $s$  indexes each manufacturing sector, and  $t$  indexes each year of measurement. Also,  $\chi_f$  is firm fixed effects, and  $\sigma_t$  is year fixed effects. Lastly,  $u_{f,s,t}$  is the residual of the dependent variable,  $\ln(\text{SG\&A Expenses})_{f,s,t}$ .

Regarding H2, as seen in Table 2.6, the coefficient of  $\text{Electronic Commerce Adoption}_{f,s,t}$  is negative, consistent with my expectations, but not statistically significant. Thus, H2 is not supported.

**TABLE 2. 6. RESULTS FOR HYPOTHESIS 2 (STUDY 2)**

| <b>Dependent Variable</b>         |            | <b>ln(SG&amp;A)</b>           |
|-----------------------------------|------------|-------------------------------|
|                                   |            | <b><math>\beta</math>(SE)</b> |
| <b>Independent Variable</b>       |            |                               |
| Electronic Commerce Adoption      | $\beta_1$  | -0.001275 (0.0008604)         |
| <b>Control Variables</b>          |            |                               |
| ln (Property, Plant, & Equipment) | $\beta_2$  | 0.2906 (0.01509)***           |
| ln (Sales)                        | $\beta_3$  | 0.3585 (0.01659)***           |
| Constant                          | $\beta_0$  | 0.8057 (0.07636)              |
| Firm Fixed Effects                | $\chi_f$   | Yes                           |
| US firm only                      |            | Yes                           |
| Year Fixed Effects                | $\sigma_t$ | Yes                           |
| Number of Observations            |            | 27,946                        |

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01  
Standard errors cluster-robust

## 2.6 Robustness Tests

In this section, I conducted one additional analysis for each hypothesis to ascertain that the results were robust.

### 2.6.1 Study 1 - Productivity-related Control Variables

The robustness check for H1 in Study 1 uses different control variables. While the original model includes inputs for capital, energy, materials, and purchased business services, this robustness check series includes productivity for capital, energy, materials, and purchased business services as control variables. Productivity of capital, energy, materials, and purchased business services is the measure of how well physical capital, energy, materials, and purchased business services are used in providing goods and services (Eldridge et al., 2018).

The reason why I also utilize the productivity of capital, energy, materials, and purchased business services as control variables is that while these inputs from the original model for H1

could be correlated with labor productivity, the productivity of inputs could also have a distinct impact on labor productivity (Eldridge et al., 2018).

$$(4) \quad \begin{aligned} \text{Labor Productivity}_{i,t} = & \gamma_0 + \gamma_1 \cdot \text{Electronic Commerce Adoption}_{i,t} + \gamma_2 \cdot \\ & \text{Capital Productivity}_{i,t} + \gamma_3 \cdot \text{Energy Productivity}_{i,t} + \gamma_4 \cdot \text{Materials Productivity}_{i,t} \\ & + \gamma_5 \cdot \text{Purchased Business Services Productivity}_{i,t} + \gamma_6 \cdot \text{Recession}_t + \zeta_i + \omega_{i,t} \end{aligned}$$

In Equation 4 in Study 1's robustness test,  $i$  indexes each manufacturing sector, and  $t$  indexes each year of measurement;  $\zeta_i$  is industry fixed effects;  $\omega_{i,t}$  is the residual of the dependent variable, *Labor Productivity* <sub>$i,t$</sub> .

Table 2.7 reports the estimation results using the productivity-related control variables. I find a positive and significant coefficient on *Electronic Commerce Adoption Rate* <sub>$i,t$</sub>  confirming that my inference is robust to the use of the productivity-related control variables. The results tell us that a 1 percentage point increase in electronic commerce adoption rate for the manufacturing sector results in an increase of 0.37706 index points in labor productivity for the manufacturing sector.



**TABLE 2. 7. RESULTS FOR HYPOTHESIS 1 (STUDY 1) ROBUSTNESS TEST**

| Dependent Variable                       | Label      | Labor Productivity   |
|------------------------------------------|------------|----------------------|
|                                          |            | $\beta(\text{SE})$   |
| <b>Independent Variable</b>              |            |                      |
| Electronic Commerce Adoption             | $\gamma_1$ | 0.37706 (0.049)***   |
| <b>Control Variables</b>                 |            |                      |
| Capital Productivity                     | $\gamma_2$ | 0.42750 (0.086)***   |
| Energy Productivity                      | $\gamma_3$ | -0.03654 (0.012)***  |
| Materials Productivity                   | $\gamma_4$ | 0.10171 (0.023)***   |
| Purchased Business Services Productivity | $\gamma_5$ | 0.07129 (0.024)***   |
| Recession                                |            | 1.23209 (0.702)*     |
| Constant                                 | $\gamma_0$ | -75.64444 (9.990)*** |
| Industry Fixed Effect                    | $\zeta_i$  | Yes                  |
| Number of Observations                   |            | 324                  |

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01

311,312; 313,314; and 315,316 are in aggregated codes.

