Unveiling the Digital Paradox: Assessing the Socio-Economic Impact of Enhanced Internet and Technological Infrastructure in Czech Rural Area

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Abstract

This paper explores the digital paradox in rural development, contrasting the prevailing notion of technological optimism with empirical evidence from the Czech Republic. It challenges the assumption that improved internet and technological infrastructure inevitably leads to socio-economic growth in rural areas by examining key variables such as population dynamics, unemployment rates, education and economic activity. Using a rigorous methodology involving difference-in-differences and propensity score matching, the study finds negligible differences between areas with improved digital infrastructure and untreated rural areas, challenging deterministic assumptions about the direct link between digitalisation and rural prosperity. The discussion underscores the need for comprehensive strategies beyond digital infrastructure to promote sustainable rural development, and highlights the nuanced complexities inherent in the relationship between technology and socio-economic dynamics.

Keywords:

digital paradox, technological optimism, rural development, Czech Republic, socio-economic indicators, propensity score matching, empirical analysis, comprehensive strategies.

JEL Classification Codes:

O33 - Technological Change: Choices and Consequences; Diffusion Processes

R11 - Regional Economic Activity: Growth, Development, Environmental Issues, and Changes

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1. Background of the Problem

The prevailing notion of technological optimism (Brynjolfsson & McAfee, 2013; Hilbert, 2016) suggests that advances in digitisation and high-tech infrastructure in rural areas* drive socio-economic growth, leading to reduced unemployment (Azu et al., 2021; Kummer et al., 2020), increased opportunities for the highly educated (McKnight et al., 2016), population growth and changed demographic indicators (Adema et al., 2021; Poutvaara et al., 2022).

Despite the abundance of literature advocating technological optimism, a new field of study has emerged that questions the digital paradox. Traditionally defined as the simultaneous increase in connectivity and convenience coupled with a decrease in personalisation and human interaction due to digital proliferation (Iveroth & Hallencreutz, 2022), our research expands this definition. We propose that the digital paradox may encompass broader scenarios, including cases where advances in digital infrastructure fail to deliver significant socio-economic benefits in the short or medium term.

Guillén (2021) expands on the traditional definition of the digital paradox, defining it as the gap between the significant dominance of digital platforms such as Amazon in certain markets, such as the United States, and their comparatively limited success in other global markets. Through new case studies, Guillén introduces fresh examples that broaden the overall understanding of the digital paradox (Guillén, 2021).

Through our empirical research, we seek to challenge traditional definitions of the digital paradox by investigating the real impact of improved internet and technological infrastructure on rural regions. Focusing on rural areas* in the Czech Republic, our study employs a thorough analysis using a balanced dataset approach with propensity score matching. In doing so, we aim to establish a new case study that has the potential to broaden the definition of the digital paradox. Figure 1 presents a comparative analysis of the digital paradox alongside the motivation driving the study objectives: to understand the expected outcomes of expanding the range of digital service options through new investments in information and communication technology (ICT) infrastructure (case study).

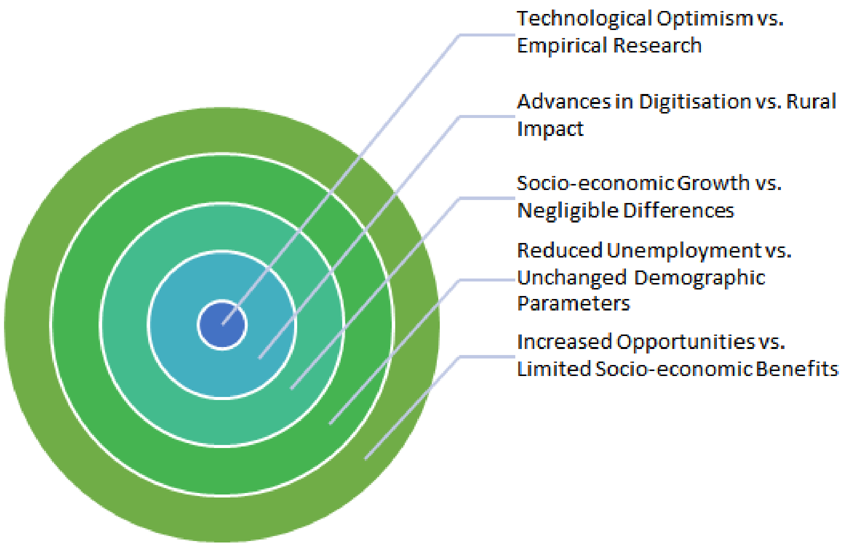

Fig. 1: Comparative analysis of the digital paradox

Notes: Authors' work based on current knowledge and the results of this research.

Using responses from local government, non-governmental organisations and businesses, we identified 74 key stakeholders representing 60 rural municipalities that have experienced significant improvements in internet and technology infrastructure over a recent five-year period. Using rigorous matching techniques, we compare this 'treated' group with an equally sized 'untreated' group of rural areas* that had not experienced such improvements. We look at key indicators such as population dynamics, economic activity, birth and death rates and unemployment levels.

