ICT and economic resilience: evidence from the natural experiment of the COVID-19

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Abstract

The purpose of this paper is to highlight the role of ICT in advancing a country's economic resilience. By concentrating on the cyclical component of GDP this study examines if European countries with higher ICT intensity reacted differentially to the adverse shock brought by the COVID-19 pandemic. Difference in differences and propensity score matching estimates show that the economic losses of the COVID-19 pandemic were not equal across countries. Instead, countries with higher internet connectivity witnessed lower output losses in terms of cyclical GDP. Several robustness and sensitivity checks confirm that cyclical output dropped differentially in countries with higher internet adoption.

JEL classification: E32; O30; O50

Keywords: COVID-19; Information and communication technology; Economic resilience; Business cycles; Difference in differences

1. Introduction

The advent of the COVID-19 pandemic brought an enormous shock on aggregate economic activity. Its outbreak in early 2020 forced governments impose severe social distancing measures to slow down the spread of the disease. These restrictions resulted in a disruption of the regular economic activity and suspension of the normal flows of goods and services. Over the course of 2020, the global economy went into recession, contracting by -3.3 per cent according to estimates of the International Monetary Fund (World Economic Outlook IMF, 2021) and with a strong recovery observed within 2021.

One of the most immediate effects of the pandemic was the increase in the digital take-up by households, firms and the government giving a boost to new, internet-based ways of doing things (e-government services, e-commerce, teleworking etc.) that would allow the uninterrupted flow of economic activity where possible. Katz and Jung (2021) note that intangible investment and internet traffic worldwide increased during the pandemic while information and communication technology (ICT) capital investment accelerated from a 0.5% annual growth rate between 2010 and 2019 to 1.8 per cent between 2019 and 2020 in OECD countries. Economies that had already made progress towards digitization were in an advantageous position to continue to work and produce remotely.

While there is a considerable amount of research that explores the role of ICT on economic performance, the existing literature faces several limitations. First and most important, drawing on Draca et al.'s (2007) review, the effect of ICT is often studied under the rubric of total factor productivity or economic growth and less on other measures of economic performance. Up until now, research into the contribution of ICTs to mitigate the economic impact of crises is limited, with few studies having so far explored whether information technology helps countries endure in periods of financial-economic crises (Bertschek et al. 2019). Given that ICT capital deepening increased substantially in the beginning of this century throughout Europe it seems natural to consider its potential role in improving resilience and fostering economic recovery during a pandemic. Thus far, empirical evidence on the role of digitization in mitigating the economic losses resulting from emergency conditions is scarce and refers mainly to natural disasters (Teodorescu 2014; O'Reilly et al. 2006) and the SARS pandemic in East Asia (Katz et al. 2020).

Second, while the general view among economists is that ICT exerts a positive effect on economic growth, the empirical evidence provided so far is not conclusive. Until now, there is there is no definite on whether ICT exerts a strong impact on economic growth. The productivity puzzle that was first stated by Solow (1987, p.36) and then by Brynjolfsson’s (1993) classic article states that the U.S. and other advanced economies witnessed a slowdown on their rate of productivity growth during 2000-2020 despite the rapid development in the expansion of ICTs in the same period. There still remains skepticism as regards the effect of ICTs on economic performance, with Gordon (2016) pointing to several limitations of ICTs in comparison with the great inventions of the past that do not allow for a long run positive effect on productivity growth. Along these lines, the recent meta-analysis of Stanley et. (2018) identified positive but rather small effects of ICT on aggregate economic growth. It could be that the development of ICTs relate to complex and nuanced effects on other domains of economic performance, besides that of long run economic growth, which have not been explored so far.

Equally important, the issue of causality is a matter of concern within the ICT-economic growth literature. Most of the existing empirical studies merely regress productivity growth or GDP per capita growth on measures of ICT without addressing issues that cause endogeneity bias. There is a great possibility that economic growth causes higher investment in ICT as per General Purpose Technology (Carlaw and Lipsey 2002). Therefore, the issues of reverse causality, time varying and time invariant unobserved heterogeneity need to be more consistently and rigorously addressed in order to provide the relevant literature with reliable estimates on the macroeconomic impact of ICT.

The purpose of this paper is to highlight the role of ICT in advancing a country's economic resilience. Resilience is a complex concept, which can be defined as the capacity of an economy to reduce vulnerabilities, to resist to shocks and to recover quickly (OECD 2016). In this paper, the term resilience is used in a rather narrow way concentrating on the cyclical component of GDP to show how countries reacted to the adverse economic shock caused by the COVID-19 pandemic. ICT intensity is defined by the proportion of a country's population that uses internet. While the pandemic is far from being defeated and long-term consequences of the COVID-19 remain to be seen, short term effects on cyclical GDP are already evident and probably most of this impact has already been exhausted. Quarterly national accounts, provided by the Eurostat, illustrate that the majority of EU countries had returned to positive growth rates by the second quarter of 2021 while negative output gaps had largely diminished (Figure 1). The research question explored in this study is the following: Did the economic losses, in terms of cyclical output, that were brought by the pandemic differentiate across countries of Europe depending on the extent of Internet connectivity? Among EU countries there exist significant disparities with respect to the share of people that use the internet. Access to connectivity differs between and within countries due to geographical, educational, economic and institutional differences, exacerbating thereby the economic effects of the pandemic. Therefore, the hypothesis tested is that a higher share of connectivity during the lockdowns would mitigate the economic loss because more people were able to work, consume and produce remotely. By contrast, the economic loss would be differentially higher in countries with lower connectivity and subsequent difficulty to quickly engage in digital transformation.

This paper makes several contributions in the literature that examines the economic impact of ICT. First, unlike the majority of the existing studies which use measures of GDP or total factor productivity to evaluate the influence of information technology on long term growth, I provide evidence on the role of ICT in raising resilience of countries in periods of an economic crisis. To my knowledge this is one of the first studies that evaluates the effect of information technology on cyclical fluctuations during periods of crisis. Such knowledge is important for economic policy in search for strategies that improve resilience and foster the ability to resist to shocks and recover quickly afterwards. ICT may be a source of economic resilience. It has been shown to be a general purpose technology (Bresnahan and Trajtenberg 1995; Jovanovic and Rousseau 2005) that facilitates product and process innovations (Bontempi and Mairesse 2015) by providing firms and individuals new ways of working and producing. Countries that extensively use ICT may be able to deal with economic shocks more flexibly through easier reorganization of the production activity and through process and organizational innovations. Recently, Acemoglu and Restrepo (2020) illustrated that digitization could accelerate the automation of production, increase the resilience of firms' operations and secure business continuity.

Second, this paper contributes to the growing literature that examines the economic impact of the COVID-19 pandemic. While quantifying the long-term influence of the COVID-19 pandemic is not possible at this stage, the evaluation of its short run effect on output losses is possible given that most countries have now returned to positive growth rates. Few studies have so far illustrated that the economic damage of the pandemic has been uneven with the most harmful impact taking place in more advanced economies (Chudik et al. 2020), in countries with a high share of contact-intensive service sectors (Glocker and Piribauer 2021) and with poor government performance (König and Winkler 2020)

Figure 2 illustrates that that intensity in the use of internet was associated with less negative output gaps during 2020 in European countries. However, estimating the cyclical influence of the COVID-19 pandemic conditional on internet connectivity faces several empirical challenges. ICT endowments differ substantially across countries depending on their affluence, institutions, economic structures and past investment decisions. These factors generate at the same time different levels of vulnerability to the pandemic. Countries also differ in time varying and time invariant unobserved characteristics that affect aggregate economic activity. Importantly, selection of a country to different endowments of ICT is non-random making difficult the estimation of the true effect of the COVID-19 pandemic on cyclical output. While there is no perfect econometric strategy for tackling all empirical challenges together, I follow a number of different estimation strategies which reassuringly provide similar results. To account for time invariant unobserved heterogeneity, I estimate difference-in-differences specifications with fixed effects. To eliminate selection bias that arises from non-randomness of ICT intensity I provide comparisons based on kernel-based propensity score matching regressions. Time varying unobserved heterogeneity at the country level is addressed with the inclusion of country-year fixed effects and aggregate time varying indicators.

Difference in differences and propensity score matching estimates show that the economic losses of the COVID-19 pandemic were not equal for every country affected. Rather than that, countries with higher internet connectivity witnessed lower output losses in terms of cyclical GDP. Several robustness and sensitivity checks are performed which confirm that cyclical output dropped differentially so in countries with higher internet adoption.

The rest of the paper is organized as follows: section 2 critically reviews the literature that examines the macroeconomic effects of ICT and provides theoretical explanations on the possible links between ICT and economic resilience. Section 3 introduces the differences in differences econometric specification and describes the data. Section 4 presents the empirical estimates. Section 5 concludes.

2. ICT and economic performance

This study relates to the literature that examines the macroeconomic impact of ICT. At the macro or industry level, a significant number of early studies provided evidence against the belief that ICT brings about widespread long-lasting effects on economic growth. Brynjolfsson (1993) highlighted that there is a missing link between massive investments in ICT and productivity in the U.S. economy while Gordon (2000) pointed that the productivity effect of computers and the internet is not comparable with that of the great inventions of the past arguing that their favorable effect is limited to few high technology sectors. Similarly, Jorgenson and Stiroh (1999) illustrate that the ICT technological revolution has not been accompanied by widespread technical change as excess returns have been captured only by few computer producing sectors. The recent meta-regression analysis of Stanley et al. (2018) that was applied to 466 estimates drawn from 59 econometric studies shows that that there is indeed a positive but rather small impact of ICT on economic growth and productivity.

Numerous studies have attempted to resolve the issue of a missing link between ICT investment and growth by offering different explanations. A popular argument is that a critical mass of ICT investment (Draca et al. 2007) or communications infrastructure (Roller and Waverman 2001; Koutroumpis 2009) is required in order to deliver positive and significant effects on aggregate growth. Another part of the literature highlights that the impact of ICT on economic growth varies substantially across different regions of the world with the most favorable influence observed in developed countries (Dewan and Kraemer 2000; Indjikian and Siegel 2005) and the U.S. economy (Cardona et al. 2013). Interestingly, Bresnahan et al. (2002) argued in favor of favorable effects of ICT which arise only when information technology is accompanied with firm-level organizational changes and use of high skilled labor.

