ICT Capital Formation, Unemployment, and the Solow Paradox

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This study explores the impact of ICT on unemployment and labour productivity. Using a time-varying modelling approach, quarterly US data from 1972 to 2020 estimates the relationships between unemployment and ICT capital investments. The results highlight that ICT capital investments reduce unemployment and increase labour productivity, showing no evidence supporting the Solow Paradox. The mechanisms behind the relationship between ICT and enhanced labour productivity are identified by Data Envelopment Analysis (DEA) and include improved access to information and an improvement in the labour structure.

Keywords**:** Solow paradox; US; Labour productivity; Unemployment; Time-varying estimates

JEL Codes**:** E24; O14; C13; C14

1. Introduction

Due to the recent COVID-19 pandemic and technological developments, economists have intensified the debate about technological unemployment. Most of them were motivated by Keynes's (1930) bleak prediction of technological unemployment induced when labour creation does not outpace labour destruction. Back in the 60s, Baumol (1967) agreed that the decline of manufacturing's share of employment resulted from high productivity growth caused by the third industrial revolution.[1] The onset of the fourth industrial revolution embraces an unprecedented Information Communication Technology (henceforth ICT) expansion and internet infrastructure capacity. The advent of new telecommunication infrastructure is expected to rapidly increase productivity growth in almost every sector of the economy, including the primary (agriculture), secondary (manufacturing), and tertiary (services) sectors. This raises important questions about the emergence of the technological discontinuity paradigm (or the existence of the Solow paradox) (Figure 1) after 2010 despite the rapid development in ICT (Figure 2). Alternatively to the data, Acemoglu et al. (2014) challenged the return of the paradigm, whereas Bessen (2019) attributed the refutation of the paradox to

[1] The advent of computer chips and computing capacity.

demand elasticity. Still, we become witnesses to rising fears of technological unemployment, which are often exacerbated by the disruptions caused due to COVID-19 pandemic.

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Aghion and Howitt (1994) postulate two effects on unemployment due to the introduction of new technologies. One is the capitalisation effect, whereby technology complements labour. Thus, new firms are encouraged to enter and hire new employees. The second effect is the creative destruction effect. According to this, technology substitutes labour, thus requiring workers to reallocate their labour supply. David and Dorn (2013) give evidence of the creative destruction effect. They identify a rise in unemployment rates in the manufacturing sector due to technological displacement of routine-intensive occupations. A common misconception is that artificial intelligence and automation are the channels for rising unemployment, when in fact, these technologies are only unlocked by higher telecommunication bandwidth or ICT, thus allowing for machine-to-machine communication.

Economists think of a healthy and dynamic economy when job creation rate is larger than the job destruction rate. This had been the trend before 2000 for the US, discussed by Leontief and Duchin (1986), Acemoglu (2002), Autor et al. (2003) and Beaudry and Green (2005); for the UK, we have Goos and Manning (2007), while for Germany Dustmann et al. (2009). Until recently, the data has not supported the argument that technological development displaces labour. The extant literature usually implies that technological advancement continues unabated. Firms that wish to satisfy additional demand will eventually demand more labour. However, since the dawning of the 21st century, there appears to be a decline in the demand even for skilled workers who have moved to occupations traditionally held by low-skilled workers (Beaudry et al., 2016). Most economists agree with the pessimistic scenario, where technological unemployment inevitably results in a higher natural unemployment rate (Lucas and Prescott, 1974; Davis and Haltiwanger, 1992; Rifkin, 1995; Pissarides, 2000).

In contrast, Mokyr et al. (2015) do not share this pessimism. They suggest that despite the anxiety caused by technology throughout history, we should not portray technology as uncontrollable. Technological advancements in this century will be centred around ICT. Nevertheless, what is ICT, and why should we study it more? ICT is a telecommunication network infrastructure essential for supporting many services and applications where the advent of technologies (e.g., internet exchange points, underground or subsea cables, wireless systems and satellites) will be required to satisfy an anticipatedly accelerating range of communications between machines known as the Internet of Things (IoT), automation, digital twins, e-governance, artificial intelligence, data storage, data migration, blockchain applications where wired and wireless communication will drive forward the digital society and Web 3.0. ICT aspires to reallocate resources and switch production towards new products.[2] The demand for these new products will be the most potent force behind employment creation (Harrison et al., 2014). Data from 1972 till 2020 helped locate the rise of Web 1.0 and Web 2.0 facilitated by an ICT expansion in the US and repeated today with Web 3.0.

The present article contributes to the literature on the negative effect of information technology on labour productivity, known as the Solow Paradox. It explores the effect of information technology on unemployment, a relationship that has long been neglected in the literature. We observe that unemployment triggers investments in ICT infrastructure, where without investment, unemployment would prolong. The mediating effect of investments in ICT infrastructure is the increase in labour productivity.

2. Literature Review

ICT and unemployment

Based on a Phillips curve model with wage constraints, Sinclair (1981) shows that technological introductions may accompany an initial loss in employment. However, the net increase in employment will be positive. Three decades later, Acemoglu and Restrepo (2020)

[2] Despite the clear insight that a transition to telecommunication infrastructure might have on business creation, some authors are not optimistic as this does not necessarily have the spillover effects promised. Past evidence from Greenstein and Spiller (1995) for the US, spanning 1986-1993, indicates that a telecommunication network modernization project impacts primarily white-collar activity while less critical for manufacturing activity. However, the implications of the existing ICT technology need to be investigated as there is a rising trend towards telecommuting or working at home with significant implications, for example, on employee activities and perceptions (Kurland and Egan, 1999). Indeed, the shift to telecommuting among many white-collar workers prompted by COVID-19 forced the adoption and training of new technologies that may have long-term impacts even after the pandemic. Working at home will become even more widespread as wireless infrastructure unlocks faster internet speed, lower latency with working materials becoming available on the cloud (datacentre infrastructure) and AI that will help a broader reconfiguration of memory optimization and power consumption reduction on data centre complexity. The AI edge computing capabilities unlocked by telecommunication infrastructure expansion include reduced traffic load, minimization of latency, reduced load on a cloud, reduced load on end-user devices, reduced energy consumption, and data centre computation offloading (Bilal et al., 2018; Cheng et al., 2018).

studied the effect of robotic installation between 1990 and 2007 on the US labour markets and showed that robots could reduce employment.[3] In particular, an additional robot per thousand employees reduces the employment-to-population ratio by about 0.18-0.34 percentage points.

