The Technology Paradox Explained in Stages and Technology Presence

Benjamin Yeo*

Seattle University, USA.

Delvin Grant

DePaul University, USA.

Abstract

The technology productivity paradox reflects scholars' disagreement about the impact of tech investment on productivity. Economic regions are not equal, and cluster theory confirms that regional clusters of specific industry types fuel growth and innovation. Furthermore, the stages of growth theory suggests regions perform differently as they go through different stages. We use U.S. regional economic data from Moody's Analytics to explain the paradox. The results show regions with a heavy tech presence are better able to leverage tech investment for regional productivity. Furthermore, tech investment impact varies with stages of growth. Our research method enables a richer analysis and improved technology productivity paradox understanding. The findings have implications for managing regional development policy and strategy and tech investment decisions in the U.S. and abroad.

Keywords: Technology Investment, Regional Productivity, Industry Cluster, Regional Development

JEL Classifications: O00, O01, O04

* Corresponding author
E-mail address: benjkyeo@gmail.com
Address: 901 12th Ave, Seattle University, Seattle, WA 98122, USA.

1. Introduction

The debate on high-tech investment influence on productivity commenced in the early 1990s (Brynjolfsson, 1993) and continues today. Some argue technology does not improve productivity (Abdi, 2008; Ho et al., 2011; Sabherwal & Jeyaraj, 2015), and others disagree (Huang et al., 2006; Kleis et al., 2012; Kossaï & Piget, 2014; Mithas & Rust, 2016). IT investment is important to an economy (Cavallo, 2016), has a strong relationship with productivity, and its absence negatively affects economies. Regions with technology clusters have a stronger tech presence that serve as a catalyst for regional economic performance (Cooke, 2001; Feser et al., 2008).

The technology productivity paradox debate reflects scholars' disagreement on tech investment impact on productivity. Some believe measurement problems challenge researcher's ability to isolate technology productivity impact (Richard et al., 2009). Others believe the paradox results from inappropriate methodological choices, mismanagement by developers and IT users, and overlooking its aggregate statistics contribution (Brynjolfsson, 1993; Brynjolfsson & Hitt, 1996). Productivity is a measure of performance that includes the economic contribution of technology (Brynjolfsson, 1993). Tech investment includes computers, software, and communications equipment (Pakko, 2002) to support operations, strategy, or innovation. Its impact is studied in companies (Mithas & Rust, 2016; Pakko, 2002), industries (Abdi, 2008), and countries (Indjikian & Siegel, 2005; Spring et al., 2017; Vranakis & Chatzoglou, 2011). However, company studies provide more consistent results (Abdi, 2008; Grant & Yeo, 2018; Sabherwal & Jeyaraj, 2015; Schryen, 2013). This prompts calls for more industry-level research (Crowston & Myers, 2004; Piget & Kossaï, 2013). Despite the disagreement and debate, the paradox does not deter companies and regions from investing in technology. This motivates our decision to employ an innovative approach to tech investment impact on regional U.S. productivity using stages of growth (Porter, 2011) and cluster theory (Porter, 1998b) to explain the technology paradox. Our findings provide new insights on the technology paradox as a tech investment decision tool for managers and regional policymakers.

The rest of the paper is organized as follows. Section 2 includes a literature review on tech investment, the impact of technology, theoretical framework, and research questions. Section 3 includes the research method, variable operationalization, and research model. Section 4 includes the descriptive findings and predictive analysis results. The paper ends with a summary, research contributions, managerial and policy implications, limitations, and future research directions.

2. Literature Review

2.1. Technology Investment

Technology investment includes both hardware and software (Gill et al., 2019) and it is known to positively influence performance (Huang et al., 2006; H. Lee et al., 2016; Pakko, 2002; Vranakis & Chatzoglou, 2011) such as growth, competitiveness, and operational efficiency (Kwon, 2007). There is a positive relationship between tech investment and economic performance of developing and developed countries (Indjikian & Siegel, 2005). Nonetheless, there are lingering concerns about tech investment impact (H. Lee et al., 2016; Vranakis & Chatzoglou, 2011). The first is the productivity paradox (Brynjolfsson & Hitt, 1998; Richard et al., 2009) and second are results from recent studies (Grant & Yeo, 2018; H. Lee et al., 2016; Vranakis & Chatzoglou, 2011).

Justifying tech investment is challenging (Joshi & Pant, 2008) and hard to quantify (Gunasekaran et al., 2001). The first reason is that the impact of tech investment on productivity is unclear. Some studies find no impact (Ho et al., 2011; Motiwalla et al., 2005), while others do (Huang et al., 2006; Im et al., 2001). The second reason is that studies with different contextual factors, research methods, and measures influence the impact of technologies (Grant & Yeo, 2018; Osei-Bryson & Ko, 2004). The third reason is that measuring tech investment impact is difficult (Joshi & Pant, 2008; Richard et al., 2009). This is why Brynjolfsson and Hitt (2003) recommend using more accurate tech systems and business practice measures to better represent different aspects of a construct. Perfect constructs that capture the complexities of the industry or country impact of tech investment are hard to construct. The end results are explanations that are less conclusive. Tech investment studies should improve how to better measure relevant constructs, restrict implications from them, and understand their strengths and weaknesses. The fourth reason is that tech ROI requires professionals to consider contextual factors such as IT-enabled intangible assets, technology capability (Huang et al., 2006), and company knowledge (Liu et al., 2014). Contextual factors vary, and their impact on firms, industries, and regions changes over time. Grant and Yeo (2018) find that technologically advanced global industries benefit less from tech investments. They found evidence that human capital is a better predictor of industry performance. Conversely, companies with effective tech capabilities perform better (Ramdani, 2012; Santhanam & Hartono, 2003). This suggests the presence of technology affects how tech investments are leveraged. Therefore, tech investment impact studies should consider technology contexts.

2.2. Technology Impact

Development is a form of economic growth (Zheng et al., 2018) which includes productivity, the environment, and societal improvement. We view technology as information and communication technologies (ICT), an umbrella term for computers, applications, systems, hardware, broadcasting technologies, and mobile devices. Other technologies include manufacturing methods, industrial and chemical processes, and development methods. The Organisation for Economic Co-operation and Development (OECD) posits that technology helps to reduce transaction costs, inventory costs, cycle times, improve flexibility, product quality, economic growth, country benefits, efficiency, and productivity (Measuring the Impacts of ICT Using Official Statistics, 2008).

Technology impact on development occurs at the individual, group, and institutional levels (Sawyer & Chen, 2003) and influences industry performance (Yeo & Grant, 2018, 2019b). This is reflected in sales and profit measures (Botello & Pedraza Avella, 2014), turnover and profitability (Koellinger, 2006) and firm profitability (Kossaï & Piget, 2014), among others. Studies have also used other macro indicators like productivity and growth (March & Sutton, 1997), employment growth (Baldwin et al., 1995), employee wages (Audretsch et al., 2001), GDP growth, jobs and service (World Development Report 2016: Digital Dividends, 2016), trade (Bankole et al., 2015), school performance (Marks & Printy, 2003), and others (Lind et al., 2000). Factors that drive performance and development include a capable workforce and country infrastructure (Archibugi & Coco, 2004; Bankole et al., 2015; Bollou, 2006). In addition, strategic and competitive factors (Kossaï & Piget, 2014) also play a role. These may include financial factors such as lending practices (Obamuyi et al., 2012), interest rates (Pradhan et al., 2015; World Development Report 2016: Digital Dividends, 2016), external financing (Asamoah, 2011; Yeo & Grant, 2019b). This study adopts a macro level analysis and focuses on regional economic performance, using real GDP data.