Another strand of the literature explains the missing link between ICT and economic growth by arguing that its favorable effect concentrates in specific parts of the economy. Stiroh (2002) and Jorgenson et al. (2008) observed a strong correlation between IT capital accumulation and labor productivity only in sectors of the U.S. economy that produce or use ICT intensively. Subsequent studies of Van Ark et al. (2003; 2008) illustrate that faster productivity of the U.S. economy and increasing productivity divergence between the U.S and Europe was due to a higher employment share of the ICT producing sector and faster productivity growth in the services industries that use of ICT intensively. Similarly, Dimelis and Papaioannou (2011) show that the effects of ICT on output growth mainly concentrate in the industries of Europe and the U.S. that either produce or extensively use ICT.

However, studies that use more sophisticated panel data econometric techniques argue that there is no missing link between information technology and economic growth. O'Mahony and Vecchi (2005) take account of country heterogeneity and show that observed differences on the effect of ICT between countries are due to the different timing of adoption. Venturini (2009) uses a dynamic panel specification and illustrates a positive long run effect of ICT which is higher than its income share. Regarding the effect of internet connectivity, the evidence provided so far indicate a favorable effect on the growth rate of output per capita (Czernich et al. 2011) and firm level labor productivity (Hagsten 2016).

These studies, although informative for a relationship between information technology and long run economic growth, tell us few things on its possible consequences during downturns and on the ability of countries to resist to large macroeconomic shocks. ICT and digital technologies are at the core of the response to the COVID-19 pandemic. The outbreak of the pandemic crisis evolved to be a catalyst for the adoption and increasing use of digitization in work and business organization. But how could the extended use of information and communication technologies mitigate the economic losses brought by the pandemic?

Economic theory suggests that information and communication technologies exert a decisive effect on the propensity to innovate. Endogenous growth models view it as contributing to economic growth through the development of new products, processes and business models resulting into increase of productivity growth. It is considered as a General Purpose Technology (Bresnahan and Trajtenberg 1995; Jovanovic and Rousseau 2005) whose diffusion can influence the economy through spillovers, technological complementariness that expand the space of possible inventions and innovations (Carlaw and Lipsey 2002).[1]

A significant number of studies have already established a favorable effect of ICT on innovative activity at the firm level. Bertschek et al. (2013) find a positive and significant effect of broadband internet on German firms' innovation activity while Polder et al. (2010) suggest that broadband internet is particularly important for the innovative activities of service firms in Netherlands. Hall et al. (2013) consider investment in ICT as a source of innovation of Italian firms which in turn enhances labor productivity. Gal et al. (2019) use firm level data from different European countries and identify a positive relationship between digital adoption and innovative activity. Chun et al. (2008) find that heterogeneity in performance of U.S. firms (variability in stock return and sales growth) is significantly correlated with ICT intensity and consider this result as evidence of creative destruction and displacement of less productive firms. In a similar spirit, Chun et al. (2014) demonstrate that technological superiority of U.S. firms leads to higher R&D investment.

Against this background, internet and the underlying infrastructure technology fulfill many characteristics of a general purpose technology that fundamentally changes how and where economic activity is organized (Harris 1998; Helpman and Trajtenberg 1998).[2] Under normal conditions, ICT usually translates into productivity improvements by facilitating the adoption of more efficient business processes (e.g., marketing, inventory optimization, and streamlining of supply chains); in accelerated

[1] Importantly, the generation and distribution of ideas and knowledge is reinforced by ICT acting as a key driver of economic growth (Lucas 1988; Romer 1990; Aghion and Howitt 1998).

[2] With its potential to facilitate decentralized information processing and to support new working modes (Bloom et al. 2014), internet may constitute a special technology with an impact on growth distinct from other technologies. Czernich et al. (2011) argue that high-speed internet via broadband infrastructure facilitates the spatial distribution of large batches of information that previously had to be collocated, which in turn allows for new business and work models as well as collaboration of firms producing specialized inputs.

innovation by introducing new consumer applications and services (e.g., new forms of commerce and financial intermediation); and in more efficient functional deployment of enterprises by maximizing their reach to labor pools, access to raw materials, and consumers (e.g., outsourcing of services, virtual call centers). All these advantages provided by better connectivity can be crucial in a context of crisis in which face-to-face interactions must be avoided.

Beyond these effects, ICT can be essential in providing economic resiliency under emergency situations, such as forced lockdowns. At the household level, broadband allows citizens to carry out many daily tasks that previously required physical contact. Examples include the access to health services, online purchase of products, distance education and teleworking. At the firm level, digitization of production is critical in keeping the economy running in the event of disruption (Katz et al. 2020). Beyond giving workers the possibility to telecommute, digitized supply chains and distribution channels can substantially contribute to keeping production active in situations where face-to-face interaction with customers and suppliers must be avoided. Finally, broadband and digitization can increase resilience at the government level, by allowing public institutions to continue their operations and deliver public services.

Investing in ICT capital has been shown to increase resilience of firms during periods of an economic crisis by adapting their production process. Bertschek et al. (2019) find evidence that during the crisis of 2008-09, ICT-intensive firms were hit less hard with respect to their productivity as they were more successful in introducing process innovations compared to non-ICT intensive firms. Similarly, Dachs et al. (2016) show that innovative firms are more resilient in downturn periods. Recently, Acemoglu and Restrepo, (2020) provided evidence that the automation of production could increase the resilience of firms' operations and secure business continuity, which could boost productivity.

3 Econometric specification and data

3.1 Difference in differences econometric specification

My analysis uses aggregate level data across 33 European countries in a period that starts from the first quarter of 1995 and ends in the second quarter of 2021 (1995Q1-2021Q2).[3] I use a difference in differences econometric specification to examine if the impact of the COVID-19 pandemic on the cyclical component of GDP was more (less) severe in countries with low (high) ICT intensity. I use as indicator of ICT intensity a measure of the percentage share of population that uses the Internet (World bank, World Development Indicators). While internet access is not a perfect measure of all aspects of ICT intensity, in that it might not capture the use of tools and applications which do not necessarily access the internet, I consider this proxy as an appropriate choice since its access and usage is the basis the underlies most modern ICT applications.

To address concerns related to reverse causality, I use a measure of internet connectivity in 2015 which was recorded well before 2020-21, ruling out from the start any concern that variation in this measure is itself informed by the emergence of the COVID-19 pandemic. I then build a difference in differences specification linking this measure of internet usage to cyclical output at the country level. This examination provides me with several advantages that are crucial for my identification strategy. First, the COVID-19 pandemic shock took place at the global level with all countries

[3] The countries under examination are: *Treated:* Austria, Belgium, Denmark, Estonia, Finland, France, Germany, Ireland, Latvia, Luxemburg, Netherlands, Norway, Slovak Republic, Spain, Sweden, Switzerland and United Kingdom. *Control:* Bulgaria, Croatia, Cyprus, Czech Republic, Greece, Hungary, Italy, Lithuania, Malta, North Macedonia, Poland, Portugal, Romania, Serbia, Slovenia and Turkey.

exposed to a treatment that was determined by nature and was largely outside the human control. Therefore, concerns about endogenous treatment assignment are alleviated as this event was randomly allocated across countries. Second, the pandemic shock was not concurrent with any other events, and thus there are no concerns of multiple treatments. Third, I use panel data that allows me to explore within country variation through the imposition of country fixed effects.

I consider the following difference-in-differences equation and ask the following question: how much did the influence of the COVID-19 pandemic on cyclical output differentiate between countries with low and high ICT intensity?

$$cycle_{it} = \alpha + \beta T + \gamma ICT + \delta T * ICT + \beta X + d_t + \theta_i + \varepsilon_{it} \quad (1)$$

Cycle refers to the short-term fluctuation of output in country *i* at year *t* that is expressed as a share of GDP. *T* is a dummy equal to one for all observations belonging to the last period of the sample (2020Q1-2021Q2) that coincides with the incidence of the COVID-19 pandemic. I consider a dichotomous treatment dummy variable *ICT* which associated with intensity in the use of information and communication technology. *ICT* receives ones for all countries with a higher than median share (%) of internet connectivity in 2015. These countries form my treatment group. My variable of interest is the interaction *T*ICT* that captures whether differences in the extent of ICT intensity map systematically into differences in cyclical output differentially so with the period of 2020Q1-2021Q2. In order to avoid possible bias due to potentially endogenous time varying coefficients country level variables are included in vector *X*. I therefore include in my specification the quarterly series of gross fixed capital formation (% share of GDP) and the growth rate of employment.

Any unobserved, country specific and time-invariant characteristics that may confound the true relationship between ICT intensity and cyclical output are eliminated by including in equation (1) country θ_i fixed effects. However, this approach does not control for unobserved time-varying characteristics that could be correlated with the outcome of interest, leading to biased and inconsistent estimates. For instance, it is possible that unobserved heterogeneous trends in omitted variables are more prevalent in ICT intensive countries and that these omitted variables cause a differential effect in output fluctuations. I therefore include in this specification pre and post treatment country specific country*quarter effects to account for possible time varying heterogeneity before and after the treatment. Additionally, equation (1) includes year fixed effects d_t to account for shocks that apply to all countries. This specification is further enriched with a time trend that is common to all countries, quarter fixed effects and the once lagged outcome variable to account for any dynamic influences in cyclical output. Finally, ε_{it} is an error term that includes all residual determinants of the outcome variable.

To reduce the risk of selection bias, difference in differences estimates of equation (1) are also based on propensity score matching. The goal is to approximate randomization by estimating the probability of ICT intensity given a vector of possible determinants. In this case, vector X includes economic and institutional characteristics that are likely to predict investments in ICT. Overall, this strategy is expected to reasonably address the most prominent identification concerns that arise from selection bias within countries and over time.

