Technology investment Impact on Regional Productivity: Empirical Evidence of S-Curve Characteristics

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ABSTRACT

Regression analysis is used to investigate the impact of tech investment on U.S. regional productivity from 1990 to 2016. Using four S-Curve characteristics, we explain tech investment's negative impact on regional productivity in the early investment stage. This is followed by rapidly increasing tech investment and significant regional productivity impact further along the S-Curve. As regional productivity approaches the top of the curve, tech investment results in diminishing returns. This signals the need to jump the S-Curve in search of new technological innovation to resuscitate tech investment and productivity gains. The S-Curve analysis indicates tech investment's impact is contextual and depends on the position on the S-Curve. This understanding of tech investment's impact on regional productivity at various points on the curve has implications for regional and global development.

Keywords:

Technology investment, productivity, high tech, S-Curve

INTRODUCTION

World IT spending is about USD 6 trillion per year and as a country's GDP, this is the third largest behind China, and twice the size of the UK. IT spending has a strong relationship with productivity and a decline in spending negatively impacts the economy by reducing labor productivity for up to three years, indicating technology is an important component of productivity (Cavallo, 2016). Nonetheless, debate on the ability of high tech investment to influence productivity as early as the 90s (Brynjolfsson, 1993), is ongoing. Technology does not

improve productivity (Abdi, 2008; Ho et al., 2011; Motiwalla et al., 2005; Sabherwal & Jeyaraj, 2015), but others disagree (Bloom et al., 2010; Botello & Pedraza Avella, 2014; Brynjolfsson, 1993; Draca et al., 2006; Huang et al., 2006; Kleis et al., 2012; Kossaï & Piget, 2014; Mithas & Rust, 2016).

The source of the debate is the inability to measure the effect of tech investment on productivity, referred to as the IT paradox, which hampers efforts to isolate the technology productivity impact (Richard et al., 2009). Ironically, it is a simple concept but notoriously difficult to measure (Brynjolfsson & Hitt, 1998). The productivity shortfall or IT paradox is due to our measuring deficiencies, inappropriate methodological choices, mismanagement by developers and IT users, and overlooking its contribution in aggregate statistics (Brynjolfsson, 1993; Brynjolfsson & Hitt, 1996).

Tech investment has been studied in companies (Im et al., 2001; Mithas & Rust, 2016; Pakko, 2002), industries (Abdi, 2008; Devaraj & Kohli, 2000), and countries (Indjikian & Siegel, 2005; Spring et al., 2017; Vranakis & Chatzoglou, 2011). Company results are more consistent than industry or country results and the latter is lacking (Abdi, 2008; Devaraj & Kohli, 2000; Sabherwal & Jeyaraj, 2015; Schryen, 2013). Scholars recommend more industry technology impact studies (Crowston & Myers, 2004; Piget & Kossaï, 2013; Sein & Harindranath, 2004).

Productivity is a measure of performance and an economic measure of technology's contribution (Brynjolfsson, 1993). To research the impact of tech investment on productivity, we apply S-Curve theory and characteristics to investigate how it affects productivity. As our research objective, we investigate the impact of tech investment on U.S. metropolitan regions' economic productivity from 1990 to 2016. The findings show how tech investment affects regional productivity using S-Curve theory, with implications for regional and global development.

The paper makes three contributions: 1. It addresses the need for industry level research on tech investment's impact on productivity (cf. Abdi, 2008; Crowston & Myers, 2004; Sabherwal & Jeyaraj, 2015; Schryen, 2013), 2. It illustrates the applicability of the S-Curve to explain regional productivity and the IT paradox and, 3. It helps managers and policy makers understand S-Curve characteristics to make better tech investment decisions. The remainder of the paper is organized as follows. Section 2 is a literature review of tech investment and S-Curve

theory. Section 3 is the research method; Section 4 presents the findings and Section 5, a discussion.

LITERATURE REVIEW

Tech Investment

Extant research suggests tech investment positively influence performance (Huang et al., 2006; Lee et al., 2016; Meliciani, 2000; Pakko, 2002; Vranakis & Chatzoglou, 2011). A positive relationship between tech investment and growth, competitiveness, customer relationship, external partnerships, and operational efficiency exists (Kwon, (2007). A 10% increase in tech investment increases innovation output by 1.7% (Kleis et al., 2012). In banking, tech investment improves performance (Byrd et al., 2006). At the country level, there is a positive relationship between tech investment and economic performance of developing and developed countries (Indjikian & Siegel, 2005). Nonetheless, company executives often question the impact of tech investment on performance (Lee et al., 2016; Vranakis & Chatzoglou, 2011).