In contrast, Graetz and Michaels' (2018) analysis concerning robots' adoption within industries in seventeen countries from 1993 to 2007 suggests that working hours have been significantly reduced for the lowest-skill groups, while for the high- and middle-skill groups, the effect is positive, implying that individuals who lack education may be the most severely affected by the introduction of new technology (Figure 3).[4] Based on these findings, technological adoption results in both winners and losers. This validates the polarisation effect (Michaels et al., 2014), implying that ICT affects medium-skill workers more than high-skilled workers. Sharp technological changes can increase employment opportunities for those who invest in new skill acquisition, which can persist due to skill obsolescence (Apergis and Apergis, 2020).[5]

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The hypothesis, dating back to the Great Depression in the 1930s, that technological changes can seriously impact unemployment is still relevant today (Figure 4). According to Field (2003), enhancing innovation despite high contemporaneous unemployment rates in the 1930s facilitated employment prosperity after World War II. For the new technological opportunities to generate employment, consumer demand for electronics and automobiles exceeded production capacity (Freeman et al., 1982).[6]

In the 60s, researchers attempted to confirm whether ICT infrastructure investment would yield economic growth (Jibb, 1963), indicating a strong and positive relationship between ICT development and country prosperity. Despite the extensive literature on the direction of the relationship between telecommunication investment and growth (Norton, 1992;

[3] Monitoring robots requires sufficient ICT technology.
[4] Facilitated by expansion in ICT technology.
[5] That is, retraining, re-education, and migration involve considerable costs and take time. Acemoglu (1997) states that for the equilibrium to exist in which new technology is adopted, firms need to train all unskilled workers immediately for the labour market to become tight and unemployment to fall.
[6] e.g., semiconductors, pharmaceuticals, electronic computing, synthetic and composite materials.

Madden and Savage, 1998; Roller and Waverman, 2001; Choi and Yi, 2009; Dimelis and Papaioannou, 2010; Gruber and Koutroumpis, 2011; Czernich et al., 2011), there has been limited investigation on the link between ICT development and employment (Figure 5).[7] One minor exception is the work by Hjort and Poulsen (2019), where they find a positive effect of submarine cable connections (fast broadband) on employment, even across educational attainment levels, based on four survey datasets from African countries.[8]

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We expand the current knowledge by testing the information–employment nexus. In particular, we argue that ICT reduces unemployment. ICT helps reduce information asymmetries, making markets more efficient in matching employers with the unemployed searching for work (Jensen, 2007).[9] Moreover, ICT reduces barriers to starting and running a business (Bhavnani et al., 2008; Moyi, 2019). According to Bhavnani et al. (2008), mobile technologies substitute for transportation, which was apparent during the COVID-19 global pandemic. Individuals can take advantage of mobile technologies and work from home rather than being laid off. This discussion leads to the following parsimonious hypothesis:

H_1: ICT capital formation negatively correlates with unemployment

ICT and labour productivity

[7] Jensen (2007) further points out that ICT has persistent and sustained effects, rather than a one-time gain, by reducing search costs and improving market coordination. Some even argue that mobile technologies lower the barriers to self-employment and entrepreneurship by reducing the cost of running and starting a business (Bhavnani et al., 2008; Moyi, 2009).

[8] The emergence of 5G radars, which is a critical component for further ICT capital formation for businesses, positively affect businesses to critically rethink their operations, create new products and processes, and induce further stagnated demand.

[9] The additional tax revenues generated by the development of ICT can be used to, for example, finance government training programs and other programs that help match employers with employees. Structural unemployment, caused by the creative destruction of a dynamic market economy like the US, transitioning toward a more digital economy, can benefit from the education and training offered quickly and cheaply by ICT (Bhavnani et al., 2008).

Telecommunication services are a vital element of ICT.[10] If information is seen as a commodity, it becomes clear why a faster circulation of that commodity will be eager to be exploited by firms which need to take an early advantage over the competition.[11]

According to Leduc and Liu (2020), automation is a labour-substituting technology because its calibration pattern indicates that technology dominates the recessionary effects in a New Keynesian dynamic stochastic general equilibrium (DSGE) framework. The idea is that the recent increase in uncertainty first contributes to reduced employment and inflation because economic agents are motivated to shift to precautionary savings, reducing aggregate demand (Leduc and Liu, 2016). As discussed above, increased aggregate demand for goods and services is necessary to avoid the re-emergence of the technological-discontinuity paradigm. At the same time, the pandemic has posed a formidable challenge.

In addition to its effects on unemployment, we argue that ICT increases labour productivity. There are at least two possible channels through which ICT can increase productivity. First, the efficient manufacturing channel is where ICT improves access to communication and information, increasing labour productivity.[12] Second, the labour structure

[10] When discussing technological progress in ICT goods manufacturing, it is essential to talk about fifth-generation (5G) technology. The first generation (the 1980s) of ICT introduced analogue mobile telecommunications and is based on essential voice services, the second generation (1990s) introduced the first digital systems, like digital standards and text messaging, the third generation (2000s) included data services for limited internet access, and the fourth generation (2010s) is based on internet protocols for functional mobile broadband. The fifth generation (2020) promises greater network capacity with lower latency to support a more significant number of connections (Brake, 2020). To this end, industry stakeholders consider the migration from 4G to 5G networks a profound milestone that will radically reshape the broadband market (OECD, 2019). ICT and the economy interact in a sophisticated manner. Thus, installing new equipment that aspires to provide a broader array of services will significantly impact other sectors' and firms' critical needs for automation.