3.2 Measure of cyclical output, data and descriptive statistics

To estimate the cyclical component of GDP, I rely on quarterly chain linked data on gross domestic product (GDP) which are seasonally adjusted. They are expressed in 2010 prices (Eurostat, National Accounts 2021) and range between the first quarter of

1995 and the second quarter of 2021. The literature proposes several different methods to separate the long-term trend from the cyclical component. For the purpose of this study, I employ the Hodrick-Prescott (HP) filter (Hodrick and Prescott 1997) to detrend the GDP series. While not without criticism, the HP filter is still widely used in the business cycle literature due to its simple estimation and implementation. The cyclical component corresponds to the output gap, whereas the trend can be interpreted as the potential output. I follow the literature and use the value of λ=1,600 as a smoothing parameter for quarterly data (Ravn and Uhlig 2002).

Table 1 provides detailed definitions, sources and descriptive statistics for all variables that enter in the econometric analysis. On average, they show that the cyclical component of GDP was no different between treated countries and control countries across the whole period of investigation (1995Q1-2021Q2). Gross fixed capital formation (% of GDP) and employment growth are on average higher in ICT intensive countries. Table 2 reports business cycle measures (% of GDP) for treated and control countries. Focusing on the second quarter of 2020, when the deepest recession was observed, the highest downturn in the group of treated countries took place in the UK, France and Belgium. On the other hand, Italy, Portugal and Malta are the economies that mostly suffered from the group of less ICT intensive economies. On average, it seems that treated countries were less severely hit by the pandemic during 2020. Importantly, when observing the first two quarters of 2021, it seems that ICT intensive economies returned more quickly to positive growth rates compared to the rest countries.

4. Econometric estimates

4.1. Difference in differences estimates

Baseline estimates of the difference in differences specification are reported in Table 3 along with the associated robust standard errors corrected for serial correlation. They cover a period that starts from the first quarter of 1995 (1995Q1) and ends in the second quarter of 2021 (2021Q2). The identifying assumption of the difference in differences specification is that had the COVID-19 pandemic not taken place the evolution of cyclical output would not have been systematically different after the first quarter of 2020. One first concern is therefore that treated, and control countries could have already been on a differential path before the timing of treatment. I formally address this issue by including in the main regression specification fully flexible differential trends defined as interactions between country and time fixed effects for observations that range twelve quarters before and six quarters after the start of 2020. Specification of column 1 also allows for year and country fixed effects which control for any unobserved country specific and time-varying common shocks that may confound the true relationship between internet connectivity and cyclical output.

The upper panel of column 1 displays average differences in cyclical output between treated and control countries before the first quarter of 2020. The lower panel presents differences for a period that starts from the first quarter of 2020 onwards. Differences of the outcome variable are not statistically significant in the pre-COVID-19 period indicating that the cyclical component of GDP was not different between low and high internet intensive countries before the advent of the COVID-19 pandemic. This difference becomes positive and statistically significant for the treatment period, showing that cyclical output of low internet intensive countries diminished relative to that of treated countries. The overall effect is estimated by the difference in differences estimate which is positive and statistically significant suggesting that the cyclical component of GDP dropped differentially in low ICT intensive countries. On average the results of column 1 imply that cyclical output lowered differentially by 5% of GDP in the treatment period. I corroborate this finding with several additional robustness checks and placebos that follow.

Columns 2 and 3 provide the estimated outcomes for specifications that include the lagged outcome variable, as a way to allow for a dynamic process in cyclical GDP (column 2) and quarter specific fixed effects (column 3). All estimates are in favor of a significantly positive differential effect in high ICT intensive countries after the outbreak of the pandemic. Interestingly, the estimated differences between treated and control countries are statistically insignificant in the pre-treatment period.

Concerns related to the influence of time varying unobservables at the country level are addressed in estimates of column 4 by the inclusion of several aggregate covariates. These variables are the quarterly series of gross fixed capital formation (% of GDP) and employment growth. Their inclusion in our model is intended to reflect the effect of the production factors of capital and labor and model the influence of a wide range of unobserved factors that affect aggregate demand and therefore short run fluctuations. For instance, lower employment growth implies lower disposable incomes and may result in a drop in aggregate consumption. Investment expenditure affects directly aggregate demand and reflects responses to profitability being shaped by expectations for future economic activity and interest rates. Results of column 4 provide us with a statistically significant estimate which is higher in magnitude compared to those of columns 1-4, indicating that possible unobserved advantages of treated countries are unlikely to have been the reason why cyclical GDP lowered differentially with the advent of the pandemic.

A further concern is that ICT intensity could be correlated with country level characteristics that might account for a differential trend in cyclical output after the timing of treatment. In particular, internet intensive countries could spend more in capital investments or enjoy higher employment rates. As a robustness check, I estimate a regression adjustment model which controls for and nets out differential changes due to time-varying characteristics. Specifically, the measures of gross fixed capital formation (% of GDP), and employment growth are interacted with a post COVID-19 dummy allowing the impact of country-level covariates to change in the post-treatment quarters (column 5). As can be seen, the effect on the cyclical component of GDP remains positive and statistically significant, confirming our priors for the diverging effect of ICT intensity. Finally, estimates of column 6 include a time trend that is common to all countries. Difference in differences estimates of the last column imply that average cyclical output of control countries would have been higher by 10% had they been more intensive in the use of internet technology.

Comparisons of cyclical output could be affected by the choice of the treatment-control group and vary across different pre-treatment periods. Therefore, columns of Table 4 provide difference in differences estimates based on a strict definition of ICT intensity and relying on earlier reference periods. Considering that the COVID-19 impact could vary with the choice of treatment status, I first choose to compare the business cycle of countries with the highest 25% ICT intensity against that of the rest ones. Difference in differences estimates of column 1 confirm that the cyclical component of GDP was less severely affected in the group of ICT intensive countries indicating that this effect holds when considering a more limited treatment group. Estimates of columns 2-3 compare the cyclical component of GDP during 2020Q1-2021Q2 with that of the post-euro period (1999Q1-2019Q4) and against that of the post-crisis period (2008Q1-2019Q4). Difference in differences estimates of columns 2-3 remain strongly positive regardless of reference period confirming the beneficial effect of internet connectivity on cyclical output. Although lower in magnitude, compared to initial estimates, estimates of Table 4 reaffirm the positively differential impact of ICT intensity on cyclical GDP during the COVID-19 pandemic.

In estimates of Table 5 I provide a number of robustness tests to show that the differential effect of ICT holds when considering different econometric specifications. First, in estimates of column 1, I consider that the effect of ICT could reflect a significant concentration of a country's economic activity on the service sector. Bertschek et al.(2019) show that their findings with respect to the role of ICT in raising firms' resilience is mainly driven by service industries which are typically more ICT-intensive. I therefore include in my baseline specification a dummy variable which receives ones for countries that have a greater than median share of services in gross value added. In columns 2-3 I distinguish the impact of ICT intensity between wealthier and less wealthy economies. Relying on annual measures of GDP per capita, I perform regressions of Equation 1 across two distinct groups with higher and lower than median GDP per capita in 2019. Considering that the economic losses may depend on the severity of the pandemic expansion at each country, in columns 4-5 I repeat the same exercise for countries that were hit with diverging severity by the COVID-19 pandemic. To measure the COVID severity in each country, I use as reference indicator the number of COVID-19 attributed deaths for every 100 thousand people, according to data from John Hopkins University[4]. All estimates of columns 1-5 confirm the main finding of

[4] See https://coronavirus.jhu.edu/data/mortality. This variable is more reliable than, for instance, the rate of infection, which is more prone to reflecting differences in testing strategies.

this study regardless of whether a country is rich or not, of whether its economic activity relies on services or if it was more or less severely hit by the pandemic.

As a further test to ensure that my estimates do not reflect pre-treatment trends in business cycle fluctuations, I follow a standard approach in the literature and perform a placebo in time test. Specifically, I re-run equation (1) by moving the treatment period six quarters earlier (2018Q3-2019Q4) and restricting my sample up to last quarter of 2019. Failure to find a significant effect in ICT intensive countries would confirm that my results are not influenced by pre-existing differential trends. This is exactly what the reported results in column 6 show, providing no evidence of a differential trend in cyclical output prior to the actual period of the COVID-19 disease. Finally, in column 7 I confirm the robustness of the obtained results by skipping outlier observations with a standardized residual higher (lower) than ± 1.96.

In estimates of Table 6, I repeat estimates by using different measures of economic activity as dependent variable of equation 1. In particular, I use the measures of GDP growth (column 1), labor productivity growth (column 2) and the growth rate of gross fixed capital formation (column 3) as outcome variables and examine how much did the influence of the COVID-19 pandemic differentiate between countries with low and high ICT intensity. Using a specification of columns 1-3 in changes rather than levels eliminates any unobserved, country specific and time-invariant characteristics that may confound the true relationship between the outcome variables and ICT intensity. In addition, any unobserved heterogeneous time varying trends in omitted variables are captured with the inclusion in estimates of country fixed effects. Difference in difference estimates of columns 1-2 are positive and highly significant and indicate that the differential effect of ICT during the pandemic holds if we consider GDP and labor productivity growth as outcome variables of equation 1. Results of column 3 confirm this favorable but weak effect on the growth rate of gross fixed capital formation which is significant at the 10%.

4.2 Event study

In this section, I further illustrate that the obtained findings are not driven by pre-existing differential trends across countries. To exclude the possibility that my results are driven by omitted factors, I re-estimate my baseline model by successively adding in my specification artificial treatment quarters. In this way, I can test for a significant difference between treated and control countries in the period immediately before the start of the treatment (Angrist and Pischke 2008). Additionally, I control for country, year and quarter effects, pre- and post-treatment differential trends, once lagged effects of the outcome variable, time varying covariates and post-treatment influences that were included in estimates of Tables 3-6.

The results of this test are shown in Figure 3 which displays the estimated difference in differences coefficients for each placebo treatment period along with corresponding confidence intervals. Doing so, I still find significant, but gradually weaker estimates as the treatment period extends backwards up to six quarters (2018Q3). Thus, these results indicate that the obtained estimates are closely related to the COVID-19 pandemic and do not reflect broader trends which existed before the advent of the disease.