Investing in technology raises three primary concerns for executives that influence our research design. First, the ability of tech investment to improve productivity is not fully understood. Some studies show there is no tech investment impact on company performance (Ho et al., 2011; Motiwalla et al., 2005), but others do (Huang et al., 2006; Im et al., 2001). These studies were conducted at different times with different contexts, using different methods and measures. To account for differences, it is appropriate to apply the same method, measures and time period for the regions, thus addressing measurement issues (Brynjolfsson, 1993; Brynjolfsson & Hitt, 2003) by controlling other factors. Consequently, this study uses time series data on U.S. metropolitan regions from 1990 to 2016. Second, it is challenging to effectively measure tech investment impact (Richard et al., 2009) hence, Brynjolfsson and Hitt (2003) recommend more accurate measures of tech systems and business practices as different measures capture different aspects of a construct. It is impossible to develop a perfect construct that captures the complexity of an industry or country tech investment impact. This explains why industry and country studies are less conclusive than company studies. Thus, tech investment studies should clearly specify the relevant construct measures, restrict implications to the measures, and understand strengths and limitations of the measures. Consequently, we use established measures to enhance the accuracy of our empirical analysis. Third, tech returns on

investment (ROI) require improvement of contextual factors such as IT-enabled intangible assets, human tech capability (Huang et al., 2006), and company knowledge characteristics (Liu et al., 2014). Contextual factors change over time and alter tech investment impact on firms, industries, and regions. Grant and Yeo (2018) show technologically advanced global industries benefit less from tech investments, and human capital is more important in predicting industry performance. However, less technologically advanced industries benefit more from tech investment impact on performance (Grant & Yeo, 2018). This corroborates evidence that companies with effective tech capabilities perform better (Ramdani, 2012; Santhanam & Hartono, 2003). Therefore, tech investment impact studies should carefully consider technology capability of firms, industries, or countries. U.S. technology capability increased over the period studied, illustrated using time series regional data with identical measures. The investment impact over time was noticeable.

The S-Curve

The S-Curve has been used in medicine (Shields et al., 2018), operations (Ağralı & Geunes, 2009), transportation (He et al., 2018), business (Modis, 2003), and tech innovation research (Sawaguchi, 2011). It is used in forecasting (Bahmani-Oskooee & Ratha, 2010; Modis, 2007), sociology, economics, mathematics (Verhulst, 1845, 1847), biology (Kucharavy & De Guio, 2011), to describe growth dynamics in Switzerland (Linstone, 2003), as well as technology forecasting and social change (Modis, 1994, 2007). We posit technological advancement in the U.S. changed from 1990 to 2016, and the S-Curve can explain these differences.

The S-Curve dates back to Belgian mathematician Pierre-Francois Verhulst in 1838. It is a logistic function originally introduced to describe self-limiting growth of a population (Verhulst, 1845, 1847). When S-Curve data are plotted, they create a pattern that resembles an "S", which represents a Sigmoidal, a mathematical term associated with the derivation of the curve. The S-Curve indicates rate of growth is proportional to the amount of growth accomplished and the remaining growth (Kucharavy & De Guio, 2011). It exhibits increasing returns to scale at small investment levels and decreasing returns at high investment (Ağralı & Geunes, 2009). These characteristics result in different growth rates along the curve, where it slows considerably as it approaches the apex, reflecting fundamental principles of limited resources throughout the

growth process. The S-Curve has four fundamental characteristics, akin to stages of growth (Shields et al., 2018):

1. Slow or limited growth in the early stages of a life cycle.

2. Followed by exponential growth, until an inflection point at its peak.

3. Followed by a plateau, or declining growth rate, as markets become saturated.

4. "Jumping the curve," represents a transition to a new S-Curve that possesses the ingredients of the preceding characteristics.

Jumping the S-Curve is necessary to exploit new growth opportunities and maintain competitive advantage. It is a difficult task but common among technologically innovative companies, such as Apple and UPS. Apple, a worldwide technology and electronics leader, jumped the S-Curve several times through innovative products and services (Shields et al., 2018). UPS, a leader in the parcel delivery service, jumped the curve on multiple occasions to innovate its business and parcel delivery services (Shields et al., 2018).