2.3. Theoretical Framework

Stages of growth explain the evolutionary behavior of technology, economic, social, and other systems (Kucharavy & De Guio, 2011). It was first applied to business in 1974 (Gibson & Nolan, 1974) to manage technology use (Galliers & Sutherland, 1991) as information systems became more complex (Duane & O'Reilly, 2017). It has been widely used to discuss lean implementation (Netland & Ferdows, 2016), social media profiles (Duane & O'Reilly, 2017), product life cycles, innovation (Schwab & Sala, 2012), end-user computing (Jayasuriya, 1993), information centers (Magal et al., 1988), technology-based ventures (Kazanjian, 1988), information systems planning (Teo & King, 1997), and IT portfolio management (Jeffery & Leliveld, 2004).

The most used version has four stages. However, it has been employed to model regional economic productivity as a three-stage model: factor, efficiency, and innovation (Porter, 2011). Nonetheless, the three-stage model is similar to the four-stage model. In stage 1 of the four-stage model, regional economic activity starts slowly as investments and innovation need time to ramp up and their impact manifested. Stage 1 sets the stage for accelerated regional growth in stage 2, the best performing stage where returns from investments are realized. Accelerated growth is unsustainable and levels off in stage 3 as regions reach their economic plateau. Growth declines in stage 4, requiring new investment, innovation, and product development to invigorate new growth (Schwab & Sala, 2012). These strategies enable companies to reinvigorate growth and maintain their competitive advantage. Examples of such strategies are exhibited by Apple and UPS (Shields et al., 2018).

Cluster theory suggests regions with a heavy concentration of a type of industry are better poised to leverage resources and induce growth. A cluster is a geographical concentration of interconnected and related organizations and institutions that share a common industry and complement each other in their operations. They have a high presence of a specific industry sector (Porter, 1998a). Notable U.S. examples are the high-tech cluster in San Jose, CA, and the life sciences cluster in Philadelphia, PA. High-tech clusters attract complementary skilled workers by providing more job opportunities than low-tech regions (Maskell & Kebir, 2006), increasing the concentration of high-tech activities. Clusters are loci of innovation, fundamental to the modern economy (Ferras-Hernandez & Nylund, 2019; Smorodinskaya & Katukov, 2019). They are necessary for high-tech production (Boldyreva et al., 2020). Therefore, high-tech regions are better able to leverage tech investment and experience stronger tech investment impact.

2.4. Research Questions

We posit that tech investment impact varies with stages of growth (Grant & Yeo, 2018) and the presence of high-tech (i.e., "tech presence"). We advance two research questions.

RQ 1: How does tech investment affect U.S. regional economic productivity from 1990 to 2016?

RQ 2: Does tech presence influence tech investment impact on U.S. regional economic productivity from 1990 to 2016?

The answers explain how tech investment influences regional productivity with a different tech presence in each stage of growth. They provide alternate explanations for the productivity paradox. Lessons learned are applicable to U.S. and international regional productivity and development.

3. Research Method

We used annual time series regional economic data from Moody's Analytics. The raw data include the following variables: high-tech wage, employment, and real GDP by U.S. Metropolitan Statistical Areas (MSAs) from 1990 to 2016. The variables provide a context for the stages of growth to explain the impact of tech investment on regional productivity.

States are large geographies with considerable economic variations. For example, in California, per capita income in 2018 dollars for Santa Clara County is $52,461, while Merced County is $21,634 (United States Census Bureau, 2018). At the same time, concentrations of economic activity often transcend smaller county boundaries. For example, the Greater Philadelphia region, known for its life sciences cluster, comprises counties in Pennsylvania, New Jersey, Delaware, and Maryland (DeVol, Yeo, et al., 2009). Metropolitan statistical areas (MSAs) are groups of counties with concentrations of economic activity, have and used in regional analyses (DeVol, Yeo, et al., 2009; Wong et al., 2006, 2007). They capture economic activity better than states and counties, thus reflecting tech investment impact better. Therefore, we use the MSA level as a geographical unit for analysis rather than states or counties.

The period of the data used in this research was selected for two historically important economic events: first, 1990 was the start of the Internet and e-commerce era, and second, it covers the Great Recession from 2007 to 2009.

3.1. Variable Operationalization

There are three primary variables in our study: tech investment, real economic productivity, and tech presence. Table 1 summarizes the operationalizations. In this section, we elaborate on these operationalizations to demonstrate how we computed them from the data.

Table 1. Variable Operationalizations

Variable	**Operationalization**
Tech investment	High tech wage growth from the preceding year by MSA
Regional economic productivity	Real GDP per worker by MSA by year
Tech presence	Location quotient of the high-tech industry in each MSA by year

Tech investment. Technology generating activities lead to wage differentials, and tech investment results in large wage premiums (Tan & Batra, 1997). Increases in high-tech investment usually accompany high-tech wage increases because investments require employing technology workers who earn a premium compared to non-technology workers (Turcotte & Rennison, 2004). Advanced technology investments such as ERP and SCM require highly skilled labor such as system administrators, database administrators, data analysts, technical support staff, and programmers to use, manage, and maintain. Wages increase highly skilled, productive, and experienced workers who cost more (Jain, 2019). Furthermore, blue collar workers in technology intensive firms earn higher wages (Betcherman, 1991). Changes in tech investment account for a substantial proportion of rising dispersion in wages (Dunne et al., 2004). These findings suggest wage growth can serve as a proxy for tech investment.

Our research objective is to understand how tech investment and not the targets of investment (tech products, services, or human capital) affect productivity. The latter cannot be adequately addressed due to data limitations. The dataset captures high-tech wage growth increase. Wages and productivity are important economic indicators (Jain, 2019). Wage growth, a measure of worker productivity in market economies (Bickenbach et al., 2015), is the reward for production. Consequently, productivity increases are reflected in higher wage growth because wages follow productivity improvements (Jain, 2019).

High-tech industries are identified by the U.S. Census North American Industry Classification System (NAICS) (United States Census Bureau, 2012). We used raw wage disbursement from the dataset to compute annual wage growth for high-tech industries from the preceding year to derive high-tech wage growth for each MSA. This is computed as the percentage change in wage disbursement by MSA from the preceding year and serves as the tech investment proxy for each MSA in a specific year (Equation 1).

Please submit tables as editable text and not as images. Tables can be placed either next to the relevant text in the article or in separate page(s) at the end. Please number tables consecutively in accordance with their appearance in the text and place any table notes below the table body. Be sparing in the use of tables and ensure that the data presented in them do not duplicate results described elsewhere in the article. A table format example appears below.

$$I_{i,t} = \left[\frac{\sum(W_{i,t}) - \sum(W_{i,t-1})}{\sum(W_{i,,t-1})}\right] * 100\% \quad (1)$$

Where

$I_{i,t}$ = tech investment in MSA *i*, and year *t*.

$W_{i,t}$ = wage disbursed per worker in MSA *i*, in the high-tech industry, in year *t*.

$W_{i,t-1}$ = wage disbursed per worker in MSA *i*, in the high-tech industry, in year *t - 1*.

Regional economic productivity. We compute regional economic productivity for each MSA by dividing the real GDP for each region in a specific year by the total number of workers in the region of the same year (DeVol, Wong, et al., 2009; Wong et al., 2006). This represents real economic output per worker for each MSA. Real GDP instead of nominal adjusts for inflation. Since technologies improve efficiencies across different business processes including both high-tech and non-high-tech (Goldschlag & Miranda, 2020; Kask & Sieber, 2002; Schreyer, 2000), and both high-tech and non-high-tech workers use the same technologies, albeit with different leverage, we use the total number of workers instead of high-tech workers only, to capture a region's productivity (Equation 2).

$$P_{i,t} = \frac{RGDP_{i,t}}{E_{i,t}} \quad (2)$$

Where

$P_{i,t}$ = real economic productivity of MSA *i*, in year *t*.

$RGDP_{i,t}$ = real GDP in MSA *i*, in year *t*.