4.3 Selection bias

The difference in differences identification strategy relies on the assumption that there should be no omitted factors that are causing the treatment status. Because this is not a randomized experiment, country level unobservables could potentially influence a country's selection into an ICT intensive economy. A comparison of means (Table 7) indicates that there is a statistically significant difference between treated and control in terms of several measures (gross fixed capital formation, national wealth, size of service sector, human capital endowment, economic freedom) that could potentially influence the investment in ICT capital. If spending in ICT is not random, then this could be a threat to the validity of causal inference. In Table 8 I explore whether the status of treatment is correlated with a battery of observable time varying characteristics. Probit regressions were run with the dependent variable being an indicator variable that equals one for higher-than-average internet intensive countries and zero for the rest. Gross fixed capital formation (column 1), economic freedom (column 3), human capital (column 4) and dummy indicators of whether a country relies on services (column 5) or is relatively richer (column 6), all reflecting the influence of observable and unobservable variables, seem to significantly predict classification of a country as an ICT intensive economy. When running a horse race regression that includes all variables (column 7), all determinants hold their positive sign and statistical significance.

A careful evaluation of the relationship between ICT intensity and cyclical output during the COVID-19 pandemic must overcome the likely occurrence of selection bias. To reduce this risk, difference in differences estimates of equation (1) are repeated based on the method of propensity score matching. This method identifies treatment and control groups with similar probabilities (or propensity scores) of being treated conditional on a number of observable variables (Rosenbaum and Rubin 1983). The goal is to mimic randomization by creating a sample of untreated observations comparable to a sample of units that received the treatment. To do so, I use a Kernel based non-parametric estimator that uses weighted averages of all units in the control group to construct the counterfactual outcome. Weights depend on the distance between each unit from the control group and the treated observation for which the counterfactual is estimated.[5]

Propensity score matching builds on the assumption of conditional independence which states that the outcome variable must be independent of treatment after conditioning on the propensity score. Hence, implementing this method requires choosing a set of variables that credibly satisfy this condition. Relying on economic theory and a sound knowledge of previous empirical research, I include in vector *X* of equation (1) economic and institutional variables that are likely to predict investment in ICT and therefore confound its relationship with the estimated outcome. Caselli and Coleman (2001) have shown that imports of information technology goods are robustly determined by the extent of investment, protection of property rights and investment human capital endowments. Therefore, vector *X* includes as explanatory variables those of economic freedom (Gwartney et al., 2021), the investment share of GDP (Eurostat Quarterly National Accounts 2021) and an aggregate index of human capital (Feenstra et al. 2015). Given that the most intensive ICT use takes place at the service sector (Van Ark et al. 2003; 2008), I include in my specification a dummy variable which receives ones for countries with a higher than median share of services in total gross value added. Finally, relying upon the reasonable view that ICT investment could be stronger in high-income countries, I include in vector *X* a dummy variable that receives ones for countries with a higher than median GDP per capita.

Results of Table 9 (column 1) provide us with a significantly positive, although lower in magnitude (as compared to the estimates of Tables 3-5) estimate suggesting

[5] Thus, one major advantage of this approach is the lower variance which is achieved because more information is used. A drawback is that possibly not all observations that are used from the control group are proper matches.

that during the COVID-19 pandemic, the cyclical component of GDP shrank differentially in low ICT intensive countries. When including as additional regressors the variables of quarterly GDP growth (column 2) and the logarithm of GDP per worker (column 3), difference in differences estimates again show that the less ICT intensive countries were those that were most hit by the COVID-19 pandemic.

In randomized studies measured (and unmeasured) covariates are balanced between treated and control groups. In our study, as in nearly any observational study, we can only try to directly balance the measured covariates and assume that balance reduces the overt bias due to the measured covariates (Rosenbaum, 2002) in the treatment effect estimate (Rubin & Thomas, 1996; Imai et al., 2008; Imai & van Dyk, 2004; Rosenbaum, 2009). To evaluate the improvement after matching and assess the balance of the measured covariates between the treatment and comparison groups I use a measure that is known as the standardized bias.[6] Figure 4 and Table 10 illustrate that standardized biases of measured covariates were significantly higher compared to those that were obtained after applying propensity score matching. The matched sample has lower standardized bias between treatment and control group covariates, providing us with stronger confidence that the two groups are observationally similar which helps towards minimizing the overt bias. Importantly, when relying only on the variables with the lowest standardized bias (economic freedom, investment share of GDP and the dummy of national wealth), estimates of column 4 of Table 9 re-affirm that during the pandemic, cyclical output remained differentially higher in high-ICT intensive economies of Europe.

[6] The standardized bias is calculated by dividing the difference in means of a covariate between the treated group and the control group by their standard deviation.

Matching is most successful when the propensity scores in the treatment and control groups lie within the same wide range (common support condition). But if the two groups do not have considerable overlap, then substantial error may be introduced. This is particularly important for kernel-based matching since all untreated observations are used to estimate the counterfactual outcome. The distribution of the estimated propensity scores and the overlap between treated and control units are shown in Figure 5. The figure illustrates the imbalanced distribution between treatment and control countries. The common support condition is not well satisfied as there is not substantial overlap in the distribution of the estimated propensity scores for the two groups. However, once we rely on propensity score estimates that satisfy the common support condition, difference in estimates of column 5 remain significantly positive illustrating that the COVID-19 pandemic affected unevenly high and low-ICT intensive economies. When applying kernel-based matching one has to choose the bandwidth parameter.[7] While the default bandwidth parameter is set equal 0.06, I choose to test its sensitivity to higher values 0.1 and 0.2. Results of columns 6-7 (Table 9) provide us with positive and statistically significant (at 10%) estimates which verify the robustness of the obtained findings.

Overall, not only the estimates from the models of Table 9 are qualitatively close to each other, but they are also similar to the estimated impact of the difference in differences estimates of section Tables 3-6. The congruence between the results of these approaches suggests that non randomness is unlikely to drive the positive and statistically significant findings reported in the difference in differences estimates. Taken all together, results from this section show that, with the advent of the COVID-

[7] High bandwidth-values usually yield a low variance between the estimated and the true underlying density function. However, underlying features may be smoothed away by a large bandwidth leading to a biased estimate. The default type of the Kernel function is the epanechnikov.

19 pandemic, the cyclical component of GDP shrank differentially more in the less ICT intensive of Europe.

5. Conclusions

The purpose of this paper was to examine the role of ICT in advancing a country's economic resilience. I used data on internet connectivity to explore how cyclical output of European countries reacted to the adverse shock brought by the COVD-19 pandemic. Difference in differences econometric and propensity score matching estimates show that the economic losses of the COVID-19 pandemic were not equal for every country. Rather than that, countries with higher internet connectivity witnessed lower output losses in terms of cyclical GDP.

The economic implications of this result are straightforward. European countries with higher ICT intensity were able to counteract part of the economic losses, as they were more resilient to the lockdowns triggered by the pandemic. In other words, although all countries did experience some negative economic effects, these were significantly less in countries with high internet connectivity. In sum, internet usage mitigated the economic damage by keeping the economy up, by allowing people to telework, firms to continue operating and governments to provide services to citizens and enterprises.

Economic results reaffirm the importance of bridging the digital divide in the region of Europe. They illustrate the need for policymakers to reduce barriers to ICT investment and increase digital literacy. Key policies to improve investments in ICT include a) the well-functioning of labor and product markets to stimulate private investments, b) training of the workforce to acquire the necessary digital skills and c) access to finance and liquidity.

References

Acemoglu, D., Restrepo, P., 2020, Robots and Jobs: Evidence from US Labor Markets, Journal of Political Economy, 128, 2188 – 2244.

Aghion, P., Howitt, P. (1998) Endogenous Growth Theory. Cambridge, MA: MIT Press.

AMECO, 2021, Annual Macroeconomics Database.

Angrist, J.D., Pischke, J.S., 2008, *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton University Press.

Bertschek, I., Polder, M., Schulte, P., 2019, ICT and resilience in times of crisis: evidence from cross-country micro moments data, Economics of Innovation and New Technology 28, 759-774.

Bertschek, I., Cerquera, D., Klein, G.J., 2013, More Bits – More Bucks? Measuring the Impact of Broadband Internet on Firm Performance." Information Economics and Policy 25, 190–203.

Bloom, N., Garicano, L., Sadun, R., Van Reenen, J., 2014, The Distinct Effects of Information Technology and Communication Technology on Firm Organization, Management Science 60, 2859-2885.

Bontempi, M.E. and Mairesse, J. (2015) "Intangible capital and productivity at the firm level: a panel data assessment", Economics of Innovation and New Technology 24(1–2), pp. 22–51.

Bresnahan, T., Brynjolfsson, E. and Hitt, L.M. (2002) Information technology, workplace organization and the demand for skilled workers: A firm-level analysis. Quarterly Journal of Economics 117(1): 339–376.

Bresnahan, T., Trajtenberg, M., 1995, General purpose technologies 'Engines of growth'?, Journal of Econometrics 65, 83-108.

Brynjolfsson, E. (1993) The productivity paradox of information technology. Communications of the ACM 36, 66–77.

Cardona, M., Kretschmer, T. and Strobel, T. (2013) ICT and productivity: Conclusions from the empirical literature. Information Economics and Policy 25(3): 109–125.

Carlaw, K.I., Lipsey, R.G. (2002) Externalities, technological complementarities and sustained technological growth. Research Policy 31: 1305–1315.

Caselli, F., Coleman, W.J., 2001, Cross country technology diffusion: the case of computers, American Economic Review, 91, 328-335.

Chudik, A., Mohaddes, K., Pesaran, M H., Raissi, M., Rebucci, A., 2020. A counterfactual economic analysis of Covid-19 using a threshold augmented multi-country model. NBER Working Papers 27855, National Bureau of Economic Research.

Chun, H., J. Ha, and J.-W. Kim. 2014. “Firm Heterogeneity, R&D, and Economic Growth.” Economic Modelling 36: 149–156.