[11] The application for future business expansion is enormous, albeit not exhaustive, and may fall under the following categories (Forge and Vu, 2020): industrial automation (e.g., sensors, robotics, remote control of heavy machinery in hazardous environments, tracking of products, logistic optimization), transportation (smart sensors on vehicles, visual empowered services and traffic information), digitalization of the living environment (smart street-light illuminations, smart grid accelerometers, acoustic sensors for copper theft, temperature sensors, smart water meters, smart gas meters, waste recycling monitoring, smart home devices), public safety (natural disaster early warning management systems for geo-allocating people after a virus, fire, earthquake and flood spreads, structural monitoring of buildings and infrastructures with a determination of their current health), telepresence services (virtual office, ultra-high-resolution of cameras, immersive 360-degree visits of historical buildings), e-health (remote surgery, telemedicine, telemonitoring), e-agriculture (sensors that monitor cultivation, irrigation, fertilization levels and harvesting time parameters), and military (drone surveillance, expansion of satellite use, cruise missile GPS navigation, tactical infantry and vehicle positioning, reliable telemetry of autonomous armour vehicles, quicker download of high volume remote sensing intelligence and reconnaissance images for battle analysis).

[12] Technology has affected the structure of employment with a varying effect, which depends on certain assumptions, such as the type of technological change considered (i.e., product innovation, process innovation, routine-biased technological changes, computerization or exposure to industrial robots), the income level of an economy (developed or developing), and the unit of analysis (firm, industry, or local labour markets) (Bogliacino et al., 2012; Vivarelli, 2015; Bessen, 2015; Arntz et al., 2016).

channel is where ICT alters the structure of employment due to automation replacing low-skilled labour. This leads us to our second hypothesis:

H_2: Labour productivity is positively influenced by ICT capital formation.

To provide more insight into the relationship between ICT and labour productivity, we further test each channel (i.e., information or employment structure) to distinguish which mechanism drives the relationship between ICT and labour productivity.

3. Methodology

Data

The analysis sources quarterly data for the US from 1972-2020. Historical data for the unemployment rate, labour productivity in the private sector, the consumer price index and unit labour costs have been obtained from the Bureau of Labor Statistics at the US Department of Labor. Unemployment is measured as the U-3 unemployment rate, or U3 rate, the most commonly reported unemployment rate in the US and represents the number of people actively seeking a job. Alternatively, unemployment is measured as the U-6 rate, or U6, which includes the country's discouraged, underemployed, and unemployed workers. Many economists perceive the U-6 rate as more meaningful because it entails a larger percentage of unemployed people (Elsby et al., 2013; Brandolini and Viviano, 2018). This rate accounts for anyone seeking employment within the previous 12 months but has not secured a job in the past four weeks. In addition, it incorporates anyone who has returned to school, become disabled, and people who are underemployed or working part-time hours.

Data on ICT gross fixed capital formation (at constant prices) and terms of trade, both measured quarterly in current US dollar prices, are from the Thompson Reuters Datastream database. For the empirical ends of our work, ICT investment is defined as the acquisition of equipment and computer software used in production for more than one year. The definition has three specific components: information technology equipment, communications equipment, and software. The last part includes the acquisition of pre-packaged software, customised software and software developed in-house. The variable is measured as a percentage of total non-residential gross fixed capital formation. When the terms-of-trade index improves, this implies that citizens in the US can purchase more imported goods with one unit of exported goods. We use the Bureau of Economic Analysis sources at the US Department of Commerce to extract data on population, the gross domestic product deflator, corporate taxes, and social security transfers. Data on foreign direct investments and 10-year bond yields are sourced from the US Federal Reserve. Productivity is measured as real GDP divided by civilian employment,[13] while labour force participation is the civilian labour force participation rate,[14] with data for both variables coming from Datastream. The percentage of the urban population is also sourced from DataStream, while data on wages come from the US Bureau of Labor Statistics.[15] Table 1 reports relevant summary statistics.

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Methodology: The Unemployment Rate Equation (Hypothesis H_1: An Innovation)

The empirical analysis will specify an econometric model that allows us to examine the effects of ICT on the unemployment rate. To construct the econometric model, we rely on the extant theoretical and empirical literature to identify the main determinants of unemployment. In particular, the presence of the GDP output gap is significant since it captures potential demand-side effects. It also conveys Okun's (1962) theoretical framework, which posits a relationship between unemployment and output growth. The central hypothesis behind this link is a significant negative relationship between output and unemployment. An increase in output above its potential value leads to lower unemployment rates (Guisinger et al., 2018).[16]

Certain empirical studies have documented that corporate taxes increase unemployment rates (Nickell, 1997; Belot and Van Ours, 2004), although others are less conclusive (Di Tella and Macculloch, 2005). Moreover, the terms of trade are defined as the ratio of imports to output multiplied by the logarithm of their relative prices. This is interpreted in such a way as its growth rate is the change in the relative price of imports weighted by the share of imports in GDP. With the widening of the wedge between consumer and producer prices, a rise in the relative price of imports should increase wage pressures and, ultimately, unemployment (Layard et al., 1991). Next, real interest rates are the difference between the 10-year nominal government bond yield and the annual GDP price inflation. They are also considered an additional driver of unemployment. A rise in real interest rates tends to reduce capital

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[13] 16 years and over.
[14] Also, for 16 years and over.
[15] Hourly pay earnings/consumer price index.
[16] US are characterized by substantial differences in terms of their labour market structures that have a significant effect on the Okun's relationship due to differences in the level of job protection, minimum wage laws, labour union power, and the demographics, but also specific labour indicators, as well as labour market flexibility.

accumulation and, secondly, labour productivity with significant implications on labour demand (at a given wage level) (Blanchard, 1999, 2000). Another variable included in the modelling specification is unemployment benefits. High unemployment benefits available for a relatively long duration can adversely affect labour market performance, including the deterioration of skills (Nickell, 1998). Benefits may raise unemployment via two mechanisms: i) by lowering the job-search intensity of the unemployed and ii) by reducing the economic cost of unemployment.