$E_{i,t}$ = total number of workers in MSA *i*, in year *t*.

Tech presence. We measured tech presence using location quotients (LQ) that identify industry specializations in a geographical region (Pavelkova et al., 2021). We computed an MSA's tech presence using the U.S. tech presence as a benchmark by dividing an MSA's share of high-tech workers to the national share of high-tech workers. High-tech workers are defined as workers in high-tech industries based on North American Industry Classification System (NAICS) codes (DeVol et al., 2016; Yeo, 2010) (Equation 3). The result is a relative concentration of the high-tech industry of the MSA. When the LQ of the high-tech industry in an MSA is greater than 1, this MSA's tech presence is stronger than the U.S. average. We define MSAs with a strong tech presence, that is, having a high-tech cluster, as those whose LQ is greater than or equal to 1.

$$LQ_{i,j,t} = \left(\frac{x_{i,j,t}}{\sum x_{i,t}}\right) / \left(\frac{1_{US,j,t}}{\sum x_{US,j,t}}\right) \quad (3)$$

Where

$LQ_{i,j,t}$ = High-tech industry location quotient of MSA *i*, in the high-tech industry, denoted by j, in year *t*.

$x_{i,j,t}$ = Employment in MSA *i*, in the high-tech industry, *denoted by j,* in year *t*.

$\sum x_{i,t}$ = Sum of all employment in MSA *i* in year *t*.

$x_{US,j,t}$ = Employment in the US, in the high-tech industry, denoted by *j*, in year *t*.

$\sum x_{US,j,t}$ = Sum of all employment in the US in year *t*.

3.2. Research Model

In this section, we use the variable operationalizations discussed in the preceding section to formulate our research model.

Technology innovation is an endogenous factor in economic production (Romer, 1990) and critical to economic growth (European Commission, 2008, p. 200; OECD, 2013). Tech investment is necessary for technical innovation. This is why it is included in our predictive model on regional performance. We built 26 regression models, one for each year to examine tech investment impact on annual productivity. Our research method, which employs 26 regression models in conjunction with cluster theory, enables a deeper annual analysis of tech investment impact on regional productivity. It enables a deeper understanding of previous studies on both sides of the productivity paradox debate. The 26 models produce 26 data points representing non-linear stages of growth.

The results from 1990-2015 represent stages of regional productivity, enable discussion of annual fluctuations in tech investment, and the relationship between tech investment and regional productivity. High-tech wage growth and real GDP per worker data are transformed by taking the natural log. This is appropriate for impact studies (Ko & Osei-Bryson, 2014) because Cobb-Douglas production functions for studying technology and productivity are exponential. They require log transformations in linear models (Brynjolfsson & Hitt, 1996; Menon & Lee, 2000).

Wage growth values were taken from 101 percentage points as the index because annual wage growth can be negative or zero. Therefore, a wage growth of 0% will be transformed to 101% to avoid the possibility of -100% high-tech wage growth. If this were to happen, we would end up with an index of 0 percentage points, and an invalid log score. There is usually a lag between tech investment and the technology impact due to periods of learning and adjustment (Brynjolfsson & Yang, 1996). Therefore, the resultant impact of technology on economic productivity is assessed in the subsequent year. This accounts for endogeneity, where high-tech wage growth, the independent variable, and the error term are correlated. For example, the technology investment impact in 2000, operationalized by wage growth from the preceding year, is assessed in the corresponding MSA real economic productivity in 2001. Figure 1 and Equation 4 illustrate our research model and operationalization. This relationship illustrates how tech investment and tech presence have impacted regional productivity over a quarter century. Since regions either have a tech industry cluster or not, we define tech presence as a dummy variable. We acknowledge other factors such as natural resources, can influence regional economic productivity (Porter, 2011). However, comparative data are not available in these denominations for this analysis. Our study focuses on tech investments operationalized by high-tech wage growth, reflecting the labor component in Porter's (2011) work. This approach is justified because technological resources impact far outweighs non-technological resources impact, such as land (Jorgenson et al., 2000; Oliner & Sichel, 2000).

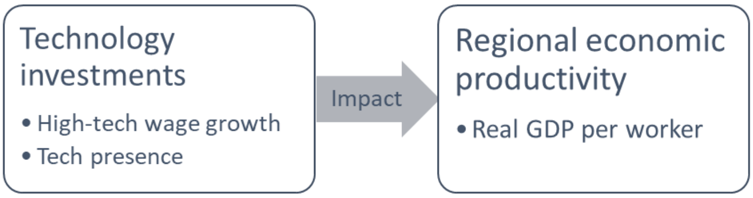

Figure 1. Research Model

$$lnP_{i,t+1} = \beta_0 + \beta_1 ln(I + 101)_{i,t} + \beta_1 T + \varepsilon_{i,t} \quad (4)$$

Where

$ln\ P_{i,t+1}$ = Natural log of real economic productivity (GDP per worker) of MSA i, in year $t+1$.

$\ln\ (I + 101)_{i,t}$ = Natural log of the technology investments using 101 as the index in MSA i, in year t.

T = Tech presence (dummy variable)

4. Findings

4.1. Descriptive Findings

Table 2 presents summary statistics (mean and standard deviation) of high-tech annual wage growth and real GDP per worker. Standard deviations of the mean high-tech wage annual growth by year are high because of unequal regional economics. Some MSAs have higher concentrations of high-tech industries. Tech investments, represented by their high-tech annual wage growth, vary considerably.

Table 2. Summary Statistics

Year	**High-tech wage annual growth**		**Annual Real GDP per worker**	
N = 373	Mean (%)	Std Dev	Mean ($Ths.)	Std Dev
1990	6.69	6.22	77.21	14.58
1991	6.02	5.27	78.06	14.47
1992	6.63	5.22	80.37	14.36
1993	4.73	4.21	81.19	14.47
1994	6.78	6.44	82.48	14.84
1995	3.14	2.72	82.60	15.28
1996	13.88	12.39	83.86	13.65
1997	10.03	9.90	85.00	13.85
1998	10.94	10.31	86.35	13.89
1999	13.05	12.56	88.34	14.37
2000	9.51	8.99	89.32	14.11
2001	0.95	0.99	89.74	14.20
2002	-3.88	-3.82	92.16	13.99
2003	0.00	-0.31	94.75	14.03
2004	5.02	4.37	96.86	14.78
2005	4.91	4.48	98.07	15.52
2006	7.63	6.79	98.89	15.50
2007	5.94	5.88	99.00	15.59
2008	3.71	3.51	98.82	15.21
2009	-1.39	-2.23	100.31	16.15
2010	2.09	2.10	102.83	16.25
2011	4.52	4.46	102.88	16.01
2012	4.19	4.40	102.78	16.27
2013	3.33	2.97	102.51	16.30
2014	5.22	4.93	102.59	16.92
2015	5.52	5.72	102.99	17.87
2016	4.26	3.99	102.50	18.07

4.2. Predictive Analysis

Figure 2 shows a summary of the R2 values plotted as a loess trend line to visualize local trends. All 26 regression models were significant ($p < 0.001$). Since the impact is assessed in the subsequent year, the range of years in Figure 3 ends in 2015; hence, the 2015 impact is manifested in 2016. Figures 3 and 4 show the coefficients of the natural log of tech wage growth and tech presence plotted as loess trendlines. All coefficients were significant ($p < 0.001$).