Chun, H., J.-W. Kim, R. Morck, and B. Yeung. 2008. “Creative Destruction and Firm-Specific Performance Heterogeneity.” Journal of Financial Economics 89 (1): 109–135.

Czernich, N., Falck, O., Kretschmer, T. and Woessmann, L. (2011) Broadband infrastructure and economic growth. Economic Journal 121: 505–532.

Dachs, B., Hud, K., Koehler, C., Peters, B., 2016, Employment Effects of Innovations over the Business Cycle: Firm-Level Evidence from European Countries, In CREA Discussion Paper 2016-20.

Dewan, S. and Kraemer, K.L. (2000) Information technology and productivity evidence from country-level data. Management Science 46: 548–66.

Dimelis, S., Papaioannou, S., 2011, ICT growth effects at the industry level: A comparison between the US and the EU, Information Economics and Policy 23, 37-50.

Draca, M., Sadun, R. and Van Reenen, J. (2007) Productivity and ICT: A review of the evidence. In R. Mansell (ed.), The Oxford Handbook of Information and Communication Technologies (pp. 100–147). Oxford and New York: Oxford University Press.

Eurostat, 2021, National Accounts.

Feenstra, R.C., Inklaar, R., Timmer, M.P., 2015. The next generation of the Penn World Table. American Economic Review 105, 3150-3182.

Gal, P., Nicoletti, G., Renault, T., Sorbe, S., Timiliotis, C., 2019, Digitalisation and productivity: in search of the Holy Grail - Firm-level empirical evidence from European countries, OECD Economics Department Working Paper No. 1533.

Glocker, C., Piribauer, P., 2021, The determinants of output losses during the Covid-19 pandemic, Economics Letters 204.

Gordon, R.J. (2016) The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War. Princeton, NJ: Princeton University Press.

Gordon, R.J. (2000) Does the "New Economy" measure up to the great inventions of the past?" Journal of Economic Perspectives 14(4): 49–74.

Gwartney, J., Lawson, R., Hall, J., Murphy, R., Callais, J., Fike, R., Geloso, V., Khalid, N., McMahon, F., Staden, M., V., 2021. Economic Freedom of the World 2021 Annual Report. Fraser Institute: Vancouver.

Hall, B. H., Lotti, F., Mairesse, J., 2013, Evidence on the Impact of R&D and ICT Investments on Innovation and Productivity in Italian Firms, Economics of Innovation and New Technology 22, 300–328.

Hagsten, E. 2016. "Broadband Connected Employees and Labour Productivity: A Comparative Analysis of 14 European Countries Based on Distributed Microdata Access." Economics of Innovation and New Technology 25 (6): 613–629.

Harris, R. (1998). The internet as a GPT: factor market implications, in (E. Helpman, ed.), General Purpose Technologies and Economic Growth, pp. 145–66, Cambridge, MA: MIT Press.

Helpman, E. and Trajtenberg, M. (1998). Diffusion of general purpose technologies, in (E. Helpman, ed.), General Purpose Technologies and Economic Growth, pp. 85–120, Cambridge, MA: MIT Press.

Hodrick, R., Prescott, E., 1997, Postwar U.S. Business Cycles: An Empirical Investigation, Journal of Money, Credit and Banking 29, 1-16

Imai, K., Van Dyk, D., A., 2004, Causal inference with general treatment regimes: generalizing the propensity score, Journal of the American Statistical Association 99, 854–866.

Imai, K., King, G., Stuart, E.A., 2008, Misunderstandings between experimentalists and observationalists about causal inference, Journal of the Royal Statistical Society 171, 481–502.

IMF, 2021, World Economic Outlook.

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.

Jorgenson, D.W., M.S. Ho, and K.J. Stiroh (2008). A Retrospective Look at the U.S. Productivity Growth Resurgence. Journal of Economic Perspectives 22 (1), 3-24.

Jorgenson, D. W., and K. J. Stiroh. 1999.“Information Technology and Growth.” The American Economic Review 89 (2): 109–115.

Jovanovic, B., Rousseau, P.L., 2005, General Purpose Technologies, In Handbook of Economic Growth, Volume 1B, 1182–1224.

Katz, R., Jung, J., 2021, The Economic impact of broadband and digitization through the COVID-19 pandemic Econometric modelling June 2021, International Telecommunication Union.

Katz, R., Jung, J., Callorda, F., 2020, Can digitization mitigate the economic damage of a pandemic? Evidence form SARS, Telecommunications Policy 44, 102044.

König, M., Winkler, A., 2020, Covid-19 and economic growth: Does good government performance pay off? Intereconomics 55, 224–231.

Koutroumpis, P. (2009). The economic impact of broadband on growth: A simultaneous approach. Telecommunications Policy, 33(9), 471–485.

Lucas, R. E. (1988) On the mechanics of economic development. Journal of Monetary Economics, 22: 3–32.

OECD, 2016, Strengthening Economic Resilience – Insights from the Post-1970 Record of Severe Recessions and Financial Crises, OECD Economic Policy Papers 20: 1.

O'Mahony, M., and M. Vecchi. 2005. "Quantifying the Impact of ICT Capital on Output Growth: A Heterogeneous Dynamic Panel Approach." Economica 72 (288): 615–633.

O'Reilly, G., Jrad, A., Nagarajan, R., Brown, T., Conrad, S., 2006, Critical Infrastructure Analysis of Telecom for Natural Disasters, Networks 2006, New Delhi: 12th International Telecommunications Network Strategy and Planning Symposium.

Polder, M., Van Leeuwen, G., Mohnen, P., Raymond, W., 2010, Product, Process and Organization Innovation: Drivers, Complementarity and Productivity Effects, Discussion paper, UN University. UNU-MERIT Working Paper Series 2010–035.

Ravn, M., Uhlig, H., 2002, On adjusting the Hodrick-Prescott filter for the frequency of observations, Review of Economics and Statistics 84, 371-375.

Roller, L.H. and Waverman, L. (2001) Telecommunications infrastructure and economic development: A ¨ simultaneous approach. The American Economic Review 91: 909–923.

Romer, P. M. (1990) Endogenous technological change. Journal of Political Economy, 98: S71–S102.

Rosenbaum, P.R., 2002, *Observational Studies* 2nd edition, Springer Verlag New York.

Rosenbaum, P.R., 2009, *Design of Observational Studies*, Springer New York.

Rosenbaum, P.R., Rubin, D.B., 1983, The Central Role of the Propensity Score in Observational Studies for Causal Effects, Biometrika 70, 41–55.

Rubin, D.B., Thomas, N., 1996, Matching using estimated propensity scores: relating theory to practice. Biometrics 52:2 49–264.

Solow, R (1987), “We'd better watch out”, New York Times Book Review, July 12, 1987, page 36.

Stanley, T.D., Doucouliagos, H., Steel, P., 2018, Does ICT generate economic growth? A meta-regression analysis, Journal of Economic Surveys 32, 705-726.

Stiroh, K. J. 2002. “Information Technology and the US Productivity Revival: What Do the Industry Data Say?.” The American Economic Review 92 (5): 1559–1576.

Teodorescu, H. N. L., 2014, Survey of IC&T in Disaster Mitigation and Disaster Situation Management. In: Teodorescu H.N., Kirschenbaum A., Cojocaru S., Bruderlein C. (eds) in Improving Disaster Resilience and Mitigation - IT Means and Tools. NATO Science for Peace and Security Series C: Environmental Security. Springer, Dordrecht.

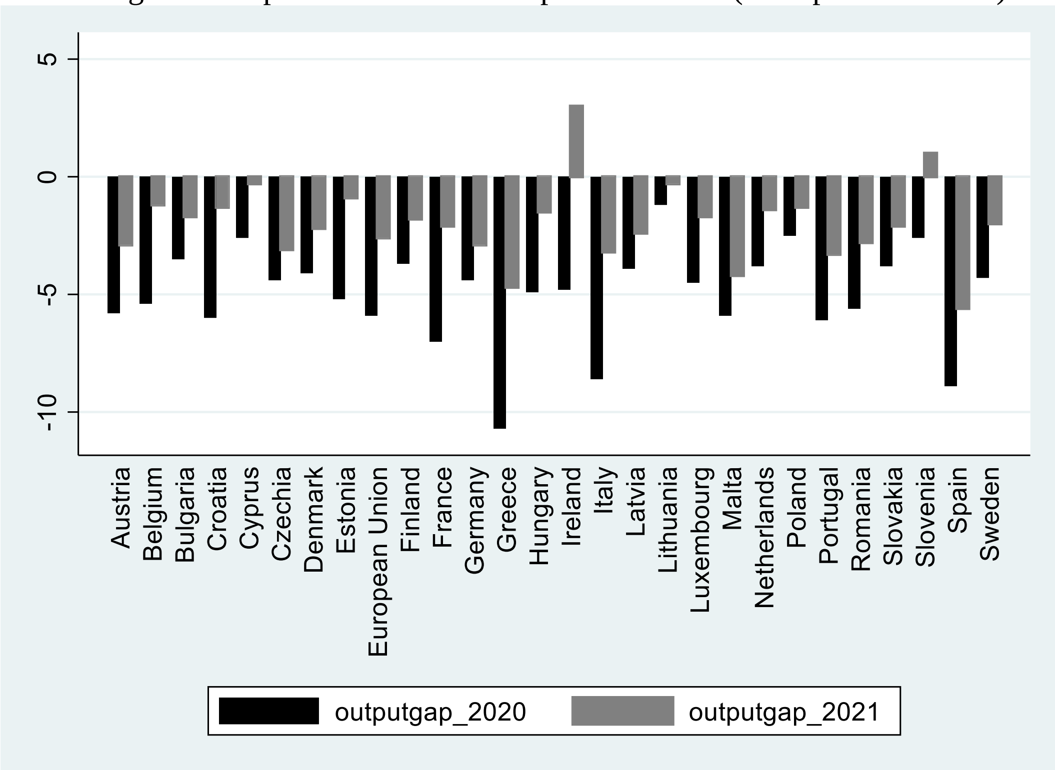
Van Ark, B., R. Inklaar, McGuckin R., 2003, ICT and Productivity in Europe and the United States Where Do the Differences Come From? CESifo Economic Studies 49, 295-318.