Standard errors cluster-robust

## 2.6.2 Raw Value of SG&A Expense

Next, I examine if our result is robust to an alternative measure of SG&A expenses, compared to the original model for H2. First, I utilize SG&A expenses as dependent variable, instead of using the natural logarithm of SG&A.

$$(5) \quad SG\&A \text{ Expenses}_{f,s,t} = \theta_0 + \theta_1 \cdot \text{Electronic Commerce Adoption}_{s,t} + \theta_2 \cdot$$

$$\ln(\text{Property, Plant, \& Equipment})_{f,s,t} + \theta_3 \cdot \ln(\text{Sales})_{f,s,t} + \kappa_f + \lambda_t + v_{f,s,t}$$

In Equation 5 in Study 2's robustness test,  $f$  indexes each firm and  $s$  indexes each manufacturing sector, and  $t$  indexes each year of measurement. Also,  $\kappa_f$  is firm fixed effects, and  $\lambda_t$  is year fixed effects. Lastly,  $v_{f,s,t}$  is the residual of the dependent variable,

$SG\&A \text{ Expenses}_{f,s,t}$ . As seen in Table 2.8, the coefficient of

*Electronic Commerce Adoption*<sub>*f,s,t*</sub> is negative, consistent with my expectations, but statistically insignificant. Thus, H2's robustness test is not supported.

**TABLE 2. 8. RESULTS FOR HYPOTHESIS 2 (STUDY 2) ROBUSTNESS TEST**

| Dependent Variable                |             | SG&A                  |
|-----------------------------------|-------------|-----------------------|
| Independent Variable              |             | $\beta$ (SE)          |
| Electronic Commerce Adoption      | $\theta_1$  | -2.7004 (3.8254)      |
| <b>Control Variables</b>          |             |                       |
| ln (Property, Plant, & Equipment) | $\theta_2$  | 183.1133 (43.9145)*** |
| ln (Sales)                        | $\theta_3$  | 131.3823 (17.5959)*** |
| Constant                          | $\theta_0$  | -943.7353 (271.6347)  |
| Firm Fixed Effects                | $\kappa_f$  | Yes                   |
| US firm only                      |             | Yes                   |
| Year Fixed Effects                | $\lambda_t$ | Yes                   |
| Number of Observations            |             | 27,946                |

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$   
Standard errors cluster-robust

## 2.7 Discussion

### 2.7.1 Theoretical Contributions

My work contributes to the body of knowledge theoretically regarding the consequences of the adoption of electronic commerce in manufacturing industries. To organize my theoretical contributions, I utilize the framework suggested by Makadok, Burton, and Barney (2018).

The first theoretical contribution of this essay is that it addresses the increasing calls for more specific and clearly-defined dependent variables in existing Logistics and SCM research papers. In particular, Richey et al (2022) claim that proposed outcomes should be coherent, measurable, and applicable in real-life situations. This essay's *Labor Productivity*, a dependent variable can easily be explained in practical terms and are major indexes for many SCM

companies. Furthermore, it is worth noting that many new technologies including electronic commerce are designed to improve *Labor Productivity*.

The second theoretical contribution is adding generalizability. Extant papers such as Brynjolfsson (1993), Kohli and Devaraj (2003), and Sabherwal and Jeyaraj (2015) point out that some of the potential reasons for the inconsistent results from extant papers on new technology adoption are sample bias, inadequate sample size, inappropriate measures. In this essay, I use data for over 20 years from the U.S. Census Bureau, which surveys a stratified random sample of companies that cover the entire U.S. manufacturing industry population.

The third theoretical contribution, which falls under Makadok, Burton, and Barney's (2018) framework, is the use of the precise variable of electronic commerce. Another potential reason for inconsistent findings from extant papers on new technology adoption is the fact that different surveys measure things differently, as Sabherwal and Jeyaraj (2015) suggest. The Census Bureau is using a consistent definition of this variable of electronic commerce while collecting over 20 years of data.

### **2.7.2 Managerial Contributions**

This essay has implications for policymakers and managers. The first implication of my findings is that new technology adoption in manufacturing industries improves labor productivity and SG&A expenses. The productivity paradox literature has debated whether investment in new technologies meaningfully benefits companies (e.g., Brynjolfsson et al. 2020; Brynjolfsson et al., 2018; Polak, 2017). However, this essay provides evidence of the positive relationship between new technology adoption and efficiency gains in both direct and indirect cost aspects.