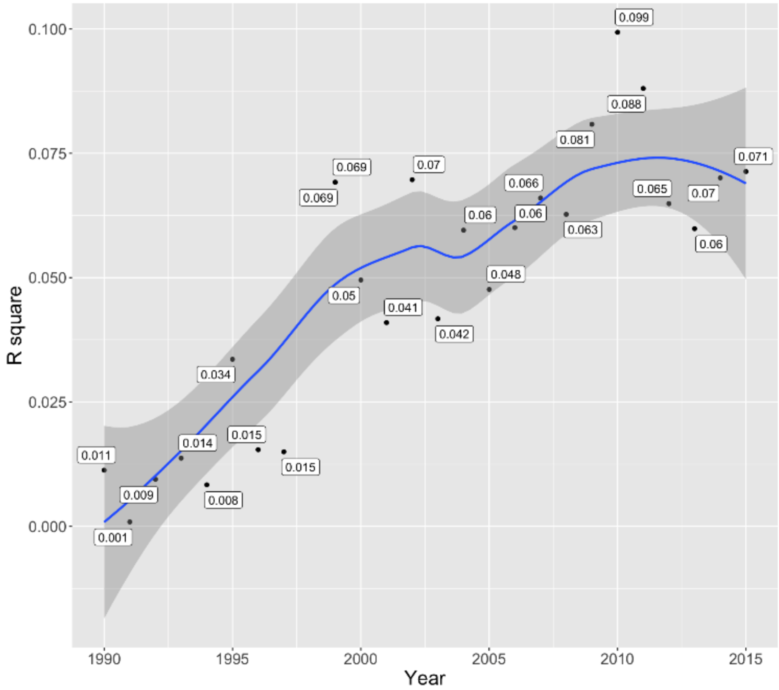

Figure 1. Summary of regression R2 Values

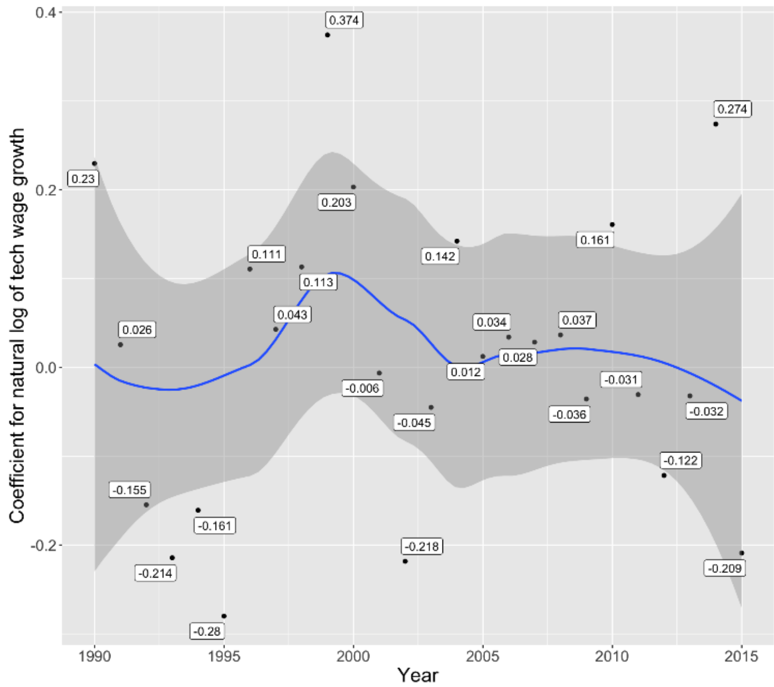

Figure 2. Summary of coefficients of tech wage growth

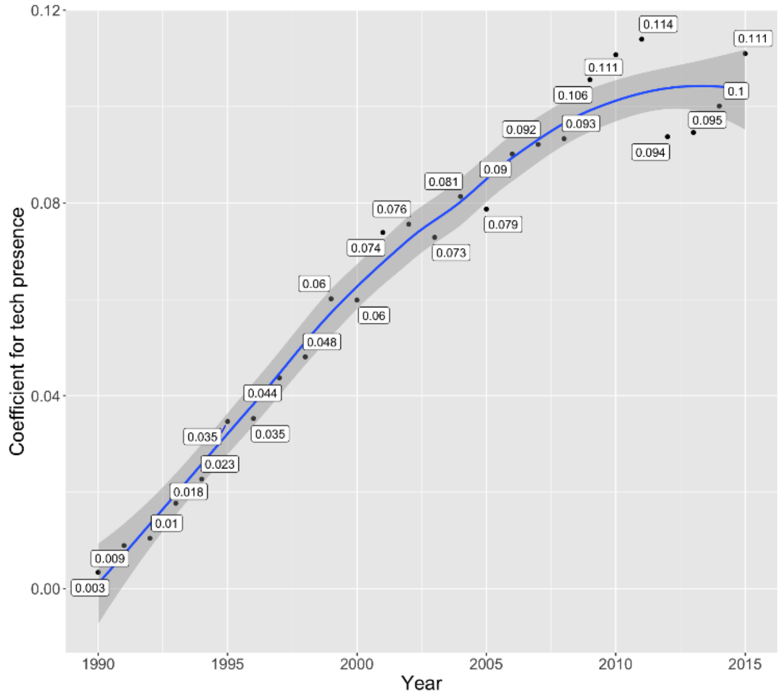

Figure 3. Summary of coefficients of tech presence

Early 1990s. The early 1990s were a period when the dot-com era began. Based on R2 values, in 1990, the model predicted only 1.13% of the variance in regional productivity, suggesting the presence of other contributing factors. However, this increased steadily, and by 1995, 3.36% of the variance was predicted (Figure 2). From 1990 to 1995, the coefficients of tech investment were very low and sometimes negative, suggesting businesses did not fully understand how to use the Internet to support business objectives (Figure 3). During this period, the profitability of dot-coms was not the main concern for investors (Whitefoot, 2017), and the most promising ones were not profitable (McCullough, 2018). Incidentally, the coefficients of tech presence show a steady increase from 0.003 in 1990 to 0.035 in 1995 (Figure 4). This suggests the increasing importance of being a high-tech cluster as the dot-com era took shape. This corresponds to stage 1, where tech investments and innovation begin to set the stage for accelerated regional growth.

Late 1990s. In the late 1990s, the years prior to the dot-com era were characterized by speculative investments (Smith, 2019) that led to the bubble (Whitefoot, 2017). The internet was a complex medium (Whitefoot, 2017), and businesses had unrealistic expectations of it (Smith, 2019). Based on R2 values after 1995, the models explained increasing proportions of the variance in regional productivity, from 1.54% in 1996 to 4.95% in 2000 (Figure 2). This period marks the height of the bullish dot-com era, where the value of equity markets grew exponentially as the technology-dominated NASDAQ index rose. This trend is exhibited in Figure 3, where the coefficients of tech investment increased from 0.111 in 1996 to 0.203 in 2000, albeit with fluctuations. The corresponding coefficients for tech presence continued to increase from 0.035 in 1996 to 0.060 in 2000, illustrating the continued importance of tech presence (Figure 4). This corresponds to Stage 2, where investment and productivity growth increase and tech investments start to have an impact.

Post millennium. In 2002, the bubble burst and the U.S. economy entered a bear market, with the NASDAQ returning to slightly over $1000 (Whitefoot, 2017), reflecting the decline of the dot-com era. From 2001 to 2003, the models' ability to explain regional productivity peaked at 6.97% in 2002 and declined to 4.18% in 2003 (Figure 2). During this period, the coefficients of tech wage growth declined and had a negative impact on regional productivity in 2003 (Figure 3). This is not surprising, as the dot-com crash resulted in a loss of confidence in tech investments. However, the importance of tech presence continued to increase, with a coefficient of 0.073 in 2003 (Figure 4). Even though tech investment impact declined, regions benefited from the output of high-tech industries. Businesses faced uncertainties about the impact of high-tech investment but continued to invest based on previous economic results. Large tech players like Amazon refocused their strategy and posted annual profits of $35 million (Whitefoot, 2017). This illustrates the start of Stage 3, where a plateauing of regional productivity growth from tech investments takes place.