Van Ark, B., M. O'Mahony, and M. P. Timmer. 2008. "The Productivity Gap Between Europe and the United States: Trends and Causes." The Journal of Economic Perspectives 22 (1): 25–44.

Venturini, F. (2009) The long-run impact of ICT. Empirical Economics, 37: 497–515.

World bank, 2021, World Development Indicators.

Figure 1: Gap between actual and potential GDP (% of potential GDP)



Source: AMECO.

Figure 2: Output gap and internet use

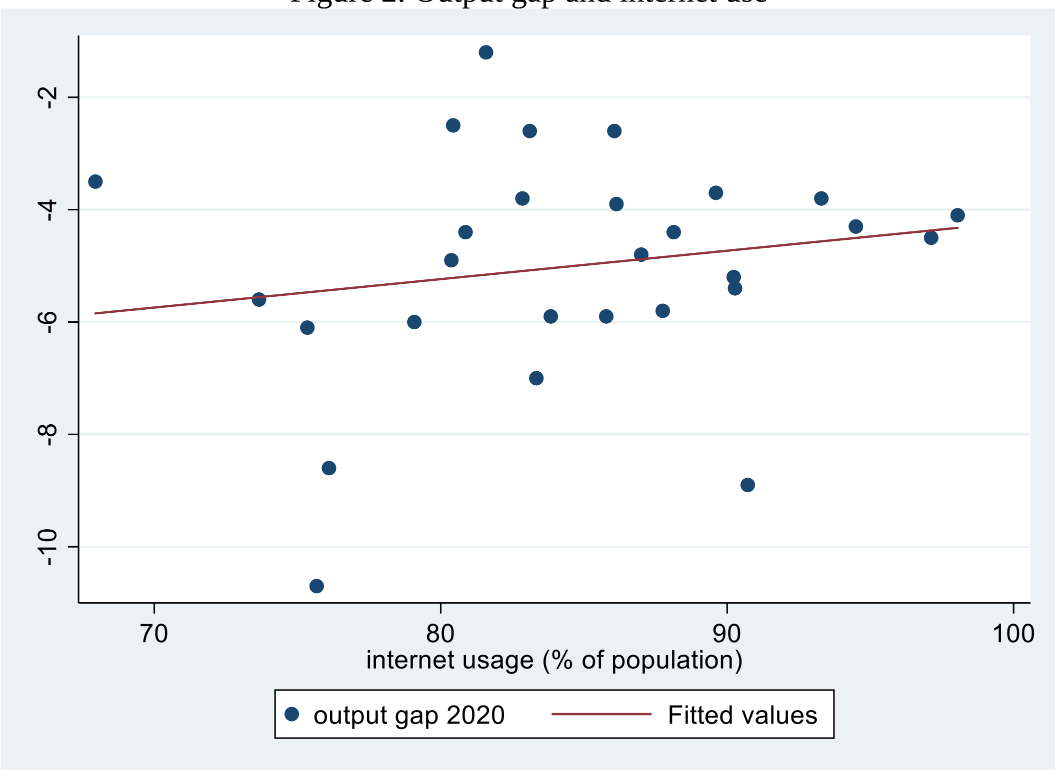


Figure 3: Event Study, differential impact on cyclical output before and after the pandemic