Policymakers can utilize this information in making better government policies, such as tax incentives or subsidies, to promote technology investment. Furthermore, this highlights the need

for SCM to make policy-making contributions (e.g., Tokar & Swink, 2019; Richey & Davis-Sramek, 2022).

For managers, this essay suggests that the implementation of electronic commerce has a significant impact on firms' labor productivity in manufacturing sectors. However, many sectors still exhibit relatively low levels of electronic commerce adoption rates, such as 46.88% and 52.76% in 2019. In particular, the Bureau of Labor Statistics indicates that overall labor productivity in the U.S. manufacturing industry has been declining since 2013. Therefore, some industries, including the food manufacturing sector, have not fully capitalized on the benefits of new technologies. My findings suggest that there is ample room for further improvement and encourage firms to prioritize the adoption of online processes and automation technologies.

### **2.7.3 Directions for Future Research**

This essay has several limitations. Firstly, the adoption rate of electronic commerce is collected at a NAICS code level, specifically in the manufacturing sector, which is bound to the essay's data source, the industry-level E-Commerce Statistics from the U.S. Census Bureau. Future research could examine the heterogeneity within a manufacturing sector using firm-level data for new technology adoption from another source. This could broaden the understanding of the new technology adoption process in firms.

Secondly, while this essay limits its scope to manufacturing sectors from NAICS 311 to 339, future research could extend to other industries such as retail and service sectors regarding the impacts of new technology adoptions.

Thirdly, this essay focuses on the electronic commerce adoption process in the United States, and therefore, it may not be representative of technology adoption processes in other

countries. Examining data from organizations in other countries to compare and contrast their adoption processes would enhance the generalizability of the findings.

Lastly, the data used in this essay is collected annually from sources such as the U.S. Census Bureau NBER-CES Manufacturing Industry Database, the U.S. Bureau of Labor Statistics, and Compustat's Fundamentals Annual. Although this data provides valuable insights, utilizing data with a higher level of temporal granularity, such as monthly or daily data, may offer a more detailed explanation of the technology adoption processes.

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## CONCLUSION

This dissertation carries significant implications for theory and practice. First, the findings from the first essay (Chapter 1) contribute to the supply chain management (SCM) literature in several ways. Firstly, it expands the knowledge of the processes of adopting new technologies by empirically examining the determinants of electronic commerce technology adoption. Existing research (e.g., Brynjolfsson, 1993; Sabherwal & Jeyaraj, 2015) has highlighted that ambiguity and inconsistent findings in new technology research may stem from inadequate sample sizes and methodological errors in previous studies. Therefore, conducting an analysis using population-level data from the U.S. manufacturing industry spanning over 20 years would enhance the generalizability of the findings. Additionally, to the best of my knowledge, this essay is the first to investigate the impact of firm closures on aggregate technology adoption, filling a significant gap in the literature. Secondly, this essay provides a better specification of boundary conditions. To the best of my knowledge, it is the first empirical study to compare different functional forms for an S-shaped curve, which contributes to a refined understanding of the shape of growth curves in the technology adoption process. By examining various functional forms, this essay enhances our understanding of the factors influencing the growth trajectory of technology adoption and provides valuable insights into the adoption patterns of electronic commerce technology. The first essay compares the Logistic curve, where 50% of the growth occurs at the inflection point, and the Gompertz curve, where about 37% of the total growth comes before the inflection point with the remainder occurring after the inflection point, to figure out which curve explains the electronic commerce adoption growth curve better.

Second, the first essay also has implications for public policymakers and managers. Turning first to public policymakers, the findings have important implications for understanding factors affecting new technology adoption in manufacturing industries, enabling policymakers to respond to changes effectively. By gaining a better understanding of the characteristics of the technology adoption growth curve, such as its nonlinear and asymptotic aspects, policymakers can allocate their resources and investments more efficiently. Furthermore, policymakers can have a clearer expectation of industry-level phenomena related to firms' adoption of new technologies, allowing them to design more effective government policies, such as tax incentives or subsidies, to promote technology investment. In particular, there have been calls for supply chain management (SCM) to make greater contributions to policymaking (e.g., Tokar & Swink, 2019; Richey & Davis-Sramek, 2022). For managers, this essay highlights the importance of industry-level characteristics, such as the firm death rate and the interaction between average firm size and industry concentration. For instance, in sectors with high import competition, such as apparel manufacturing, firms may feel greater pressure to adopt electronic commerce compared to sectors with low import competition, such as food manufacturing. Similarly, organizations operating on a national scale, such as Ford, GM, Chrysler, and Tesla, may need to consider increased investment in technological innovation compared to regional organizations, such as local wood products and printing firms.