The economy recovered in 2003, bringing revitalized confidence in tech investments. The models predict increasing amounts of variance – 6.60%, 6.27%, and 8.08% – in regional productivity during the Great Recession from 2007 to 2009, respectively (Figure 2). The uptrend, however, was slower than the late 1990s dot-com boom. Tech investment coefficients were positive after 2003 but fell to -0.036 in 2009 (Figure 3). Nonetheless, the coefficients of tech presence continued to increase until 0.106 in 2009 (Figure 4). Overall, the results indicate a slowing of growth in Stage 3, as tech investment impact decreased (Figure 3), but tech presence increased (Figure 4).

After the Great Recession. From 2010 to 2011, investments grew moderately as the economy recovered from the 2007–2009 Great Recession. Both tech investments and their magnitude of impact were higher than the preceding recession years but decreased by 2012 (Figure 3), reflecting economic skepticism and uncertainty. From 2014 to 2015, high-tech investments plateaued, accompanied by a decrease in variance explained (Figure 2). The tech investment impact was negative for several years (Figure 3), and the tech presence impact plateaued (Figure 4). These trends illustrate market saturation and lack of growth, suggesting a need to jumpstart another growth cycle (i.e., Stage 4) as tech investments result in diminishing regional productivity. Stage 4 characteristics signal the point where financial and other factors have more impact on productivity than technology (Grant & Yeo, 2018).

5. Discussion and Conclusion

5.1. Summary

This research employs stages of growth and cluster theory to investigate the impact of tech investment and tech presence on U.S. regional productivity from 1990 to 2015. Stage 1 exhibits slow productivity growth from tech investments as regions invest in tech infrastructure, spend time implementing it, and hire and train skilled labor to leverage technology. Stage 2 exhibits rapid productivity from speculative tech investment (Whitefoot, 2017) due to better leveraging of technology, increased efficiencies, and the use of best practices. At the peak of the dot-com, companies were better equipped to utilize technology, resulting in significant regional economic productivity. Stage 3 exhibits a flattening effect as the technology infrastructure matures, causing regional productivity to decline from additional tech investment. This is the effect of diminishing productivity where skilled labor (Grant & Yeo, 2018) and financial factors are more impactful than technology (Yeo & Grant, 2019b). This motivates regions to take action to move to Stage 4 to start a new cycle of growth and innovation to overcome diminishing returns (Sawaguchi, 2011). The dot-com era was fueled by hyped internet and e-commerce technology (Smith, 2019). Though necessary, after the Great Recession, they were no longer the primary drivers of regional productivity, consistent with previous industry findings (Grant & Yeo, 2018).

The stages of growth are consistent with efficiency and innovation (Porter, 2011), which are applicable to regional economic performance (Kucharavy & De Guio, 2011). In Stage 1, the reliance on factor endowments is similar to the presence of technology. In Stage 2, efficient technology use is critical for leveraging technology and strong performance. Stages 3 and 4 are reflected in the innovation stage, where tech investment is not the primary driver. Developing new products and processes are critical to sustainability (Schwab & Sala, 2012), while non-technical factors are also necessary for innovation and regional performance.

Regarding RQ1, we demonstrate that tech investment impact fluctuates yearly and that positive and negative tech investment impact regional economic productivity, sometimes significantly. With respect to RQ2, consistent with cluster theory, regions with a strong tech presence are better positioned for productivity growth from tech investments. Our findings show positive and negative tech investment impacts at different stages of growth.

5.2. Research Contributions

This study makes four contributions to the extant tech investment literature regarding the technology paradox. First, it fulfils a need for more industry research on tech investment impact on productivity (Crowston & Myers, 2004; Sabherwal & Jeyaraj, 2015; Schryen, 2013), and inconsistent findings (Schryen, 2013). Second, it provides alternate and plausible technology paradox explanations regarding how tech investment impact on U.S. regional productivity varies with Gibson and Noland’s (1974) stages of growth and cluster theory (Porter, 2011). Third, the impact of tech investment is not straightforward (Brynjolfsson & Hitt, 1998), due in part to measurement challenges (Grant & Yeo, 2018; H. Lee et al., 2016; Vranakis & Chatzoglou, 2011). Conventional methods are problematic (Hinton & Kaye, 1996), and challenging (Joshi & Pant, 2008), particularly when a single regression model is used, making it difficult to quantify (Gunasekaran et al., 2001). Nevertheless, using 26 regression models improve the findings, and is more rigorous to a single regression model. They enable an annual assessment of tech investment impact on regional productivity that would have been challenging. Fourth, the findings and lessons learned inform tech investments decisions with management and policy implications. The operationalization of regional economic productivity is a composite measure of industry productivity. Firms make up industries and their aggregate performance represents the industry. This allows our findings to be generalized to firms (A. Lee & Baskerville, 2003).

5.3. Managerial and Policy Implications

It is important for regional managers to recognize stages of growth and tech presence to inform decisions on tech investment, the presence of technology, and productivity. The relationship between tech investment and productivity is not straightforward. Technology is not the silver bullet to sustain economic growth (Zheng et al., 2018), as contexts affect its use and impact (Yeo & Grant, 2018, 2019b). California's Silicon Valley and Boston's Route 128 have contrasting economic performances based on different cultural contexts (Saxenian, 1996). In this research, contexts are stages of growth and tech presence that represent different economic conditions.

Between 1990 and 2016, tech investment positively and negatively influenced regional economic productivity. This does not imply that technology is immaterial. Rather, each growth stage requires different investment and innovation strategies, appropriate skilled labor, managing tech investment outcomes, and expectations. Ignoring stages of growth may lead to mismanagement of investment resources and stifle economic growth and development.

5.4. Using Stages of Growth to Inform Technology Investment

Regional managers and policymakers benefit from being familiar with the stages of growth. Technology investments are influenced by each stage of growth that has different outcomes. Each stage requires a different management strategy to be effective. Regional managers and policymakers should prioritize tech investment based on a region's stage of growth and adjust policies to the social contexts (Akpan, 2003; Mukand & Rodrik, 2002; Yeo & Trauth, 2009).

In Stage 1, technology is in its infancy. This requires regional managers and policymakers to exercise caution in heavily investing when it is unclear how best to utilize investment resources. This is consistent with our findings where tech investment had a negative impact because dot-coms during the dot-com era relied on hype rather than actual profitability (Whitefoot, 2017), and many crashed. For example, applying this to our current context, new technologies like artificial intelligence (AI) enjoy strong hype but are in their infancy. Even though AI is poised to be a mainstay of technological innovation in the foreseeable future, a region or firm that is beginning to see growth in AI may benefit from a more cautious approach to rapid heavy investments.

Stage 2 exhibits significant productivity gains as technologies are better utilized. This is consistent with our findings during the peak of the dot-com era. Productivity gains are often accompanied by human capital investments to train and hire skilled workers to exploit technologies. Therefore, investment strategies and policies should address the growth of human capital. For example, universities and trade schools may be incentivized to recruit, train, and develop new talent to fill jobs during Stage 2.

In Stage 3, a region's technology matures. This is coupled with productivity declines as diminishing returns set in. Our results show that tech presence continues to be important in driving regional economic productivity in this stage. Regional managers and policymakers should be cautious about increasing tech investments and recognize the relevance of non-technical factors to drive innovation. For example, access to finance can be a driver of industry performance (Yeo & Grant, 2019b). Leveraging synergies between a region's mature tech presence and the established financial industry can be instrumental in maintaining competitive advantage.

Finally, growth declines in Stage 4. Innovation becomes key to trigger new growth opportunities (Schwab & Sala, 2012). Prior to this stage, regional managers and policymakers should have identified opportunities to revitalize regional productivity and growth. These become new targets for tech investment.