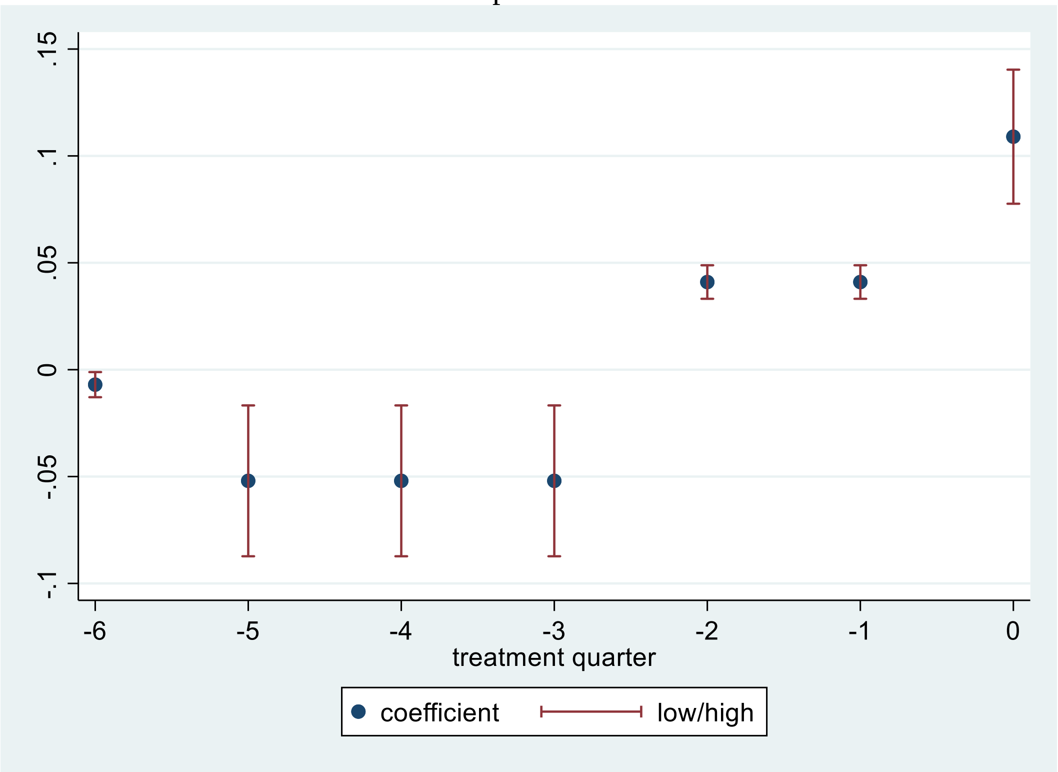


Figure 4: Standardized % bias across covariates

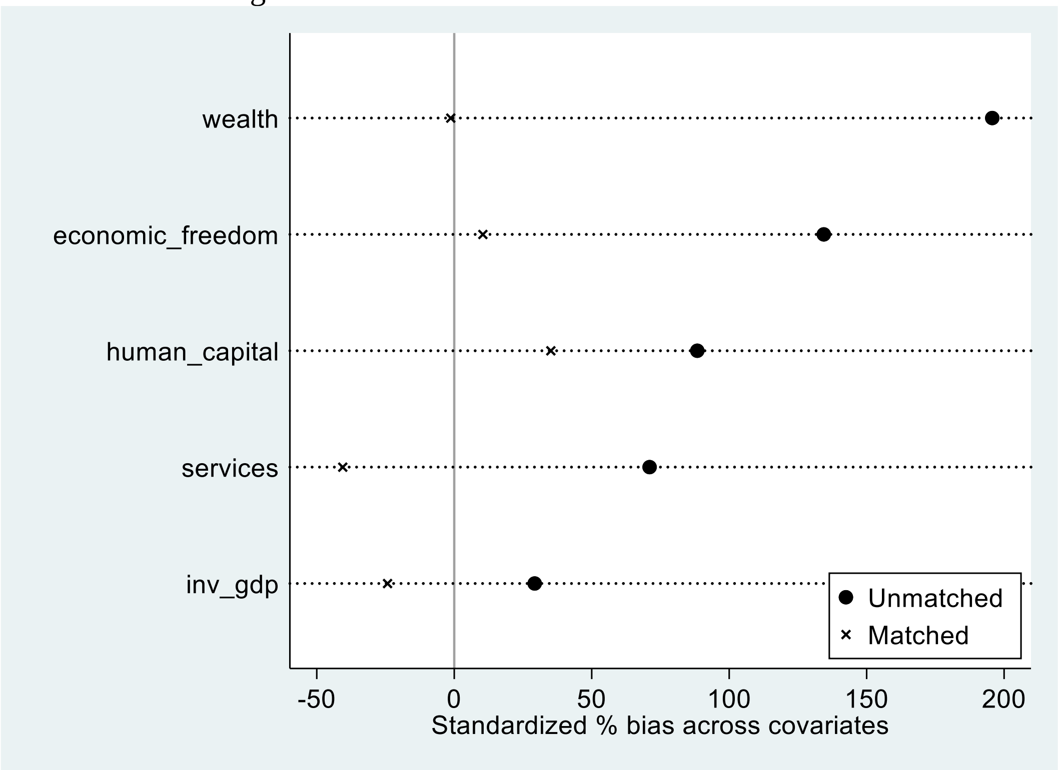


Figure 5: Validity of the common support assumption

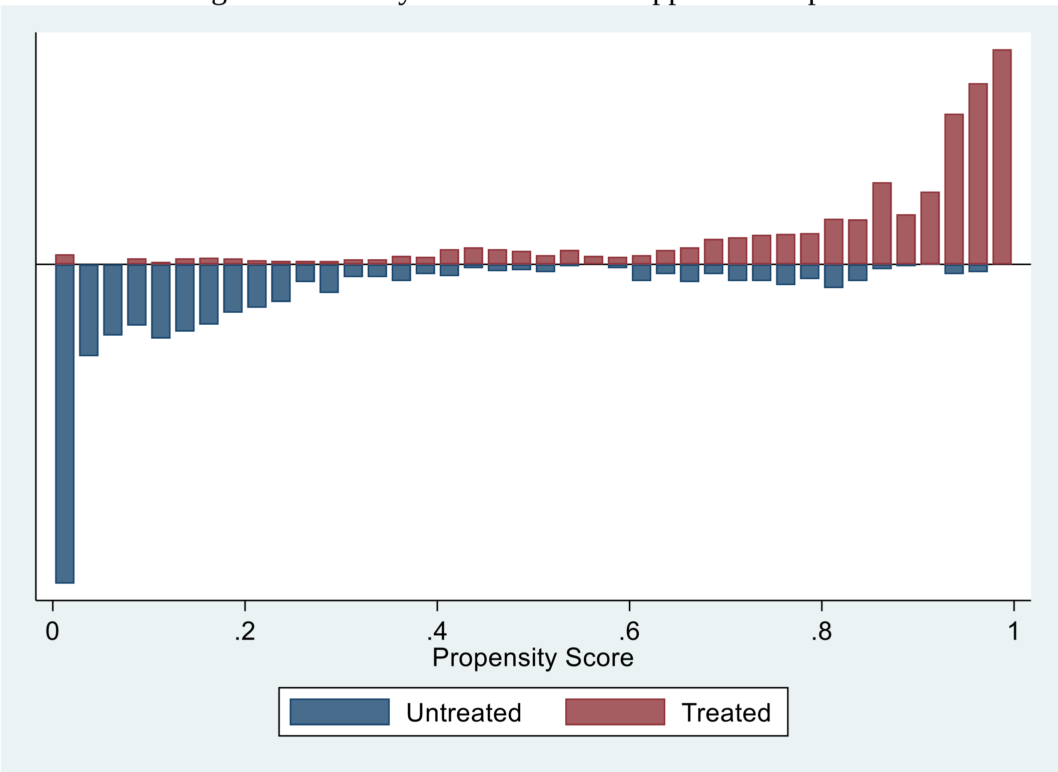


Table 1: Descriptive statistics, definitions and sources of variables

Variable	Definition	Observations	Mean	Standard deviation	Min	Max	Source
Total Sample							
Cyclical output	Cyclical component of output (% of GDP)	3,435	-0.001	0.026	-0.217	0.119	Eurostat, Quarterly National Accounts
Investment	Gross fixed capital formation (% of GDP)	3,345	0.216	0.046	0.018	0.951	Eurostat, Quarterly National Accounts
Employment growth	Growth rate of employed persons (on a quarter basis)	2,412	0.002	0.010	-0.110	0.055	Eurostat, Quarterly National Accounts
Internet usage	Internet users (% of population)	3,384	51.678	31.130	0.000	98.820	World Development Indicators, Worldbank
Treated Countries							
Cyclical output	Cyclical component of output (% of GDP)	1,795	-0.001	0.024	-0.210	0.119	Eurostat, Quarterly National Accounts
Investment	Gross fixed capital formation (% of GDP)	1,795	0.222	0.044	0.087	0.951	Eurostat, Quarterly National Accounts
Employment	Growth rate of employed persons (on a quarter basis)	1,572	0.002	0.009	-0.077	0.055	Eurostat, Quarterly National Accounts
Internet usage	Internet users (% of population)	1,760	61.143	31.226	0.000	98.820	World Development Indicators, Worldbank
Control Countries							
Cyclical output	Cyclical component of output (% of GDP)	1,640	-0.001	0.027	-0.217	0.102	Eurostat, Quarterly National Accounts
Investment	Gross fixed capital formation (% of GDP)	1,550	0.209	0.046	0.018	0.415	Eurostat, Quarterly National Accounts
Employment	Growth rate of employed persons (on a quarter basis)	840	0.001	0.012	-0.110	0.039	Eurostat, Quarterly National Accounts
Internet usage	Internet users (% of population)	1,624	41,420	27.581	0.000	90.800	World Development Indicators, Worldbank

Table 2: Cyclical output (% of GDP)
(2019Q3-2021Q2)

Treated Countries																	
	Austria	Belgium	Denmark	Estonia	Finland	France	Germany	Ireland	Latvia	Luxembourg	Netherlands	Norway	Slovakia	Spain	Sweden	Switzerland	United Kingdom
2019Q3	0.034	0.029	0.016	0.022	0.018	0.038	0.024	-0.019	0.017	0.013	0.023	0.002	0.028	0.051	0.019	0.017	0.039
2019Q4	0.031	0.035	0.013	0.016	0.013	0.035	0.023	-0.020	0.017	0.006	0.026	0.018	0.030	0.057	0.017	0.019	0.041
2020Q1	0.008	0.001	0.002	-0.001	0.007	-0.023	0.006	-0.012	0.003	-0.009	0.007	0.002	-0.015	0.006	0.007	0.001	0.014
2020Q2	-0.120	-0.134	-0.070	-0.065	-0.061	-0.181	-0.103	-0.061	-0.079	-0.082	-0.085	-0.048	-0.096	-0.204	-0.083	-0.066	-0.210
2020Q3	-0.008	-0.014	-0.010	-0.046	-0.016	0.005	-0.011	0.017	-0.027	-0.008	-0.011	-0.006	-0.008	-0.028	-0.010	-0.004	-0.040
2020Q4	-0.027	-0.014	-0.005	-0.027	-0.011	-0.005	-0.002	-0.048	-0.015	-0.005	-0.013	0.000	-0.005	-0.022	-0.010	-0.006	-
2021Q1	-0.031	-0.003	-0.012	0.004	-0.011	-0.003	-0.022	0.019	-0.013	0.022	-0.023	-0.007	-0.021	-0.025	-0.004	-0.013	-
2021Q2	0.010	0.014	0.013	0.039	0.009	0.009	-0.004	0.061	0.010	0.013	0.013	0.002	-0.003	-0.012	0.002	0.003	-
Control Countries																	
	Bulgaria	Croatia	Cyprus	Czechia	Greece	Hungary	Italy	Lithuania	Malta	North Macedonia	Poland	Portugal	Romania	Serbia	Slovenia	Turkey	
2019Q3	0.028	0.039	0.045	0.037	0.032	0.036	0.037	0.013	0.059	0.033	0.033	0.047	0.027	0.025	0.031	-0.012	
2019Q4	0.030	0.042	0.043	0.041	0.032	0.037	0.036	0.018	0.069	0.026	0.030	0.055	0.028	0.037	0.040	-0.006	
2020Q1	0.030	0.033	0.029	0.005	0.029	0.030	-0.019	0.021	0.018	0.019	0.023	0.012	0.026	0.023	-0.013	-0.010	
2020Q2	-0.083	-0.139	-0.112	-0.094	-0.116	-0.135	-0.168	-0.044	-0.142	-0.135	-0.084	-0.165	-0.102	-0.085	-0.124	-0.141	
2020Q3	-0.042	-0.077	-0.034	-0.026	-0.074	-0.033	-0.004	-0.023	-0.076	-0.004	-0.013	-0.015	-0.057	-0.018	-0.008	0.011	
2020Q4	-0.024	-0.036	-0.026	-0.020	-0.037	-0.020	-0.019	-0.013	-0.032	0.000	-0.022	-0.012	-0.021	-0.001	-0.015	0.015	
2021Q1	-0.002	0.016	-0.016	-0.026	0.008	-0.009	-0.013	0.001	-0.018	-0.007	-0.015	-0.045	-0.001	0.011	-0.004	0.028	
2021Q2	0.000	0.013	-0.005	-0.018	0.041	0.014	0.017	0.013	-0.029	-0.007	-0.001	0.001	0.012	0.017	0.009	0.029	

Table 3: Internet use and cyclical output (baseline difference in differences estimates)

Outcome variable: Cyclical output (% of GDP)						
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-treatment period (1995Q1-2019Q4)						
Control group (internet usage lower than median)	0.003	-0.001	-0.001	-0.006	-0.006	-0.032
Treatment group (internet usage higher than median)	0.002	-0.001	-0.001	-0.006	-0.006	-0.032
Difference (Treatment-Control)	-0.001 (0.003) †	0.001 (0.002)	0.001 (0.002)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Treatment period (2020Q1-2021Q2)						
Control group (internet usage lower than median)	-0.037	0.107	0.107	-0.134	-0.134	-0.179
Treatment group (internet usage higher than median)	0.013	0.149	0.148	-0.025	-0.025	-0.069
Difference (Treatment-Control)	0.049*** (0.001)	0.042*** (0.006)	0.041*** (0.006)	0.109*** (0.017)	0.109*** (0.017)	0.109*** (0.017)
Difference in differences	0.050*** (0.003)	0.041*** (0005)	0.041*** (0.005)	0.109*** (0.016)	0.109*** (0.016)	0.109*** (0.016)
R-square	0.54	0.76	0.76	0.80	0.80	0.80
Country, year fixed effects	Included	Included	Included	Included	Included	Included
Pre-and post- treatment differential trends	Included	Included	Included	Included	Included	Included
Lagged outcome variable		Included	Included	Included	Included	Included
Quarter fixed effects			Included	Included	Included	Included
Time varying covariates				Included	Included	Included
Post-treatment influences					Included	Included
Time trend						Included
Number of observations (pre-treatment period, control group)	1,544	1,528	1,528	789	789	789
Number of observations (pre-treatment period, treatment group)	1,696	1,679	1,679	1,481	1,481	1,481
Number of observations (treatment period, control group)	96	96	96	48	48	48
Number of observations (treatment period, treatment group)	99	99	99	87	87	87
Total number of observations	3,435	3,402	3,402	2,405	2,405	2,405

† Robust standard errors are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Note: The outcome variable is cyclical output (% of GDP). Differences between treated and control countries are estimated as the difference between cyclical output of treated countries and cyclical output of control countries.

Table 4: Internet use and cyclical output (different treatment group and periods of comparison)

Outcome variable: Cyclical output (% of GDP)			
	(1)	(2)	(3)
	(Treated countries: top 25% of internet usage)	(Pre-treatment period: post euro 1999Q1-2019Q4)	(Pre-treatment period: post crisis 2008Q1-2019Q4)
Pre-treatment period			
Control group	-0.032	-0.064	-0.015
Treatment group	-0.031	-0.065	-0.012
Difference (Treatment-Control)	0.001 (0.001) †	-0.001 (0.001)	0.004 (0.004)
Treatment period			
Control group	-0.069	-0.175	-0.015
Treatment group	-0.038	-0.131	0.035
Difference (Treatment-Control)	0.031*** (0.005)	0.044*** (0.004)	0.050*** (0.010)
Difference in differences	0.030*** (0.005)	0.045*** (0.004)	0.047*** (0.008)
R-square	0.80	0.84	0.87
Country, year fixed effects	Included	Included	Included
Pre-and post- treatment differential trends	Included	Included	Included
Lagged outcome variable	Included	Included	Included
Quarter fixed effects	Included	Included	Included
Time varying covariates	Included	Included	Included
Post-treatment influences	Included	Included	Included
Time trend	Included	Included	Included
Number of observations (Before schooling reform, control group)	1,482	672	384
Number of observations (Before schooling reform, treatment group)	788	1,260	720
Number of observations (After schooling reform, control group)	90	48	48
Number of observations (After schooling reform, treatment group)	45	87	87
Total number of observations	2,405	2,067	1,239

† Robust standard errors are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Note: The outcome variable is cyclical output (% of GDP). Differences between treated and control countries are estimated as the difference between cyclical output of treated countries and cyclical output of control countries.