Research Question

Based on Grant and Yeo (2018), we hypothesize that U.S. growth from technological advancement depends on the location on the S-Curve. The impact of tech investment on productivity differs significantly along discrete positions of the curve. At the initial stages of the curve, tech investment impact on productivity is very slow (Stage 1). This is followed by accelerated or exponential growth (Stage 2), and finally higher levels of tech investment lead to a flattening or diminishing of productivity impact (Stage 3). Therefore, we advance the following research question.

RQ: How does the impact of tech investment change over time among U.S. metropolitan regions?

METHOD

We used annual time series regional economic data from Moody's Analytics for the empirical investigation. The data include high-tech wage, employment, and real GDP by U.S. metropolitan statistical areas (MSAs) from 1990 to 2016. MSAs are groups of counties defined by the U.S. Census as geographical concentrations of economic activity. Each MSA has a unique code that

identifies it. The time frame was selected for two historically important economic reasons: 1. 1990 is the beginning of the Internet and ecommerce era, and 2. A major recession occurred during this period.

Variable Operationalization

Technology generating activities lead to wage differentials, and tech investments result in large wage premiums (Tan & Batra, 1997). This explains why changes in tech investment account for a substantial proportion of rising dispersion in wages (Dunne et al., 2004). An investment in an enterprise resource planning system to support business processes requires additional system administrators, database administrators, data analysts, technical support staff, and programmers. A company that invests in high end technologies requires highly skilled labor to manage and maintain them. High-tech workers are highly skilled and earn an above average wage. Therefore, wage growth in high-tech industries is a proxy for tech investment.

We identify high-tech industries using the North American Industry Classification System (NAICS). They include pharmaceutical and medicine manufacturing, computer and peripheral equipment manufacturing, communications equipment manufacturing, semiconductor and other electronic component manufacturing, navigational, measuring, electromedical, and control instruments manufacturing, medical equipment and supplies manufacturing, software publishers, wired telecommunications carriers, wireless telecommunications carriers (except satellite), satellite telecommunications, other telecommunications, other information services, data processing, hosting, and related services, computer systems design and related services, scientific research and development services, other professional, scientific, and technical services, and medical and diagnostic laboratories. We computed annual wage growth for high-tech industries from the preceding year to derive the high-tech wage growth for each MSA. This serves as the proxy for tech investment for each MSA in a specific year (See Equation 1).

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

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.

Equation 1 Tech investment computation

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 that region for the same year. This translates to the real economic output per worker for each MSA. We use real GDP instead of nominal GDP to adjust for inflation. Since technologies improve efficiencies across different business processes including high-tech, we use the total number of workers instead of high-tech workers only. The computation is illustrated in Equation 2.

$$P_{i,t} = \frac{RGDP_{i,t}}{E_{i,t}}$$

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.

Equation 2 Real economic productivity computation

Research Model

A single regression model of regional economic productivity on the entire data set is not the best way to understand the full effect of tech investment impact. There are 26 years, controlling for them in a single regression model requires too many dummy variables that make the findings difficult to interpret. Hence, we created 26 OLS regression models, one for each year. The data on high-tech wage growth and real GDP per worker are transformed by taking the natural log, which is appropriate for impact studies (Ko & Osei-Bryson, 2014), because production functions such as Cobb-Douglas used to study technology and productivity are exponential, requiring log transformations in linear model specifications (Brynjolfsson & Hitt, 1996; Menon & Lee, 2000). Since annual wage growth can be negative or zero, the wage growth values were taken from 101 percentage points as the index. In other words, a wage growth of 0% will be transformed to 101%. The choice of 101% instead of 100% as the index is to avoid the possibility of a -100% high-tech wage growth, which results in an indexed 0 percentage points, and an invalid log score. There are impact lags due to periods of learning and adjustments (Brynjolfsson & Yang, 1996), so we assess the resultant impact on economic productivity in the subsequent year. This addresses endogeneity, where high-tech wage growth, the independent variable, and the error term are correlated. For example, the impact of technology investments in 2000, operationalized by wage growth from the preceding year, is assessed in the corresponding MSA real economic