Surprisingly, our findings contradict the prevailing paradigm of technological optimism. Statistical analysis, including graphical comparisons using box plots, reveal negligible differences between the treated and untreated groups on all indicators examined.

In particular, there is no discernible correlation between improved ICT infrastructure and positive changes in social and demographic parameters. Our study thus suggests that the advent of improved internet and technological infrastructure neither guarantees nor hinders rural development.

However, this research has certain limitations. While we have identified the impact on the general rural population, the impact on local stakeholders such as businesses, NGOs and local authorities remains unexplored and warrants further investigation. Consequently, this study contributes to the academic discourse by questioning the deterministic link between digital infrastructure and socio-economic progress, especially in the context of Czech rural areas*.

Furthermore, our findings have practical implications for policy makers. Our research underlines that the mere injection of financial resources into digital infrastructure may not be sufficient to promote rural prosperity. Instead, our findings argue for a comprehensive approach that empowers local residents to reap the benefits of technological progress. Ultimately, this research promotes a nuanced understanding of the complex relationship between technology, socio-economic development and the need for multi-faceted strategies to revitalise rural communities.

** Note: "Rural areas", "rural municipalities" and "rural communities" are used interchangeably in the study and are considered synonymous terms for stylistic variation as distinct from economic terminology.*

2. Research Questions and objectives

The research questions (RQ) for this paper:

- ✓ RQI: To what extent does improved internet and technological infrastructure correlate with socio-economic growth in rural areas?
- ✓ RQII: Does the paradigm of technological optimism hold true in the context of Czech rural regions, or are there other underlying factors influencing socio-economic indicators?
- ✓ RQIII: How does improved digital infrastructure affect demographic trends, including birth rates and population growth, in rural communities?

The aims of this paper:

- ✓ To challenge the prevailing notion of technological optimism by examining the real impact of improved internet and technological infrastructure on rural regions, specifically in the Czech Republic.

- ✓ To broaden the understanding of the digital paradox by exploring scenarios where advances in digital infrastructure fail to deliver significant socio-economic benefits in the short or medium term.
- ✓ To contribute to the academic discourse by questioning the deterministic link between digital infrastructure and socio-economic progress, especially in the context of Czech rural areas.
- ✓ To provide practical implications for policy makers by highlighting the need for comprehensive strategies that empower local residents to effectively use technological progress for rural prosperity.
- ✓ To promote a nuanced understanding of the complex relationship between technology, socio-economic development and the revitalisation of rural communities.

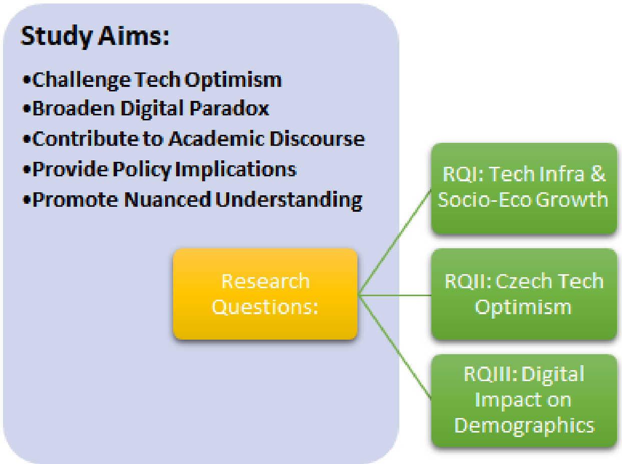

Fig. 2: Aims and research focus

Notes: Authors' work.

3. Data and Methodology

The data

The empirical analysis in this study is based on a carefully curated dataset that sheds light on the impact of digital infrastructure improvements on rural areas in the Czech Republic. This dataset is the culmination of a comprehensive survey conducted among local municipal administrations, non-governmental organisations (NGOs) and business entities operating in rural regions, merged with the official statistics of the Czech Republic (Český statistický úřad, 2022) on their municipalities (employment, population, demography). The survey was designed to provide a holistic view of the socio-economic landscape before and after the implementation of improved internet and technology facilities. As a result of this multifaceted approach, the dataset encompasses a wide range of perspectives and insights, contributing to a robust examination of the research questions at hand.