Table 5: Internet use and cyclical output (robustness estimates)

Outcome variable: Cyclical output (% of GDP)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	(Services)	(Wealthier countries)	(Less wealthy countries)	(Severely hit countries from COVID-19)	(Less severely hit countries from COVID-19)	(False treatment period: 20018Q3-2019Q4)	(Drop outliers)
Pre-treatment period (1995Q1-2019Q4)							
Control group (internet usage lower than median)	-0.032	0.058	-0.022	-0.008	-0.052	0.065	-0.032
Treatment group (internet usage higher than median)	-0.034	0.057	-0.022	-0.009	-0.052	0.066	-0.032
Difference (Treatment-Control)	-0.001 (0.001) †	-0.002 (0.002)	0.000 (0.002)	-0.001 (0.003)	-0.000 (0.002)	0.000 (0.001)	0.000 (0.001)
Treatment period (2020Q1-2021Q2)							
Control group (internet usage lower than median)	-0.178	0.105	-0.168	-0.165	-0.199	0.083	-0.179
Treatment group (internet usage higher than median)	-0.071	0.152	-0.042	-0.014	-0.112	0.081	-0.069
Difference (Treatment-Control)	0.108*** (0.017)	0.047*** (0.005)	0.125*** (0.009)	0.151*** (0.008)	0.088*** (0.028)	-0.002 (0.003)	0.109*** (0.017)
Difference in differences	0.109*** (0.016)	0.049*** (0.006)	0.125*** (0.009)	0.152*** (0.006)	0.088*** (0.027)	-0.002 (0.003)	0.109*** (0.016)
R-square	0.80	0.81	0.82	0.83	0.77	0.74	0.80
Country, year fixed effects	Included	Included	Included	Included	Included	Included	Included
Pre-and post- treatment differential trends	Included	Included	Included	Included	Included	Included	Included
Lagged outcome variable	Included	Included	Included	Included	Included	Included	Included
Quarter fixed effects	Included	Included	Included	Included	Included	Included	Included
Time varying covariates	Included	Included	Included	Included	Included	Included	Included
Post-treatment influences	Included	Included	Included	Included	Included	Included	Included
Time trend	Included	Included	Included	Included	Included	Included	Included
Number of observations (Before schooling reform, control group)	789	96	693	690	99	741	789
Number of observations (Before schooling reform, treatment group)	1,481	1,184	297	495	986	1,391	1,481
Number of observations (After schooling reform, control group)	48	6	42	42	6	48	48
Number of observations (After schooling reform, treatment group)	87	69	18	27	60	90	87
Total number of observations	2,405	1,355	1,050	1,254	1,151	2,270	2,405

† Robust standard errors are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.
Note: The outcome variable is cyclical output (% of GDP). Differences between treated and control countries are estimated as the difference between cyclical output of treated countries and cyclical output of control countries.

Table 6: Internet use and other performance indicators

Outcome variable	(GDP GROWTH)	(LABOR PRODUCTIVITY GROWTH)	(INVESTMENT GROWTH)
	(1)	(2)	(3)
Pre-treatment period (1995Q1-2019Q4)			
Control group (internet usage lower than median)	0.034	0.033	0.879
Treatment group (internet usage higher than median)	0.032	0.031	0.882
Difference (Treatment-Control)	-0.002* (0.001) †	-0..003* (0.001)	0.002 (0.004)
Treatment period (2020Q1-2021Q2)			
Control group (internet usage lower than median)	-0.027	-0.026	1.698
Treatment group (internet usage higher than median)	0.099	0.100	1.995
Difference (Treatment-Control)	0.126*** (0.017)	0.126*** (0.017)	0.297* (0.181)
Difference in differences	0.128*** (0.017)	0.129*** (0.017)	0.295* (0.180)
R-square	0.63	0.59	0.58
Country, year fixed effects	Included	Included	Included
Pre-and post- treatment differential trends	Included	Included	Included
Lagged outcome variable	Included	Included	Included
Quarter fixed effects	Included	Included	Included
Time varying covariates	Included	Included	Included
Post-treatment influences	Included	Included	Included
Time trend	Included	Included	Included
Number of observations (Before schooling reform, control group)	782	782	780
Number of observations (Before schooling reform, treatment group)	1,466	1,466	1,466
Number of observations (After schooling reform, control group)	48	48	48
Number of observations (After schooling reform, treatment group)	87	87	87
Total number of observations	2,383	2,383	2,381

† Robust standard errors are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.
Note: The outcome variable is GDP growth in column1, labor productivity growth in column 2 and growth rate of gross fixed capital formation in column 3. Differences between treated and control countries are estimated as the difference between the outcome variable of treated countries and the outcome variable of control countries.

Table 7: Variables and means differences between treated and control countries

	Mean-Treated countries	Mean-Control countries	Difference	t-statistics
Gross fixed capital formation (% GDP)	0.222	0.208	-0.013***	(-8.448)†
GDP growth (quarterly % change)	0.594%	0.629%	0.034	(0.464)
Economic freedom (0-10)	7.877	7.245	-0.631***	(-35.494)
Human capital index	3.267	2.966	-0.300***	(-25.192)
Services (0-1)	0.647	0.312	-0.334***	(-20.991)
National Wealth (0-1)	0.823	0.125	-0.698***	(-57.718)

† t-statistics are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Table 8: Determinants of treatment status (probit estimates)

Outcome variable: higher-than-average internet use (0, 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gross fixed capital formation (% GDP)	4.602***						6.303***
	(0.542)						(1.057)
GDP growth (quarterly % change)		-0.455					0.976
		(0.994)					(2.531)
Economic freedom (0-10)			2.207***				0.931***
			(0.162)				(0.182)
Human capital index				1.666***			2.042***
				(0.069)			(0.116)
Services (0-1)					0.866***		0.614***
					(0.043)		(0.084)
National Wealth (0-1)						2.079***	1.632***
						(0.052)	(0.081)
R-squared	0.016	0.000	0.314	0.133	0.082	0.389	0.536
Observations	3,345	3,402	2,732	3,200	3,498	3,498	2,617

† Robust standard errors are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Table 9: Internet use and cyclical output
(Kernel based propensity score matching estimates)

	(1)[1]	(2)[2]	(3)[3]	(4)[4]	(5)[1]	(6)[1]	(7)[1]
Pre-treatment period (1995Q1-2019Q4)							
Control group (internet usage lower than median)	0.011	0.011	0.020	0.008	0.009	0.011	0.007
Treatment group (internet usage higher than median)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Difference (Treatment-Control)	-0.011*** (0.004) †	-0.011*** (0.004)	-0.019*** (0.003)	-0.008*** (0.002)	-0.009*** (0.003)	-0.010*** (0.003)	-0.006*** (0.002)
Treatment period (2020Q1-2021Q2)							
Control group (internet usage lower than median)	-0.034	-0.043	-0.025	-0.040	-0.037	-0.032	-0.040
Treatment group (internet usage higher than median)	-0.022	-0.022	-0.022	-0.022	-0.019	-0.022	-0.022
Difference (Treatment-Control)	0.013 (0.011)	0.021 (0.017)	0.003 (0.011)	0.019 (0.015)	0.018 (0.012)	0.010 (0.011)	0.018 (0.015)
Difference in differences	0.023** (0.012)	0.031* (0.017)	0.022** (0.011)	0.027* (0.015)	0.027** (0.013)	0.020* (0.012)	0.024* (0.015)
R-square	0.10	0.14	0.20	0.12	0.11	0.09	0.11
Number of observations (Before schooling reform, control group)	1,220	1,209	668	1,220	1,170	1,220	1,220
Number of observations (Before schooling reform, treatment group)	1,696	1,696	1,696	1,696	1,257	1,696	1,696
Number of observations (After schooling reform, control group)	66	72	36	78	66	72	72
Number of observations (After schooling reform, treatment group)	99	99	99	99	78	99	99
Total number of observations	3,081	3,076	2,499	3,093	2,571	3,087	3,087

† Robust standard errors are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.
[1]Kernel based propensity score matches are based on the variables of gross fixed capital formation (% of GDP), economic freedom, human capital index and the dummy variables of services and national wealth.
[2]Kernel based propensity score matches are based on the variables of gross fixed capital formation (% of GDP), economic freedom, human capital index, the dummy variables of services and national wealth and quarterly GDP growth.
[3]Kernel based propensity score matches are based on the variables of gross fixed capital formation (% of GDP), economic freedom, human capital index, the dummy variables of services and national wealth and quarterly labor productivity (log).
[4]Kernel based propensity score matches are based on the variables of gross fixed capital formation (% of GDP), economic freedom and the dummy variable of national wealth.

Table 10 Measured covariate standardized biases between treatment and comparison groups pre- and post- propensity score adjustment

Variable	Matched/ Unmatched	Mean Treated	Mean Control	Standardized bias %	Reduction % of bias
Investment share (%) of GDP	Unmatched	0.222	0.208	29.3	17.0
	Matched	0.222	0.233	-24.3	
National wealth (0,1)	Unmatched	0.823	0.125	195.7	99.3
	Matched	0.823	0.828	-1.3	
Services (0,1)	Unmatched	0.647	0.312	71.0	42.9
	Matched	0.647	0.838	-40.6	
Economic freedom (0-10)	Unmatched	7.877	7.245	134.4	92.3
	Matched	7.877	7.828	10.4	
Human capital	Unmatched	3.267	2.966	88.4	60.3
	Matched	3,267	3.148	35.1	