5.5. Setting Expectations by Context

Likewise, each stage of growth comes with different expectations. Tech investment is not a magical bullet that triggers economic performance. Regional managers and policymakers should set realistic growth expectations by benchmarking regions with similar stages of growth contextual factors, such as technology, human capital capabilities, and performance. Appropriate benchmarking is necessary for managing tech investment and productivity expectations. Regions have different resources, and regional performance varies widely. Leveraging best practices from appropriately benchmarked regions helps regional managers and policymakers understand what it takes to grow a region.

Stage 2 exhibits significant productivity gains as technology is better utilized. This is consistent with our findings during the peak of the dot-com era. In Stage 3, productivity sharply declines as diminishing returns set in as a region's technology matures, placing emphasis on non-technical factors to drive innovation. This is corroborated by our findings and with Grant and Yeo's (2018) global study of industry performance of technological advancement. When technological advancement is high, human capital becomes more impactful than tech investment. These types of human capital and technologies depend on regional contexts for inherent advantages. For example, regions with strong tech presence may rely on information technology investments to spur growth in Stage 2. By the same token, heavy manufacturing regions should rely on manufacturing technologies, and pharmaceutical regions should focus on healthcare technologies.

Regardless of the types of technologies, regional managers and policymakers should be wary of Stage 4, where there is a need for a new growth. This is because tech investment is no longer the primary economic performance driver (Grant & Yeo, 2018). However, this requires innovation, an endogenous factor of production (Romer, 1990), which may be unavailable or unaffordable to some regions. As our findings show, tech presence continues to play an important role in regional economic productivity (Figure 4). Without establishing a strong and mature tech presence, some regions may need to rely on other regional resources to spur growth.

5.6. Going Beyond Technology Investment

Finally, low R2 values (Figure 2) suggest tech investment is relevant in explaining a small portion of regional performance. However, there are other factors that come into play. Tech investment impact can also vary as identical technology may be utilized differently, resulting in different outcomes (Yeo & Grant, 2018). Access to finance and lending practices (Yeo & Grant, 2019b), a skilled workforce (Yeo & Grant, 2019a), management practices (Yeo & Grant, 2018) and technology also play important roles and regions possess varying amounts of them. This work illustrates stages of growth and tech presence can inform decisions on how much to invest, when to invest, targets of investment, and innovation strategy.

The coefficients of tech investment in each period (Figure 3) suggest the corresponding importance of tech investment. They suggest the presence of other factors that trigger economic performance. Since tech presence is continuously important (Figure 4), and not every region has an equal tech presence, these other factors may differ for different regions. For example, some regions may be driven by agriculture rather than high tech industries. Nonetheless, there is technological innovation in all industries and regional managers and policymakers should identify factors based on each region's unique context.

5.7. Limitations and Future Research

Regarding measurement complexities (Brynjolfsson, 1993; Brynjolfsson & Hitt, 2003), technology investments are better measured with decomposed components rather than aggregated. Such components are not easily obtainable for every MSA and for the period of this study. Nonetheless, the aggregated measure provides an in-depth view of tech investment and relevant factors. Future studies can control macroeconomic downturns to enrich the study.

Even though stages of growth and tech presence explain how contexts influence regions' tech investment impact, each stage is influenced by financial, social, economic, cultural, and political contextual factors. Data on these aspects are difficult to obtain, measure, and compute consistently by MSA over 26 years. Regions are not equally endowed with the same tech presence and resources. Hence, measuring access to natural resources in each region can enrich the analysis. Another measure is the degree of how leveraging technology changes the role of tech investment. Comparative data on technology spending and use can also further enhance the model.

This study used high-tech wage growth as the proxy for tech investment, for lack of a better measure. We are unable to exclude annual wage increases unrelated to productivity. However, increasing tech investment is accompanied by high-tech wage growth. While the literature supports its use (Dunne et al., 2004; Tan & Batra, 1997; Turcotte & Rennison, 2004), direct measures of each tech investment target can improve the analysis. It is likely tech investment impact on productivity and development differ globally for financial, social, economic, cultural, and political reasons. An important research question is the type of tech investment to make, (technological vs non-technological) and the timing, based on a region's stage of growth. Internet and mobile investments are more beneficial for underdeveloped and developing regions than enterprise systems investments, and insufficient funding leads to poorly developed and maintained internet and mobile platforms, which negatively affects performance (Yeo & Grant, 2018). Therefore, the ability to separate tech investment spending can narrow down how specific tech investments may impact outcomes and productivity performance.

References

Abdi, T., (2008), "Machinery & equipment investment and growth: Evidence from the Canadian manufacturing sector," *Applied Economics*, 40(4), 465-478.

Akpan, P. I., (2003), "Basic-needs to globalization: Are ICTs the missing link?" *Information Technology for Development*, 10(4), 261-274.

Archibugi, D. and Coco, A., (2004), "A new indicator of technological capabilities for developed and developing countries (ArCo)," *World Development*, 32(4), 629-654.

Asamoah, G. N., (2008), "The impact of the financial sector reforms on savings, investments and growth of gross domestic product (GDP) in Ghana," *International Business & Economics Research Journal (IBER)*, 7(10), 30-34.

Audretsch, D. B., van Leeuwen, G., Menkveld, B., and Thurik, R., (2001), "Market dynamics in the Netherlands: Competition policy and the role of small firms," *Competition Policy in Dynamic Markets*, 19(5), 795-821.

Baldwin, J. R., Raffiquzzaman, M., and Statistics Canada, G. of C., (1995), "Selection Versus Evolutionary Adaptation: Learning and Post-entry Performance," *International Journal of Industrial Organization*, 13(4), 501-522.

Bankole, F. O., Osei-Bryson, K. M., and Brown, I., (2015), "The Impacts of Telecommunications Infrastructure and Institutional Quality on Trade Efficiency in Africa," *Information Technology for Development*, 21(1), 29-43.

Betcherman, G., (1991), "Does technological change affect union wage bargaining power?" *British Journal of Industrial Relations*, 29(3), 447-462.

Bickenbach, F., Liu, W. H., and Niehues-Jeuffroy, H., (2015), "On the puzzling slowdown of wage and productivity growth in T aiwan: Evidence from a comparison with S outh K orea," *Asian-Pacific Economic Literature*, 29(1), 82-101.

Boldyreva, S. B., Alimov, A. K., Adilchaev, R. T., Idzhilova, D. V., and Chadlaeva, N. E., (2020), "On the development of cluster theory," *International Journal of Management (IJM)*, 11(11).

Bollou, F., (2006), "ICT infrastructure expansion in sub-Saharan Africa: An analysis of six West African countries from 1995 to 2002," *The Electronic Journal of Information Systems in Developing Countries*, 26(1), 1-16.

Botello, H. A. and Pedraza Avella, A., (2014), "Las Tecnologías De La Información Y La Comunicación Y El Desempeño De Las Firmas: Evidencia De Las Firmas Industriales Del Ecuador (The Information Technology and Communication and Firm Performance: Evidence from Firms Industrialists Ecuador)," *CPR LATAM-Communication Policy Research Conference*.

Brynjolfsson, E., (1993), “The productivity paradox of information technology,” *Communications of the ACM*, 36(12), 66-77.

Brynjolfsson, E. and Hitt, L., (1996), “Paradox lost? Firm-level evidence on the returns to information systems spending,” *Management Science*, 42(4), 541-558.

Brynjolfsson, E. and Hitt, L. M., (1998), “Beyond the productivity paradox: Computers are the catalyst for bigger changes,” *Communications of the ACM*, 41(8), 49-55.

Brynjolfsson, E. and Hitt, L. M., (2003), “Computing Productivity: Firm-Level Evidence,” *The Review of Economics and Statistics*, 85(4), 793-808.

Brynjolfsson, E. and Yang, S., (1996), “Information technology and productivity: A review of the literature,” *Advances in Computers*, 43, 179-214.