productivity in the following year, 2001. Figure 1 illustrates our research model, operationalized by Equation 3. It illustrates the impact of technology investments on the left, operationalized by high-tech wage growth on regional economic productivity on the right, operationalized by real GDP per worker. This relationship investigates tech investment impact on regional productivity over a quarter century.
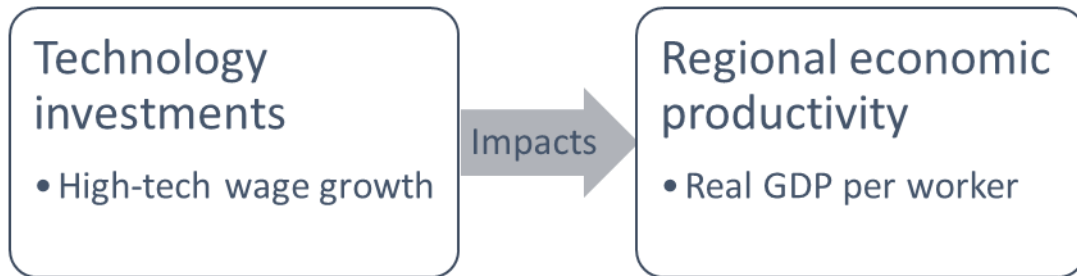

Figure 1 Research model

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

Where

$lnP_{i,t+1}$ = 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.

Equation 3 Research model operationalization

FINDINGS

Descriptive Findings

There are 373 MSAs as defined by the U.S. census annually (N = 373). Table 1 (see Appendix) provides the summary statistics – mean and standard deviation – of high-tech annual wage growth and real GDP per worker per year. The standard deviations of the mean high-tech wage annual growth by year are a bit high because of unequal regional economics. Some have more

and higher concentrations of high-tech industries and so tech investments, represented by their high-tech annual wage growth, vary considerably. The real GDP per worker standard deviations are comparatively smaller, suggesting less worker annual productivity variation measured by real GDP.