Eita et al. (2010) provide supportive evidence that changes in labour cost positively affect unemployment. Corroborating the previous results, Nunnenkamp and Bremont (2007) document a significant relationship between FDI and unemployment. Zaman et al. (2011) provide supportive evidence of a strong relationship between inflation and unemployment, thus, justifying the presence of a Phillips curve. Moreover, the inclusion of inflation explicitly considers potential monetary and/or fiscal policy effects.

Based on the preceding discussion on the determinants of unemployment, the analysis constructs the following relationship between the unemployment rate and its main drivers, including the primary variable of interest, the ICT capital formation; however, the impact of ICT on unemployment comes through two parts, the direct impact measured as the time-varying coefficient b_{it}, and the indirect impact through the interactive term of ICT and labour productivity captured by the coefficient b_{13}:

$$\begin{aligned}(Unemployment\ rate)_t &= b_0 + b_{1t} ICT_t + b_2 (Corporate\ taxes)_t + b_3 FDI_t + b_4 (Output\ gap)_t \\ &+\ b_5 (Labour\ productivity)_t + b_6 (Social\ secirity\ benefits)_t \\ &+ b_7 (terms\ of\ trade)_t + b_8 (Real\ rate)_t + b_9 (Labor\ cost)_t + b_{10} CPI_t \\ &+ b_{11} (10 - year\ bond\ rates)_t \\ &+ b_{12} (Revenues\ from\ corporate\ taxation)_t \\ &+ b_{13} (ICT \times Labour\ productivity)_t + u_t \end{aligned} \tag{1}$$

The interaction term (ICT x Labour Productivity) can be used to explore the validity of hypothesis H_2 (the Challenging Solow Paradox), while it can also validate the role of labour productivity as the connection link between ICT and unemployment. In Equation (1), the unemployment rate is the dependent variable, while the main control/explanatory variable is ICT. The remaining right-hand side variables are the remaining controls/explanatory variables that help us estimate Equation (1) by avoiding omitted bias.

A time-varying methodology helps us bypass any endogeneity issues that may arise. More specifically, the analysis uses the Kalman filter methodology to estimate the time-vary coefficient of Equation (1). The method assumes that the b_{it} coefficient is unobservable and mean-reverting, with the loading having an autoregressive structure. The following state-space form can represent the time-varying parameter model:

$$b_{jt} = a_0 + a_1 b_{j(t-1)} + \varepsilon_t \tag{2}$$

The error term ε_t is a scalar. Note that u_t and ε_t are independent of each other. The details of the Kalman filter methodology are found in Kim and Nelson (1999). This filter method is a dynamic procedure that can update unobservable ICT loadings by learning prediction errors that contain new information. In principle, the Kalman filter recursively delivers the optimal estimator of the system's current states by a two-step process depending on available information. It first calculates the expectations of the unobserved state coefficient based on previously available information. It then updates the state coefficient when a new observation becomes available. Estimating the model is carried out using the Quasi-Maximum Likelihood (QML) method, which provides asymptotic and robust estimates.

In terms of the presence of the endogeneity problem, the time-varying estimate follows the methodological approach recommended by Kim and Kim (2011). The joint procedure estimates all the parameters in the models jointly and is developed by specifying the appropriate state-space representation of those models. Once a state-space form is obtained, applying the Kalman filter leads to the joint procedure. This approach is free from any issue of 'generated regressors', with the appropriate number of lags determined through the Akaike criterion. Regarding the instrumental ICT equation, the Akaike criterion showed up to two lags for the instruments used for Equation (1).

4. Empirical Analysis

The first part of the empirical analysis investigates the presence of stationarity across all variables included in Equation (1). To test for the order of integration of each time-series variable in the model, we employ the General Least Squared Dickey-Fuller test, recommended by Elliott et al. (1996). As reported in Table 2, the unit root test results illustrate the presence of a unit root in the levels across all variables under consideration, except for the output gap, which is stationary in its levels. Once the variables are first differenced, they turn out to be stationary.

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Next, the analysis is carried out from the graphical analysis of the b_{1t} parameter. The results are reported through graphical (time-varying) representations to depict the changing nature of the coefficient over the time horizon. This method permits identifying how the coefficient has changed in time, as certain events may affect one period but not another. With a visual examination of the evolution of this coefficient, the analysis examines whether the direct effect of ICT on unemployment is positive or negative, or both over time, depending on the period under consideration. The time-varying path of the ICT coefficient is plotted with a 95% confidence interval in Figure 6 when unemployment is measured as U-3. The graph reveals that the impact of ICT was positive until 2000. Next, it shows a downward trend, with a stronger (negative) impact after 2009, when technological investments were more rapid and significant. In addition, the estimates obtained from the time-varying coefficient model highlight that the average value of the b_{1t} coefficient is -0.0205, suggesting that ICT negatively impacts US unemployment over the entire period under examination. This coefficient also appears to be significant at the 5% level. Consistent with Hypothesis H_1, the effect of ICT on unemployment is negative after 2009, although the time-varying estimation results reveal that the impact of ICT on unemployment varies over time. Interestingly, the effect started to decline around when 3G was introduced and turned negative right around the time 4G was introduced, indicating the beginning of capitalisation effects from technology.