Cavallo, M. A., (2016), “The growing importance of the technology economy,” *CIO*.

Cooke, P., (2001), “Clusters as key determinants of economic growth,” *Cluster Policies-Cluster Development*, 2, 23-38.

Crowston, K. and Myers, M. D., (2004), “Information technology and the transformation of industries: Three research perspectives,” *The Journal of Strategic Information Systems*, 13(1), 5-28.

DeVol, R., Lee, J., and Ratnatunga, M., (2016), “*2016 State Technology and Science Index. Sustaining America's Innovation Economy*,” Milken Institute.

DeVol, R., Wong, P., Bedroussian, A., and Yeo, B., (2009), “*Energizing California: Mapping Chevron's Economic Impacts on the Golden State*,” Milken Institute.

DeVol, R., Yeo, B., Chatterjee, A., Wong, P., and Bedroussian, A., (2009), “*The Greater Philadelphia Life Sciences Cluster 2009*,” Milken Institute.

Duane, A. and O'Reilly, P., (2017), “A conceptual stages-of-growth model for managing a social media business profile,” *The Irish Journal of Management*, 36(2), 78-98.

Dunne, T., Foster, L., Haltiwanger, J., and Troske, K. R., (2004), “Wage and productivity dispersion in United States manufacturing: The role of computer investment,” *Journal of Labor Economics*, 22(2), 397-429.

European Commission, (2008), Knowledge for Growth European Issues and Policy Challenges (EUR 23725 EN).

Ferras-Hernandez, X. and Nylund, P. A., (2019), “Clusters as Innovation Engines: The Accelerating Strengths of Proximity,” *European Management Review*, 16(1), 37-53.

Feser, E., Renski, H., and Goldstein, H., (2008), “Clusters and economic development outcomes: An analysis of the link between clustering and industry growth,” *Economic Development Quarterly*, 22(4), 324-344.

Galliers, R. D. and Sutherland, A. R., (1991), "Information systems management and strategy formulation: The 'stages of growth'model revisited," *Information Systems Journal*, 1(2), 89-114.

Gibson, C. and Nolan, R. L., (1974), "The four stages of EDP growth," *Harvard Business Review*, 52, 74-88.

Gill, A., Mand, H. S., Amiraslany, A., and Obradovich, J. D., (2019), "The Impact of Internal Financing Sources and Bank Financing on Information Technology Investment," *International Journal of Business & Economics*, 18(1).

Goldschlag, N. and Miranda, J., (2020), "Business dynamics statistics of high tech industries," *Journal of Economics & Management Strategy*, 29(1), 3-30.

Grant, D. and Yeo, B., (2018), "A global perspective on tech investment, financing, and ICT on manufacturing and service industry performance," *International Journal of Information Management*, 43, 130-145.

Gunasekaran, A., Love, P. E., Rahimi, F., and Miele, R., (2001), "A model for investment justification in information technology projects," *International Journal of Information Management*, 21(5), 349-364.

Hinton, C. M. and Kaye, G. R., (1996), "The hidden investments in information technology: The role of organisational context and system dependency," *International Journal of Information Management*, 16(6), 413-427.

Ho, J. L., Wu, A., and Xu, S. X., (2011), "Corporate governance and returns on information technology investment: Evidence from an emerging market," *Strategic Management Journal*, 32(6), 595-623.

Huang, S.-M., Ou, C.-S., Chen, C.-M., and Lin, B., (2006), "An empirical study of relationship between IT investment and firm performance: A resource-based perspective," *European Journal of Operational Research*, 173(3), 984-999.

Im, K. S., Dow, K. E., and Grover, V., (2001), "A reexamination of IT investment and the market value of the firm—An event study methodology," *Information Systems Research*, 12(1), 103-117.

Indjikian, R. and Siegel, D. S., (2005), "The impact of investment in it on economic performance: Implications for developing countries," *World Development*, 33(5), 681-700.

Jain, H., (2019), "Wage–Productivity Relationship in Indian Manufacturing Industries: Evidences from State-level Panel Data," *Margin: The Journal of Applied Economic Research*, 13(3), 277-305.

Jayasuriya, R., (1993), "Stages of growth in end-user computing: Applications in the health sector of developing countries in Asia-Pacific," *Journal of Information Technology*, 8(3), 151-159.

Jeffery, M. and Leliveld, I., (2004), "Best practices in IT portfolio management," *MIT Sloan Management Review*, 45(3), 41-49.

Jorgenson, D. W., Stiroh, K. J., Gordon, R. J., and Sichel, D. E., (2000), "Raising the speed limit: US economic growth in the information age," *Brookings Papers on Economic Activity*, 2000(1), 125-235.

Joshi, K. and Pant, S., (2008), "Development of a framework to assess and guide IT investments: An analysis based on a discretionary–mandatory classification," *International Journal of Information Management*, 28(3), 181-193.

Kask, C. and Sieber, E., (2002), "Productivitiy growth in high-tech maufacturing industries," *Monthly Lab. Rev.*, 125, 16-31.

Kazanjian, R. K., (1988), "Relation of dominant problems to stages of growth in technology-based new ventures," *Academy of Management Journal*, 31(2), 257-279.

Kleis, L., Chwelos, P., Ramirez, R. V., and Cockburn, I., (2012), "Information technology and intangible output: The impact of IT investment on innovation productivity," *Information Systems Research*, 23(1), 42-59.

Ko, M. and Osei-Bryson, K.-M., (2014), "Reexamining the impact of information technology investments on productivity using regression tree-and MARS-based analyses," In *Advances in Research Methods for Information Systems Research*, 109-126, Springer.

Koellinger, P., (2006), "*Impact of ICT on Corporate Performance, Productivity, and Employment Dynamics*," 01/2006; European Commission Enterprise and Industry Directorate General.

Kossaï, M. and Piget, P., (2014), "Adoption of information and communication technology and firm profitability: Empirical evidence from Tunisian SMEs," *The Journal of High Technology Management Research*, 25(1), 9-20.

Kucharavy, D. and De Guio, R., (2011), "Application of S-shaped curves," *Procedia Engineering*, 9, 559-572.

Kwon, S. O., (2007), "Impact of IT investment on firm performance: Focusing on four moderators," Master's Thesis, Korea Advanced Institute of Science and Technology.

Lee, A. and Baskerville, R., (2003), "Generalizing generalizability in information systems research," *Information Systems Research*, 14(3), 221-243.

Lee, H., Choi, H., Lee, J., Min, J., and Lee, H., (2016), "Impact of IT investment on firm performance based on technology IT architecture," *Procedia Computer Science*, 91, 652-661.

Lind, P., Sepúlveda, E., and Nuñez, J., (2000), "On the applicability of a computer model for business performance analysis in SMEs: A case study from Chile," *Information Technology for Development*, 9(1), 33-44.

Liu, X., Yeung, A. C. L., Lo, C. K. Y., and Cheng, T. C. E., (2014), "The moderating effects of knowledge characteristics of firms on the financial value of innovative technology products," *Journal of Operations Management*, 32, 79-87.

Magal, S. R., Carr, H. H., and Watson, H. J., (1988), "Critical success factors for information center managers," *MIS Quarterly*, 12(3), 413-425.

March, J. G. and Sutton, R. I., (1997), "Organizational performance as a dependent variable," *Organization Science*, 8(6), 698-706.

Marks, H. M. and Printy, S. M., (2003), "Principal leadership and school performance: An integration of transformational and instructional leadership," *Educational Administration Quarterly*, 39(3), 370-397.

Maskell, P. and Kebir, L., (2006), "What qualifies as a cluster theory," *Clusters and Regional Development: Critical Reflections and Explorations*, 30-49.

McCullough, B., (2018), "*A revealing look at the dot-com bubble of 2000—And how it shapes our lives today*," Ideas.Ted.Com.