Using a combo boxplot and line chart, we describe the median and range of values and high-tech annual wage growth mean, a proxy for tech investments, over the period (Figure 2). With the exception of 1995, at least 50% of MSAs on or before 2000 made investments in high-tech, with medians ranging from 2.71% to 12.56%, and means ranging from 3.14% to 13.05%, in 1995 and 1999 respectively. Investments between 1990 and 2000 reflect the rapid growth of the dot com era. Not surprisingly, around the time of the dot com bust, technology investments decreased between 2000 and 2002, as close to 50% of MSAs had negative annual wage growth. In 2002, the median and mean high-tech annual wage growth were -3.82% and -3.38% respectively, reflecting high-tech worker layoffs. High-tech wages improved in 2004 through 2008, where at least 50% of MSAs had positive high-tech annual wage growth, with medians ranging from a high of 6.79% in 2006 to a low of 3.51% in 2008 and means with a high of 7.63% to a low of 3.71%. An economic downturn occurred from 2007 to 2009, due to a recession. After 2010, at least 50% of MSAs maintained positive high-tech wage growth (i.e. they invested in technologies), but they were not as high as during the dot com era, with the lowest median and mean of 2.10% and 2.09% in 2010, to the highest of 5.72% and 5.52% in 2015 respectively. This reflects a more cautious tech-investment approach and an emphasis on business fundamentals.
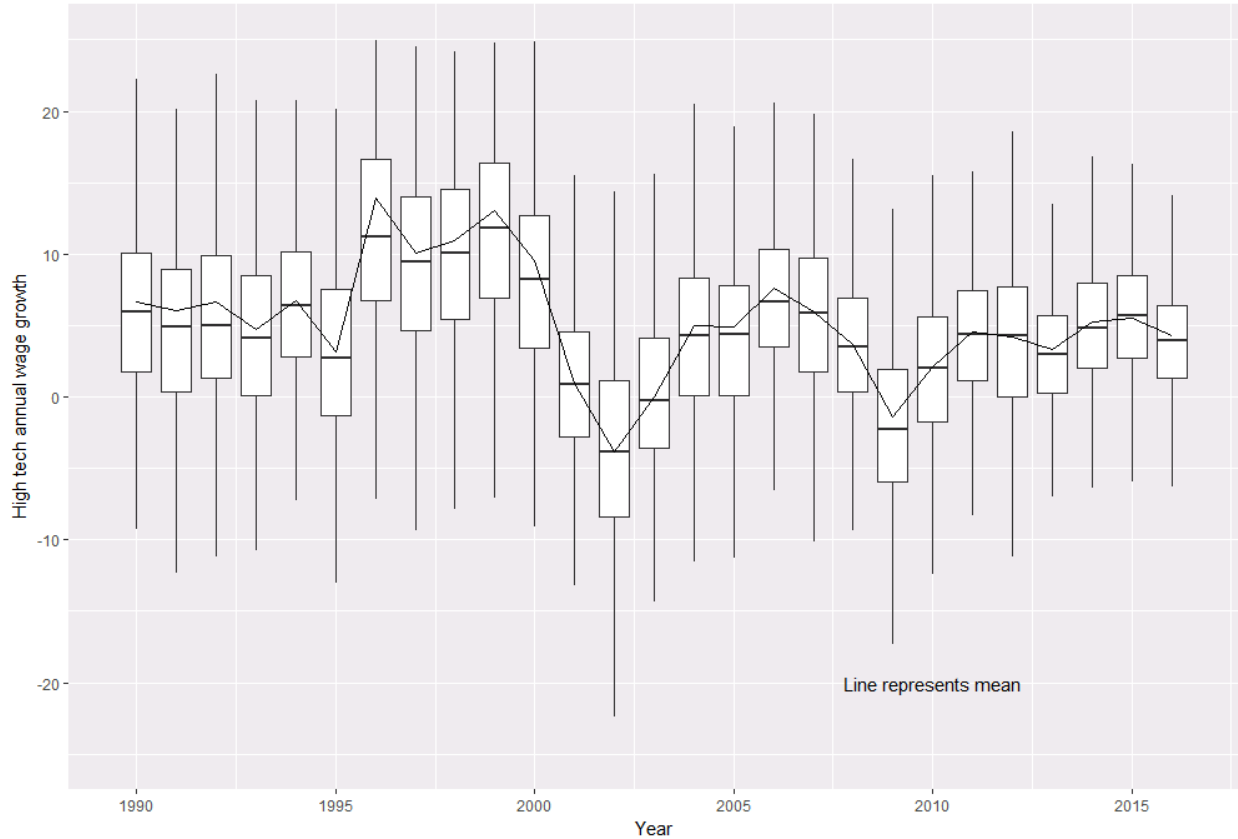
Figure 2 High-tech annual wage growth by year