Moreover, **Table 3** reports the quantitative estimates of Equation (**1**). The results provide with respect to the coefficient b_{1t} support the direct negative effect of ICT on unemployment (-0.0314), while they also highlight that the coefficient of the interactive term (which identifies the indirect effect of ICT on unemployment through labour productivity) is also negative, with a value of -0.0162, providing support to the argument that ICT increases productivity (Hypothesis H_2) and thus their combined effect reduces unemployment.

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Next, Figure 7 reports the time-varying coefficient of ICT on US unemployment (with the output being measured through the Hodrick-Prescot filter). However, this time unemployment is measured as U-6. The graphical results provide supportive evidence to those reported previously. This time, the overall impact turns out to be -0.0279, statistically significant at 5%. The results resemble those reported above in **Figure 6**.

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Figure 8 repeats the analysis, but the output gap is determined through the band-pass filter developed by Baxter and King (1995). An alternative inflation measure is also calculated as the percentage changes for the GDP deflator. The implied GDP-deflator is calculated based on the ratio of the nominal GDP and the real GDP in chained 2010 dollars. Data on this measure of the price index are sourced from DataStream. Unemployment is measured as U-3. The results confirm those initially reported previously in **Figure 6**. The average value of the ICT coefficient is now -0.386, providing supportive evidence of the negative association between ICT and unemployment in the US over the period after 2009.

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Overall, the main results are robust to alternate measures of unemployment and the output gap, thus confirming support for *Hypothesis 1 (**H_1**)* for the period after 2009. Nonetheless, a decline appeared after 2000, reflecting a process starting in the new millennium.

5. Channels through which ICT affects labour productivity

This section explores potential channels through which ICT can affect workers' productivity. More specifically, i) ICT improves access to information (e.g., access to ultra plus internet) and communication (e.g., mobile technologies). Based on a natural experiment in Norway, Akerman et al. (2015) show that broadband internet improves workers' productivity for high-skilled workers but decreases productivity for low-skilled workers. Improved access to information and communication can improve employee performance, such as manufacturing efficiency (Bartel et al., 2007). Moreover, ii) ICT can also alter the structure of employment (Viollaz, 2019). For instance, labour productivity is improved as low-skilled jobs are replaced by automation.

A. The Manufacturing Efficiency Channel

The literature has identified that ICT technologies directly affect the growth of ICT-producing industries (Farooquie et al., 2012). ICT creates new models of e-businesses, improves product quality and quantity, and increases market competition.[17] Therefore, this subsection aims to explicitly determine the impact of ICT on the efficiency in manufacturing using the Data Envelopment Analysis (DEA) modelling approach.

DEA is a non-parametric method for computing and assessing the relative efficiency of homogeneous decision-making units with different inputs and outputs (Tohidi and Khodadadi, 2013). It provides efficiency scores onto an efficient frontier. DEA was introduced by Charnes et al. (1978) and extended by Banker et al. (1984).[18] DEA is favored where measurement errors are unlikely to pose much of a threat. Let the inputs and outputs be represented by x and y, respectively. Assuming the general case, which includes variable returns to scale, and following Färe et al. (1989) and Färe et al. (1994), the DEA model of output, given the current use of inputs, is given as the measure of technical efficiency, which is derived from the data envelopment form defined by optimisation. The model considers a vector of inputs x to generate a vector of outputs. The inefficiency (TE) is assessed regarding the production technology T that transforms inputs into outputs. More details about the DEA methodology can be found in the Appendix. **Figure 9** illustrates the course of technical efficiency. The years 1981-1982 (1981 crisis), 1986 (oil price crisis), 2001 (September 11 event), and 2008-2009 (2008-2009 financial crisis) represent critical periods when TE dramatically declines.

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Next, the impact of ICT on the aggregate technical efficiency of production can be tested by regressing the degree of technical efficiency TE on ICT and a set of other relevant drivers (control variables). The following model is adopted:

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[17] Badescu and Garces-Ayerbe (2009) document the impact of ICT on Tunisian manufacturing using the Stochastic Production Frontier method. They emphasize the positive impact of ICT on this efficiency. They argue that the initial preparation for the emergence of ICT effects is to invest in human capital and complementary concerns.

[18] It does not deal with the other concept of efficiency that is widely known as 'allocative efficiency'. Technical and allocative efficiencies sum up to what is usually defined as 'economic or cost efficiency'. Since from a cost-minimizing perspective, allocative efficiency can be interpreted as an input-price component of cost-efficiency. It is not usually considered when the quantity-based concept of productivity is examined (Farrell, 1957).

$$TE_t = \beta_0 + \beta_1 SOFT_t + \beta_2 ICT_t + \beta_3 R\&D_t + \beta_4 SIZE_t + \beta_5 RIP_t + \beta_6 \left(\frac{K}{L}\right)_t + \beta_7 FATTAD_t + \beta_8 DEB_{K_t} + \varepsilon_t \quad (3)$$

where TE is technical efficiency scores, SOFT represents the ratio between software stock and total tangible and intangible assets. ICT denotes the ICT variable used previously, R&D is the ratio between the stock of R&D expenses at constant prices and turnover, SIZE is a dummy variable for small and medium-sized enterprises (employing from 20 to 99 workers) and large enterprises (employing over 99 workers), RIP shows a dummy variable for the firm's territorial location (North, South, East, West, and Central), K/L is the ratio between tangible plus intangible assets and the number of employees, FATTAD denotes the turnover per worker employed, and DEB_K is the ratio between total debt and capital. Finally, ε represents stochastic errors (normally distributed).

Table 4 reports the results of DEA in terms of the mean, the standard deviation from the mean, and the coefficient of variation of technical efficiency. They illustrate that the manufacturing sector's mean value of T.E. is relatively high. In contrast, the coefficient of variation is relatively low, reflecting a low degree of concentration relevant to the nearness of the efficient frontier.