Menon, N. M. and Lee, B., (2000), "Cost control and production performance enhancement by IT investment and regulation changes: Evidence from the healthcare industry," *Decision Support Systems*, 30(2), 153-169.

Mithas, S. and Rust, R. T., (2016), "How information technology strategy and investments influence firm performance: Conjecture and empirical evidence," *MIS Quarterly*, 40(1), 223-245.

Motiwalla, L., Khan, M. R., and Xu, S., (2005), "An intra-and inter-industry analysis of e-business effectiveness," *Information & Management*, 42(5), 651-667.

Mukand, S. W. and Rodrik, D., (2005), "In search of the holy grail: Policy convergence, experimentation, and economic performance," *American Economic Review*, 95(1), 374-383.

Netland, T. H. and Ferdows, K., (2016), "The S-curve effect of lean implementation," *Production and Operations Management*, 25(6), 1106-1120.

Obamuyi, T. M., Edun, A. T., and Kayode, O. F., (2012), "Bank Lending, Economic Growth and the Performance of the Manufacturing Sector in Nigeria," *European Scientific Journal*, 8(3), 19-36.

OECD, (2008), Measuring the Impacts of ICT Using Official Statistics.

OECD, (2013), Innovation-driven Growth in Regions: The Role of Smart Specialisation.

Oliner, S. D. and Sichel, D. E., (2000), "The resurgence of growth in the late 1990s: Is information technology the story?" *Journal of Economic Perspectives*, 14(4), 3-22.

Osei-Bryson, K.-M. and Ko, M., (2004), "Exploring the relationship between information technology investments and firm performance using regression splines analysis," *Information & Management*, 42(1), 1-13.

Pakko, M. R., (2002), "Investment-specific technology growth: Concepts and recent estimates," *Federal Reserve Bank of St. Louis Review*, Nov, 84, 37-48.

Pavelkova, D., Zizka, M., Homolka, L., Knapkova, A., and Pelloneova, N., (2021), "Do clustered firms outperform the non-clustered? Evidence of financial performance in traditional industries," *Economic Research-Ekonomska Istraživanja*, 1, 1-23.

Piget, P. and Kossaï, M., (2013), "The relationship between information and communication technology use and firm performance in developing countries: A case study of electrical and electronic goods manufacturing SMEs in Tunisia," *African Development Review*, 25(3), 330-343.

Porter, M. E., (1998b), "Clusters and the new economics of competition," *Harvard Business Review Boston*, 76(6), 77-90.

Porter, M. E., (1998b), "The Adam Smith address: Location, clusters, and the "new" microeconomics of competition," *Business Economics*, 33(1), 7-13.

Porter, M. E., (2011), "Competitive advantage of nations: Creating and sustaining superior performance," Simon and Schuster.

Pradhan, R. P., Arvin, M. B., and Ghoshray, A., (2015), "The dynamics of economic growth, oil prices, stock market depth, and other macroeconomic variables: Evidence from the G-20 countries," *International Review of Financial Analysis*, 39, 84-95.

Ramdani, B., (2012), "Information technology and organisational performance: Reviewing the business value of IT literature," *In Information Systems Theory*, 283-301, Springer.

Richard, P. J., Devinney, T. M., Yip, G. S., and Johnson, G., (2009), "Measuring organizational performance: Towards methodological best practice," *Journal of Management*, 35(3), 718-804.

Romer, P. M., (1990), "Endogenous Technological Change," *Journal of Political Economy*, 98(5), 71-102.

Sabherwal, R. and Jeyaraj, A., (2015), "Information technology impacts on firm performance: An extension of Kohli and Devaraj (2003)," *MIS Quarterly*, 39(4), 809-836.

Santhanam, R. and Hartono, E., (2003), "Issues in linking information technology capability to firm performance," *MIS Quarterly*, 27(1), 125-153.

Sawaguchi, M., (2011), "Innovation activities based on s-curve analysis and patterns of technical evolution-From the standpoint of engineers, what is innovation?" *Procedia Engineering*, 9, 596-610.

Sawyer, S. and Chen, T. T., (2003), "Conceptualizing information technology and studying information systems: Trends and issue," *In Global and organizational discourse about Information Technology*, 109-131, Springer.

Schreyer, P., (2000), The Contribution of Information and Communication Technology to Output Growth.

Schryen, G., (2013), "Revisiting IS business value research: What we already know, what we still need to know, and how we can get there," *European Journal of Information Systems*, 22(2), 139-169.

Schwab, K. and Sala, X., (2012), The global competitiveness report 2012-2013 World Economic Forum.

Shields, L. B. E., Gertz, T. A., Wilson, K. C., Figg, G. L., Hester, S. T., and Honaker, J. T., (2018), "The S-curve discontinuity theory predicts the path towards a 'well' society and increased longevity," *Medical Hypotheses*, 121, 99-102.

Smith, K., (2019), History of the dot-com bubble burst and how to avoid another, Money Crashers.

Smorodinskaya, N. V. and Katukov, D. D., (2019), "When and why regional clusters become basic building blocks of modern economy," *Baltic Region*, 11(3), 61-91.

Spring, M., Hughes, A., Mason, K., and McCaffrey, P., (2017), "Creating the competitive edge: A new relationship between operations management and industrial policy," *Journal of Operations Management*, 49-51, 6-19.

Tan, H. and Batra, G., (1997), "Technology and firm size-wage differentials in Colombia, Mexico, and Taiwan (China)," *The World Bank Economic Review*, 11(1), 59-83.

Teo, T. S. and King, W. R., (1997), "Integration between business planning and information systems planning: An evolutionary-contingency perspective," *Journal of Management Information Systems*, 14(1), 185-214.

Turcotte, J. and Rennison, L. W., (2004), "The link between technology use, human capital, productivity and wages: Firm-level evidence," *International Productivity Monitor*, 9, 25-36.

United States Census Bureau, (2012), North American Industry Classification System, United States Census Bureau.

United States Census Bureau, (2018), North American Industry Classification System, United States Census Bureau.

Vranakis, S. and Chatzoglou, P., (2011), "A conceptual model for machinery & equipment investment decisions," *International Journal of Business and Management*, 7(1), 36-57.

Whitefoot, J., (2017), *The dotcom bubble crash explained in a timeline*, Lombardi Letter.

Wong, P., Yeo, B., Bedroussian, A., and DeVol, R., (2007), "Nemours Children's Hospital: Advancing Orlando's Life Science and Economic Development," Milken Institute.

Wong, P., Yeo, B., and DeVol, R., (2006), "Pittsburgh Technology Strategy: SWOT Analysis," Milken Institute.

World Development Report 2016: Digital Dividends, (2016), World Bank.

Yeo, B., (2010), "Driving the knowledge economy: The impact of regional innovation capacity," *International Journal of Contemporary Management Research*, 6(1), 73-88.

Yeo, B. and Grant, D., (2018), "Predicting service industry performance using decision tree analysis," *International Journal of Information Management*, 38(1), 288-300.

Yeo, B. and Grant, D., (2019a), "Exploring the effects of ICTs, workforce, and gender on capacity utilization," *Information Technology for Development*, 25(1), 122-150.

Yeo, B. and Grant, D., (2019b), "Exploring the factors affecting global manufacturing performance," *Information Technology for Development*, 25(1), 92-121.

Yeo, B. and Trauth, E., (2009), "The call for transformational governance in the knowledge economy," In V. Weerakkody, M. Janssen, & Y. DWivedi (Eds.), Handbook of Research on ICT-Enabled Transformational Government: A Global Perspective, 271-290, IGI Global.

Zheng, Y., Hatakka, M., Sahay, S., and Andersson, A., (2018), "Conceptualizing development in information and communication technology for development (ICT4D)," *Information Technology for Development*, 24(1), 1-14.