Predictive Analysis

A summary of results from the 26 regression models is shown in three graphs (Figure 3). The top graph represents the percent of high-tech wage growth, a proxy for high-tech investment from 1990 to 2015. The middle graph represents the R^2 of the 26 regression models, illustrating the variance explained by tech investment (operationalized by high-tech wage growth). The bottom graph represents the coefficient of the 26 regression models, signifying the magnitude of tech investment impact. The shaded portions of the graphs represent years where tech investment has a significant impact on regional productivity. Since the impact is assessed in the subsequent year, the range of years in Figure 3 ends at 2015, and the impact shown for 2015 is manifested in 2016. The subsequent discussion of the findings refers to these three graphs.
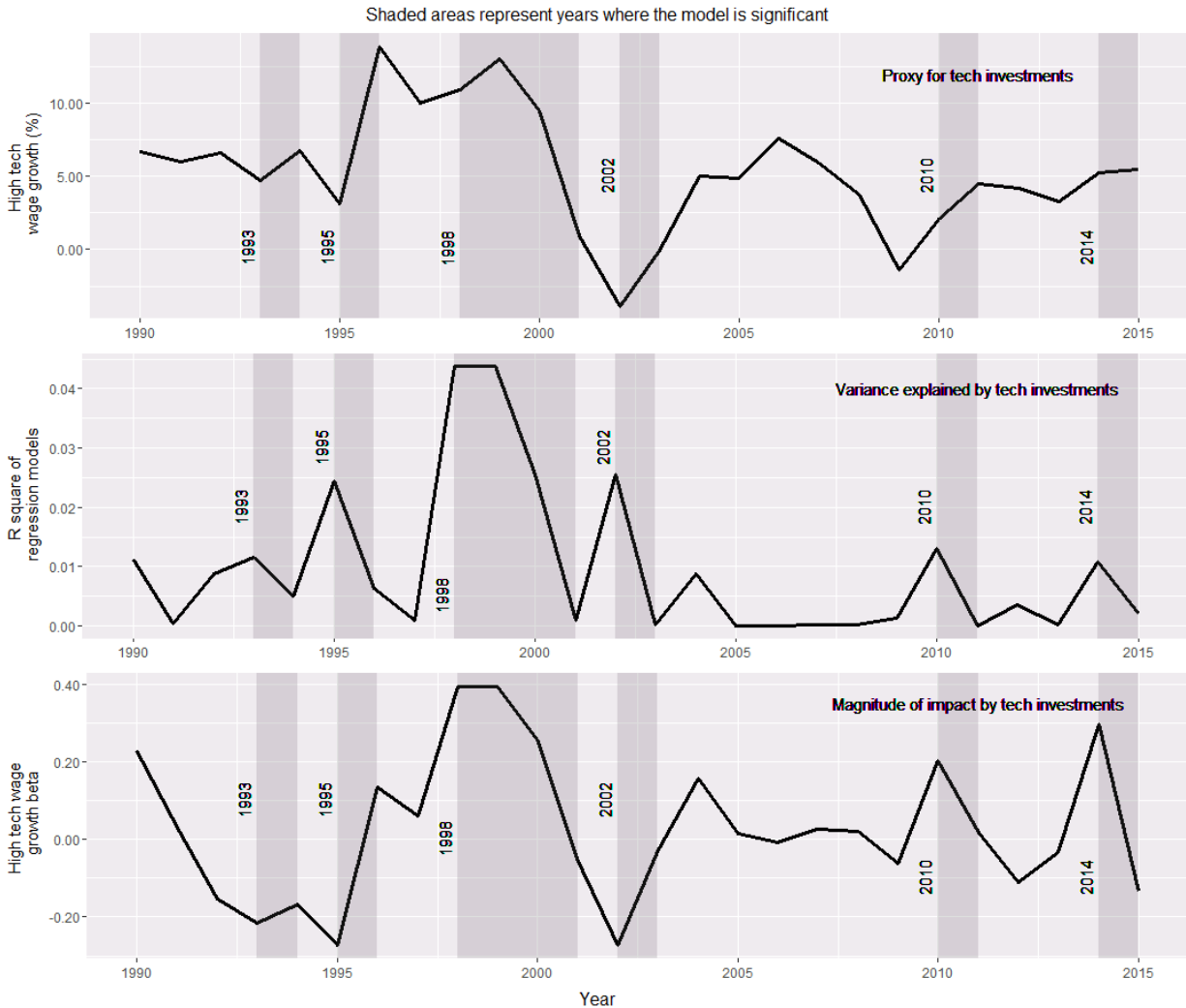
Figure 3 Summary of findings

There are similarities between years 1993-1994 and 1995-1996: the level of tech investment increased (top graph) and resulted in wage growth regional productivity increase (bottom graph), despite a decrease in the variance explained (middle graph) towards the end of 1996. This decrease, coupled with the low R^2, suggests the presence of other contributing factors. More importantly, the coefficient of impact is negative, suggesting that businesses did not fully understand how the Internet should be used to support business objectives. During this period, profitability among dot coms was not a main concern for investors (Whitefoot, 2017), and the most promising ones were actually not profitable (McCullough, 2018). This corresponds to the

first characteristic of the S-Curve, reflecting the initial stages of technology growth and productivity.

The years leading to the dot com era in the late 1990s were characterized by speculative investments (Smith, 2019) that eventually led to the bubble (Whitefoot, 2017). The internet was a complex medium (Whitefoot, 2017) and businesses had unrealistic expectations of it (Smith, 2019). This explains why tech investments during this period did not significantly increase regional productivity. This phase is reflected in Stage 2 of the S-Curve as investment and productivity growth rates increase further up the curve (Ağralı & Geunes, 2009).

During the height of the bullish dot com era, particularly between 1996 to 2000, the value of equity markets grew exponentially, as the technology-dominated NASDAQ index rose from $1000 to its peak at over $5,000. By 2002, the bubble burst and the U.S. economy entered a bear market, with the NASDAQ index returning to slightly over $1000 (Whitefoot, 2017). This trend is reflected in Figure 3. Between 1996 and 1998, tech investment held steady albeit with some fluctuation. Simultaneously, its explanation of regional productivity increased sharply, akin to being further along the S-Curve.