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Next, Table 5 presents the econometric estimates of the ICT parameter on technical efficiency. The findings highlight ICT's strong positive and statistically significant effect on technical efficiency.

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In the following step, the analysis includes the estimated TE variable from Model (3) to explore its impact on labour productivity. In particular:

$$prod_t = d_0 + d_{1t}\widehat{TE}_t + d_2 labpart_t + d_3 infl_t + d_4 INV_t + d_5 FDI_t + d_6 Urb_t + d_7 W_t + \theta_t \quad (4)$$

The new time-varying coefficient of technical efficiency, that is d_{1t}, is depicted in Figure 10. It illustrates that the coefficient evolves positively throughout the period under study.

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B. The Labour Structure Channel

Wolcott (2021) argues that low-skilled workers are less likely to be employed today than high-skilled workers, offering three competing explanations, a) automation and trade reduce the demand for low-skilled workers (Acemoglu and Restrepo, 2020), b) factors increasing the value of leisure, such as health, welfare, and recreational gaming/computer technology that reduce the supply of low-skilled workers (Aguiar de Medeiros and Trebat, 2017), and c) factors affecting job search (e.g., online job boards), which may have reduced search frictions for high-skilled workers. According to this mechanism, high technological advances generate the *worker composition effect*; growth in high-tech sectors increases the number of jobs, but mainly for the high-skilled members, mostly in the segment of the labour market associated with tradeable sectors (Lee and Clark, 2021).

In this part of the empirical analysis, we first examine the impact of ICT on the labour structure variable, measured as the ratio of high-skilled workers to low-skilled workers. The modelling approach follows a version of the equation model from Lee and Clark (2021):

$$logS_t = c_0 + c_1 logICT_t + c_2 UN_t + c_3 logEMPL_t + u_t \qquad (5)$$

where LS is the labour market structure variable defined above, UN_t is the unemployment rate and $EMPL_t$ is the proxy of total employment. u_t is the error term. Data on low- and high-skilled workers are obtained from the US Department of Labor, while those on the unemployment rate and total employment are sourced from the Eikon database. The results are reported in Table 6. They document that improving ICT leads to a higher proportion score of high-skilled to low-skilled workers. More specifically, the estimated figure of 1.139 highlights that a 1% increase in ICT leads to a 1.14% increase in the employment of high-skilled workers.

- -
INSERT TABLE 6 ABOUT HERE
- -

Finally, we include the predicted labour structure variable (L.S.) from Model (5). In particular:

$$prod_t = g_0 + g_{1t} LS_t + g_2 labpart_t + g_3 infl_t + g_4 INV_t + g_5 FDI_t + g_6 Urb_t + g_7 W_t + \lambda_t \qquad (6)$$

The new time-varying coefficient of labour, that is g_{1t}, is depicted in Figure 11 and illustrates that the coefficient evolves positively throughout the period under concern.

- -
INSERT FIGURE 11 ABOUT HERE
- -

Overall, the results show ICT's impact on labour productivity through improved manufacturing efficiency channels and labour structure channels.

6. Conclusion

By increasing productivity, technological advancements liberate resources to satisfy other economic needs. That is, technological-induced unemployment frees up laborers to work in other productive sectors. Total replacement of employees by machines is only possible in a scenario where all desires have been satiated and the problem of resource scarcity has been eliminated.[19] A positive relationship between ICT and employment implies a job-creating effect, where automation fills existing job vacancies, thus raising the incentive for firms to create vacancies elsewhere or retrain existing employees who might have otherwise been redundant.

Adopting ICT/5G technology has been frenzied, and the COVID-19 pandemic intensified. The US is carefully thinking through how to maximise the next-generation telecommunication networks and developing the applications that rely on them, along with the risk of foreign vendors. It is often argued that the combined effect with other technologies, such as artificial intelligence and machine learning in sensors, will destroy many low-skilled jobs currently performed by labour workers. Deployment would require allocating the high- and mid-band 5G spectrum and more numerous cell sites compared to previous networks, plus the transition to virtualised radio access network infrastructures. The diffusion effects on employment are necessary since the labour market impact of new technologies does not depend only on any direct effect but also on adjusting other parts of the economy.

This study aimed to test whether the Solow productivity paradox (which occurred in the US in the 1970s-1980s) emerged in the 21st century, given the rapid development of ICT. The findings indicated that the gross fixed capital formation of ICT equipment reduced the unemployment rate after 2009; however, a trend started following the year 2000. An inverted U-shaped effect between ICT and unemployment has been identified over the period 1972 – 2020, where the negative coefficients have been followed by positive coefficients until succeeded by negative coefficients again. Additionally, the analysis examined the impact of

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[19] Nordhaus (2015).

ICT investments on labour productivity. Over the entire period under study, the results of the empirical analysis documented a positive influence of ICT on labour productivity. Moreover, empirical evidence suggests that ICT improves labour productivity by improving access to communication and information and the structure of the labour force.

The results in this paper point to specific important policy implications. The beneficial aspects of ICT in reducing unemployment and improving labour productivity suggest that the macroeconomy may benefit from private and public sector investments in ICT capital. Indeed, recent research has shown the benefits of "e-government", i.e., the use of ICT to improve the functioning of government. In the private sector, the beneficial spillovers of ICT technology may result in under-investment in ICT. Thus, government policy (e.g., tax credits) used to incentivise ICT investments may pay dividends. Finally, taking a more global perspective, the efforts of the US Department of Commerce to increase ICT exports will likely help other countries improve their employment outcomes and raise productivity.