Third, the results for the second essay (Chapter 2) makes a significant contribution to the SCM literature in various ways. The first theoretical contribution of this essay addresses the increasing demand for more specific and clearly defined dependent variables in existing logistics and SCM research papers. Richey et al. (2022) argue that proposed outcomes should be coherent, measurable, and applicable in real-life situations. The dependent variable of this essay, labor

productivity, fulfills these criteria and serves as a major index for many SCM companies. Moreover, it is worth noting that many new technologies, including electronic commerce, are designed to enhance labor productivity. The second theoretical contribution is related to generalizability. Previous papers, such as Brynjolfsson (1993), Kohli and Devaraj (2003), and Sabherwal and Jeyaraj (2015), have identified sample bias, inadequate sample size, and inappropriate measures as potential reasons for the inconsistent results in studies on new technology adoption. In this essay, I utilize data spanning over 20 years from the U.S. Census Bureau, which surveys a stratified random sample of companies covering the entire U.S. manufacturing industry population. The third theoretical contribution lies in the precise measurement of the variable of electronic commerce. Another potential reason for inconsistent findings in previous studies on new technology adoption is the variation in how different surveys measure concepts, as suggested by Sabherwal and Jeyaraj (2015). By employing a consistent definition of the electronic commerce variable and collecting data for over 20 years, the Census Bureau dataset used in this essay ensures a more robust analysis.

Fourth, the second essay also provides implications for practitioners. Firstly, the findings offer additional evidence of the positive relationship between new technology adoption and efficiency gains in both direct and indirect cost aspects. Policymakers can utilize this information to create better government policies, such as tax incentives or subsidies, to promote technology investment. For managers, the essay suggests that the outcomes of electronic commerce adoption encompass not only direct costs, such as labor productivity, but also indirect costs, such as selling, general, and administrative expenses (SG&A). Furthermore, the second essay has implications for both policymakers and managers. The first implication of the findings is that new technology adoption in manufacturing industries improves labor productivity and reduces

SG&A expenses. The productivity paradox literature has debated whether investment in new technologies brings meaningful benefits to companies (e.g., Brynjolfsson et al., 2020; Brynjolfsson et al., 2018; Polak, 2017). However, this essay provides evidence of the positive relationship between new technology adoption and efficiency gains in both direct and indirect cost aspects. Policymakers can utilize this information to develop better government policies, such as tax incentives or subsidies, to promote technology investment. For managers, the second essay suggests that the implementation of electronic commerce has a significant impact on firms' labor productivity in the manufacturing sector. However, many sectors still exhibit relatively low levels of electronic commerce adoption rates, around 50% in 2019. In particular, the Bureau of Labor Statistics indicates that overall labor productivity in the U.S. manufacturing industry has been declining since 2013. Therefore, some industries, including the food manufacturing sector, have not fully capitalized on the benefits of new technologies. The findings in the second essay suggest that there is ample room for further improvement and encourage firms to prioritize the adoption of online processes and automation technologies.

Last but not least, apart from the implications for theory and practice, the findings from this dissertation have a few limitations and suggest several fruitful directions for future research. Firstly, the analysis in the first essay is limited to the industry level, as it is constrained by the available data sources. Consequently, my analysis focuses on variations between industries. This limitation raises concerns regarding the generalizability of the findings to individual firms, as the essay does not explore the heterogeneity within manufacturing sectors. For example, examining the impact of firm size within an industry on the adoption of new technology would enhance the understanding of the technology adoption process in firms. Secondly, this dissertation examines the antecedents and outcomes of electronic commerce adoption process using data exclusively

from the United States. While the findings contribute valuable insights, they may not represent technology adoption processes in organizations outside of the U.S. It would be interesting to examine data from firms in other countries to compare and contrast their technology adoption processes. Thirdly, the data sources used in my research provide yearly data. However, utilizing quarterly data or even monthly data could offer a more detailed explanation of the technology adoption processes. If there are sources available with monthly data, they would provide greater temporal granularity for analysis. Furthermore, the adoption rate of electronic commerce is collected at a NAICS code level, specifically within the manufacturing sector, due to the constraints of the dissertation's data source, the industry-level E-Commerce Statistics from the U.S. Census Bureau. Future research could examine the heterogeneity within manufacturing sectors using firm-level data from alternative sources. This would broaden the understanding of the technology adoption process in firms. Moreover, while this essay focuses on the electronic commerce adoption process within the manufacturing sector (NAICS 311 to 339), future research could extend its scope to other industries, such as retail and service sectors, to investigate the impacts of new technology adoption.

In summary, the results derived from this dissertation present more fresh inquiries than the initial set of questions of this research project. I aspire for these findings to serve as a compass for enhancing managerial practices and to contribute adjustments to current theories, enabling scholars to achieve the ultimate objective of scientific investigation: advancing our understanding of the connections between phenomena within our respective fields of study.



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