From 1998 to 2001, a decline in tech investment was accompanied by a decrease in variance explained. By 2002, the low NASDAQ index (Whitefoot, 2017) reflected the bust of the dot com era. Between 2002 and 2003, the economy began to recover. From Figure 3, increased high-tech investment (top graph) had a significant impact on regional productivity (bottom graph), but the variance explained decreased (middle graph). Businesses faced uncertainties on the impact of high-tech investment, but continued to invest based on past economic impact. Large tech players like Amazon refocused its strategy and posted annual profit of $35 million (Whitefoot, 2017).

From 2010 to 2011, investments grew moderately, as the economy recovered from the 2007 – 2009 recession. Both tech investments and their magnitude of impact were higher than the preceding recession years, but these decreased by the end of 2011, reflecting economic skepticism and uncertainty. From 2014 to 2015, high-tech investments plateaued, accompanied by a corresponding decrease in explained variance. This characteristic is reflected in the top of the S-Curve, where marginal diminishing returns occur (Ağralı & Geunes, 2009). It is associated with market saturation and the lack of future growth. The evidence suggests a need to jump to another S-Curve (i.e. Stage 4) as technology investments experience diminishing impact on

regional productivity. These observations signal a point where financial and other factors impact productivity more than technology (Grant & Yeo, 2018).

CONCLUSION AND DISCUSSION

This research addresses the need for industry research on tech investment and productivity (cf. Abdi, 2008; Crowston & Myers, 2004; Devaraj & Kohli, 2000; Sabherwal & Jeyaraj, 2015; Schryen, 2013). It illustrates the versatility of the S-Curve and its usefulness as a theoretical framework to investigate regional productivity, thus contributing to the extant literature on S-Curve theory, tech investment, and productivity paradox. It does not settle the ongoing technology paradox debate but explains tech investment impact on productivity, at different points on the S-Curve. It provides lessons learnt that could be applied to regional development in other parts of the world.

The findings represent the impact of tech investment on U.S. regional productivity from 1990 to 2015. The investigation relies on four S-Curve characteristics to frame the analysis. The first characteristic corresponds to slow technology growth in the early stages that resulted from Internet and ecommerce technology investments, as companies struggle to leverage technology. This is followed by the second characteristic of rapid productivity growth that resulted from speculative tech investment in the years leading to the dot com era (Whitefoot, 2017). At the height of the dot com, companies were better equipped to utilize the internet and ecommerce technology, which led to high regional economic productivity. The third characteristic is the flattening and decline of regional productivity that resulted from additional tech investments. This signifies diminishing productivity at the top of the S-Curve from additional tech investments. This part of the S-Curve, other factors such as skilled labor (Grant & Yeo, 2018) and financial factors (Yeo & Grant, 2019b) are better predictors of productivity. The fourth characteristic postulates the need to jump to another S-Curve to overcome diminishing returns exhibited in characteristics #3. This is accomplished by technology or product innovation to spur additional growth (Sawaguchi, 2011). The dot com era was fueled by hyped internet and ecommerce technology (Smith, 2019). Even though these technologies are necessary, after the 2007 – 2009 recession, they were no longer the primary drivers of regional productivity. This is consistent with the findings of technologically advanced industries (Grant & Yeo, 2018).

Theoretical Implications

The literature leans towards a positive impact of tech investment on productivity (Huang et al., 2006; Lee et al., 2016; Meliciani, 2000; Pakko, 2002; Vranakis & Chatzoglou, 2011), despite contrary evidence (Ho et al., 2011; Motiwalla et al., 2005). The debate is sometimes framed in the context of the technology paradox, refuted by Brynjolfsson and Hitt (2003) because its impact is hard to accurately measure (Brynjolfsson, 1993; Brynjolfsson & Hitt, 2003). This investigation addresses measurement complexity by using consistent measures on time series data to show tech investment has a positive impact on U.S. productivity from 1990 and 2016, corroborating relevant aspects of the literature (Huang et al., 2006; Lee et al., 2016; Meliciani, 2000; Pakko, 2002; Vranakis & Chatzoglou, 2011). It also corroborates opposing views that tech investment has no significant impact on productivity (Ho et al., 2011; Motiwalla et al., 2005), by explaining the variation of tech investment impact over the years.