In parallel to investing in the ICT infrastructure such as internet exchange points (IXP), terrestrial and subsea cables, satellites, and wireless systems (e.g., 5G), we need to reform ICANN (formerly a subsidiary of the US Department of Commerce). This monopoly connects I.P. addresses to Domains. A new structure should allow more decentralised formats, so countries should not be scared to be thrown off the internet (off the ROOT, not the infrastructure) and take them back to the telegraph era. If decentralisation is not achieved, other countries will want to create their parallel internet (a mechanism to link I.P. Addresses with domains). Decentralisation and free competition from its current natural monopoly will offer higher data rates and fewer communication delays than today's obsolete internet standard, TCP/IP. Specifically, changing the rules of the Transmission Control Protocol (TCP), i.e. ensures that the information reaches the end-user after the sender breaks it down to the recipient. Also, changing the algorithm of the Internet Protocol (I.P.) is how information packets will move between nodes or network nods. Helping the EU, for example, create its mechanism linking IP addresses with domains will enhance its digital sovereignty.

In addition, the findings support that the digitalisation of the economy should prompt a rethinking of the role of education policy. More specifically, to maximise the gains of digitalisation and generate new entrepreneurial opportunities, it is fundamental to invest in raising the overall abilities of the workforce. Additionally, the close link between ICT and labour markets indicates the role of an emerging collaborative economy, a new form of production of goods and services. Technological innovations, such as smartphones, new algorithms, and powerful broadband connections, have grown in importance. Future investigations should look at labour productivity by looking at GDP per hour and the hypotheses above in different cultural contexts using panel data and a more comprehensive sample of countries.

APPENDIX

We are measuring technical efficiency through the non-parametric DEA methodology. Data Envelopment Analysis (DEA) was initially developed for performance measurement. It is a linear programming method, and it is effectively used in our paper to assess the relative performance or technical efficiency of the ICT factor on an aggregate level through the employment of certain inputs and outputs. The efficiency level is calculated by comparison with the best production in the sample to derive compared efficiency. The DEA approach calculates a single relative ratio by comparing total weighted outputs to total weighted inputs, and the distinctive feature is that any specific functional form is not required. The DEA efficiency value ranges from 0 to 1. The literature has used either the input-oriented (cost minimisation) approach or the output-oriented approach (output maximisation) models. To our ends, we make use of the latter approach.

The DEA method does not require the prior specification of a functional form for the production function. DEA concentrates on the revealed 'best-practice' frontiers. It uses a 'data-oriented approach to evaluate the performance of each decision-making unit (DMU), i.e., firm, in production. Each DMU is separately analysed, and those with the 'best practice' are identified. A frontier of the units with the best practice is constructed. DEA then evaluates the technical efficiency of comparable DMUs relative to the best practice frontier. If a DMU's input-output combination lies on the best practice frontier, it is considered efficient. In contrast, if the input-output combination lies below the frontier, it is considered inefficient. In a DEA analysis, it is generally assumed that there are n DMUs using amounts of
m different inputs to produce s outputs. The notation is as follows:

$$x_{ij} = input(i), i = 1, \dots, m;$$

$$DMU_j, j = 1, \dots, n;$$

$$y_{rj} = output(r), r = 1, \dots, s \; and$$

$$a_j = non-negative\ weights\ attached\ to\ \ DMU_j' sinputs\ and\ outputs.$$

The analysis uses $F_0(x_j, y_j) = maximum(\varphi)$ to represent the output-oriented Farrell efficiency score that shows the maximum possible expansion of output for DMU_j. We next consider the following output-oriented DEA model with the maximisation of φ subject to:

$$\sum_{j=1}^{n} a_j y_{ri} \geq \varphi y_{ri}, r = 1, \dots, s$$

$$\sum_{j=1}^{n} a_j x_{ij} \leq x_{ij}, i = 1, \dots, m$$

$$a_j \geq 0, j = 1, \dots, n$$

here it assumes constant returns to scale (Charnes et al., 1978). The assumption is only appropriate when all DMUs operate at an optimal scale. However, more often than not, a DMU may not operate at an optimal scale for various reasons, such as imperfect competition and constraints on finance. Banker et al. (1984) extended the CRS DEA model to account for variable returns to scale. Mathematically, if the condition:

$$\sum_{j=1}^{n} a_j = 1$$

is added, then variable returns to scale are imposed, which are assumed in our analysis. The linear programming that is entailed in the DEA model is solved for every DMU in the sample to obtain its relative performance. The efficiency measure is compiled as the inverse of the maximum proportional output achieved with input quantities held constant. The efficiency measure obtained in this way defines a technical efficiency score that varies between zero and one.

The analysis uses a firm-based approach in which the value-added is measured as the operating income before depreciation and amortisation plus the labour expenses (product of several employees and the average wage index of the Social Security Administration). As inputs are used: material inputs (at constant 2000 prices), labour (measured as the number of workers), and capital. The deflator for the material inputs is the price index of such materials. The capital stock is given by firms' capital formation, including gross property, plant, and equipment, deflated by the price deflator for investment. The price index of machinery and equipment is used as the deflator. The firm-level data are obtained from the Compustat Fundamental Annual database, while the deflators are sourced from the US Bureau of Economic Analysis. Each year considered a different number of firms, totalling 171,594 manufacturing firms. Specific filtering was followed based on Imrohoroglu and Tuzel's (2014) recommendation concerning removing regulated and financial firms from the sample.

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Figure 1 Caption: *US Labour Productivity*

Figure 1 Alt Text: *This figure presents the labour productivity in manufacturing and its rate of change in US over the last three decades. Notice that the rate stagnated after 2000, meaning labour productivity has not changed much.*

Figure 1. *US Labour Productivity. The Solow Paradox is shown by the decrease in labour productivity in the manufacturing sectors in the early 2000s and the steep decline in labour productivity during the Great Recession. Following the Great Recession, labour productivity was relatively stagnant before turning negative due to the COVID-19 pandemic in the first quarter of 2020.*

Figure 2 Caption: *US Labour Productivity and ICT*

Figure 2 Alt Text: *This figure presents the labour productivity in manufacturing and the evolution of ICT. Notice that the ICT has declined after 2000 as an after-effect of the dot com crisis.*

Figure 2. *US Labour Productivity and ICT. The figure demonstrates the evolution of labour productivity in manufacturing and ICT. The figure demonstrates that ICT has been continuously rising until the dot com bubble, where a sharp decline is demonstrated.* H_2 *assumes that US information and communication technology positively relates to US labour.*

Figure 3 Caption: *US Unemployment*

Figure 3 Alt Text: *This figure presents the peaks and troughs of unemployment in US. Notice in grey areas the recessions. Different levels of unemployment are presented as influenced by the level of education. As education increases, the curves move downwards.*

Figure 3. *US Unemployment. Historical evolution of Total Unemployment, Total Unemployment Rate and Unemployment Rates for Highly and Low Skilled individuals for the period starting from the* 1^{st} *Quarter of 1992 to the* 2^{nd} *Quarter of 2020. We observe how unemployment and unemployment rates exhibit similar trajectories over time. For instance, unemployment and unemployment rates peaked in the early 1990s recession due to the liquidity trap from the FED and the oil price shock of the Iraqi invasion of Kuwait. Both peaked during the early 2000s recession in the aftermath of the dot-com bubble. During the Great Recession, both series exhibit substantial increases; however, these pale in comparison to the current COVID-19 pandemic, which reports the highest levels of* unemployment thus far. Furthermore, the figure reports that higher levels of education mitigate unemployment with lower rates.

Figure 4 Caption: *US Unemployment and ICT*

Figure 4 Alt Text: *This figure presents the peaks and troughs of US unemployment compared to the peaks and troughs of ICT in US. Notice in grey areas the recessions. Notice the opposite movement of ICT with Unemployment.*

Figure 4. *US Unemployment and ICT. The figure depicts the historical evolution of ICT and Unemployment from the early 90s till the second quarter of 2020. The early insight indicates that unemployment had increased since the early 1990s recession when ICT increased. During the early 2000s recession in the aftermath of the dot-com bubble, ICT declined rapidly, followed by a simultaneous increase in unemployment. During the*

Great Recession, both series exhibited opposite movements; however, these pale in comparison to the current COVID-19 pandemic, which reported the highest levels of unemployment thus far, as these have not been followed by increases in ICT investments. Furthermore, the figure provides an early insight into the first testable hypothesis.

Figure 5 Caption: *US GDP and Unemployment*

Figure 5 Alt Text: *The figure depicts how GDP and Unemployment evolve relevant to the documented ICT Gross Fixed Capital Formation. The general trend for GDP is negative, while for unemployment, the trend appears positive.*

Figure 5. *US GDP and Unemployment. The GDP and Unemployment Rate evolution on ICT Gross Fixed Capital Formation from Q1 1972 to Q2 2020. The figure reveals a positive trend for the GDP Deflator – ICT Gross Fixed Capital formation relationship and a negative trend for the Unemployment Rate – ICT Gross Fixed Capital Formation relationship. Notice the effect of the exogenous shocks on the trend from the 2008 crisis and the COVID-19 pandemic. The blue line has been suggested by the literature so far, whilst the red line represents our innovation.*

Figure 6 Caption: *Time-Varying Coefficient of ICT on U-3 Unemployment: Output Gap is Measured Through the Hodrick-Prescott Filter*

Figure 6 Alt Text: *The figure depicts the correlated values of the time-varying coefficient of ICT on U-3 unemployment between 1972 and 2020 for every quarter using the Hodrick-Prescott Filter. The red line represents the confidence intervals.*

Figure 6. *Time-Varying Coefficient of ICT on U-3 Unemployment: Output Gap is Measured Through the Hodrick-Prescott Filter*

Figure 7 Caption: *Time-Varying Coefficient of ICT on U-6 Unemployment: Output Gap is Measured Through the Hodrick-Prescott Filter*

Figure 7 Alt Text: *The figure depicts the correlated values of the time-varying coefficient of ICT on U-6 unemployment between 1972 and 2020 for every quarter using the Hodrick-Prescott Filter. The red line represents the confidence intervals.*

Figure 7. *Time-Varying Coefficient of ICT on U-6 Unemployment: Output Gap is Measured Through the Hodrick-Prescott Filter*

Figure 8 Caption: *Time-Varying Coefficient of ICT on U-6 Unemployment: Output Gap is Measured Through the Band Pass Filter*

Figure 8 Alt Text: *The figure depicts the correlated values of the time-varying coefficient of ICT on U-6 unemployment between 1972 and 2020 for every quarter using the Band Pass Filter. The red line represents the confidence intervals.*

Figure 8. *Time-Varying Coefficient of ICT on U-6 Unemployment: Output Gap is Measured Through the Band Pass Filter*

Figure 9 Caption. *Technical efficiency of US manufacturing firms.*

Figure 9 Alt Text: *The figure depicts the course of estimated technical efficiency in relevance to US manufacturing firms.*

Figure 9. *Technical efficiency of US manufacturing firms.*

Figure 10 Caption: *Time-Varying Coefficient of Technical Efficiency on US Labour Productivity*

Figure 10 Alt Text: *The figure depicts the correlated values of the time-varying coefficient of Technical Efficiency on Labour productivity unemployment between 1972 and 2020 for every quarter. The red line represents the confidence intervals.*

***Figure 10**. Time-Varying Coefficient of Technical Efficiency on US Labour Productivity*

Figure 11 Caption: *Time-Varying Coefficient of Structural Labour on US Labour Productivity*

Figure 11 Alt Text: *The figure depicts the correlated values of the time-varying coefficient of Labour structure on Labour productivity between 1972 and 2020 for every quarter. The red line represents the confidence intervals.*

***Figure 11**. Time-Varying Coefficient of Structural Labour on US Labour Productivity*