If Brynjolfsson and Hitt (2003) are correct that measurement complexity is the source of the IT paradox, then it is necessary to ask under what conditions do tech investment matter and how do we improve our ability to measure its impact. Tech investment impact appears to be a function of the region's position on the S-Curve. This suggests the IT paradox measurement solution is not simply a measurement problem and is more complex than some scholars suggest. Nonetheless, the S-Curve is versatile in explaining productivity and growth in various domains (cf. Bahmani-Oskooee & Ratha, 2010; He et al., 2018; Kucharavy & De Guio, 2011; Linstone, 2003; Modis, 1994, 2003, 2007; Sawaguchi, 2011; Shields et al., 2018; Verhulst, 1845, 1847) and is part of the IT paradox puzzle. The findings show periods where tech investment significantly or insignificantly influences regional productivity on different parts of curve. The shape of the curve is indicative of tech investment impact on productivity. The findings suggest tech investments are not always impactful along the S-Curve, providing an alternative explanation to the IT paradox. The findings illustrate how the S-Curve explains regional economic productivity, where positions on the curve represent different contexts that determine the impact of tech investments on productivity.

Regional Implications

Between 1990 and 2015, there were periods where technology investments had no influence on regional productivity. This does not imply technology does not matter because research suggests

non-technology factors, such as access to finance and lending practices (Yeo & Grant, 2019b), skilled workforce (Yeo & Grant, 2019a), and various management practices (Yeo & Grant, 2018) play an important role. The findings based on the S-Curve suggests companies should ascertaining their position on it to guide their tech investment strategy. Furthermore, it aids decisions on when to jump to another S-Curve, as diminishing returns set in. The lower and top parts of the S-Curve require different investment strategies, such as employing the appropriate skilled labor to exploit technology or plot strategic directions.

Underdeveloped, developing, or developed regions should consider various investment and business strategies. Despite economic development differences across regions the investigation may be modified to account for them. This includes the type (technological vs non-technological), timing (position on the curve) of investments appropriate for specific regions. For example, internet and mobile investments are more beneficial for underdeveloped and developing regions than enterprise systems investments that are negatively impactful when skilled labor or maintenance funds are unavailable (Yeo & Grant, 2018).

Development Implications

Understanding S-Curve characteristics and applying lessons learned are beneficial to policymakers who implement technology strategies for e-commerce, e-government, and education. Different regions have different contexts, and policymaking is effective when tailored locally (Mukand & Rodrik, 2002). Policymakers can determine where regions are on the S-Curve to set expectations on technology investments' impact on productivity. It also helps to guide tech investment decisions. In Stage 1, it is ill-advised to jump on the bandwagon when it is unclear how best to utilize technology and whether a region is in position to do so. A cautious tech investment strategy is wiser than going all in. Over investing causes disappointment when expected productivity returns do not materialize, stifling future investment and consolidating losses. Productivity expectation is a function of the S-Curve and encourages future investments where productivity is significant. Hence, setting realistic expectations is important and it is unwise to look at technologically advanced regions because different contexts may exist: their technological and human capital capabilities may provide suitable conditions to leverage technology investments, therefore yielding superior regional performance. Appropriate benchmarking is necessary for understanding tech investment and productivity expectations. It is important to understand tech investment impact on productivity at different stages on the curve.

In Stage 2, significant productivity gains are expected, while in Stage 3, productivity sharply declines as diminishing returns set in. These determine technology investment impact at different stages. Lastly, the top of the curve is a signal for moving to a new one. This applies to technologically advanced regions, where technology investments are no longer primary drivers of economic performance (Grant & Yeo, 2018). This is the point where human capital and other factors become more important.

Limitations, and Future Research

Given measurement complexities (Brynjolfsson, 1993; Brynjolfsson & Hitt, 2003), technology investments can be better measured using decomposed components rather than aggregates. These components are not easily obtainable since they are likely to be measured differently in various regions. Nonetheless, decomposed components provide a more in-depth view of tech investments and the conditions under which they matter. Even though we use the S-Curve to posit how different contexts influence tech investment impact, each stage of the S-Curve can be influenced by contextual factors such as financial, social, economic, and political. This understanding helps regions, industries, and countries assess their location on the S-Curve and how it affects tech investment decisions, business strategy, employment, and innovation. Macroeconomic conditions of post dot com era recession and the 2007 – 2009 recession, appear to influence the impact of tech investment. Future studies should control for macroeconomic downturns, to enrich the study. Data on the types of technology investment can enrich the analysis on productivity.

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