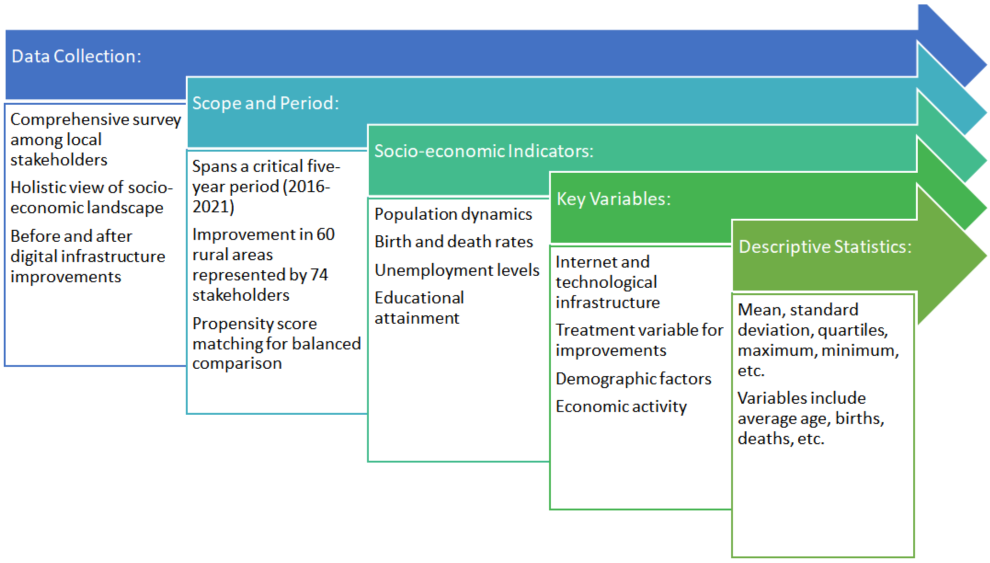

Fig. 3: Overview of data collection and variables

Notes: Authors' work.

The data spans a critical five-year period, culminating in 2021-2022*, during which 60 rural areas (represented by 74 local stakeholders) in the Czech Republic underwent significant improvements in internet and technological infrastructure. These treatment areas, where improvements were made, are carefully matched with an equivalent number of control areas that did not experience such improvements. The matching process is informed by a number of pre-treatment covariates, including the type of respondent (NGO, business or local authority), regional internet and technology infrastructure, and travel time to local and regional urban centres. This propensity score matching technique ensured a balanced comparison, mitigating potential bias and allowing a more accurate assessment of the causal relationship between digital infrastructure improvements and socio-economic outcomes.

The dataset covers a wide range of socio-economic indicators, including but not limited to population dynamics, birth and death rates, unemployment levels and educational attainment of the local stakeholders. Importantly, the data not only allows a direct comparison between treated and untreated rural areas, but also provides an insight into the wider impacts on the local population.

It should be noted, however, that the scope of the dataset is primarily focused on the general rural population, and the impact on specific stakeholders such as businesses and NGOs is outside the immediate scope of this analysis. Thus, while acknowledging the limitations of the dataset selected for this study, its richness and depth provide a solid foundation for drawing nuanced insights into the interplay between digitalisation and rural development in the Czech Republic.

This detailed and meticulously collected dataset serves as the basis on which our research draws conclusions and challenges conventional notions of technological optimism in rural contexts. Its comprehensive nature allows us to examine not only the direct effects of digital infrastructure improvements, but also to highlight potential disparities and complexities that may emerge within this dynamic socio-economic landscape.

** Note: The study involved questionnaires with face-to-face interviews during the second half of 2021 and the first half of 2022. Respondents were asked about the difference in digital service options and ICT infrastructure improvements (treatment) in their rural communities over the past five years. It's important to note that answers may vary slightly due to the one-year gap between the first and last respondents, as the questionnaires were not administered to all respondents at the same time.*

The five-year period was chosen for two main reasons:

Firstly, from a psychological point of view, people tend to have difficulty in accurately recalling events that occurred too far in the past (Chase & Simon, 1973; DK & Hemmings, 2018). Therefore, a five-year period was considered optimal for asking people about their memories, striking a balance between recency and accuracy of recall.

Secondly, given the rapid pace of technological progress (Laitner, 2000), particularly in the field of information and communication technologies (ICTs (Bauerlein, 2011)), longer periods would introduce significant disparities in terms of technological infrastructure and skills. As ICT revolutions occur frequently (Bauerlein, 2011; Guillén, 2021; Silva, 2019), a five-year period ensures greater comparability in terms of technologies and infrastructure issues, making it an optimal choice for this study.

Key variables

Overall Internet and technological infrastructure equipment: This binary variable comprises two distinct states: 'well equipped', which refers to municipalities with a significant level of internet development, - this assessment is derived by experts and takes into account factors such as the number and quality of internet connections; and 'poorly equipped', which includes municipalities with no significant internet development. This binary classification method succinctly captures the different levels of Internet and technology infrastructure in the municipalities surveyed.

Improvement in internet and technological infrastructure (treatment variable): This binary variable categorises rural areas into two groups: those that experienced significant improvements in internet and technological infrastructure within the five-year study period, and those that did not. It serves as a treatment variable for assessing the impact of digitisation on various socio-economic indicators.

Population dynamics: This variable captures changes in the total population of rural areas, including birth and death rates. It provides insights into demographic shifts and possible correlations with digital infrastructure improvements.

Unemployment rate: This variable measures the unemployment rate in treated and untreated rural areas, providing an understanding of labour market dynamics and the potential impact of improved digital services on job creation.

Educational attainment: This variable assesses the educational attainment of the local stakeholders, with a particular focus on highly educated individuals.

Proximity to urban centres: Measuring travel time to local (ORP) and regional (KRM) urban centres, these variables explore the potential influence of spatial factors on the impact of digitalisation on rural areas.

Stakeholder type (NGO, business, local authority): Categorised according to the type of respondent, this variable explores potential differences in the perspectives of NGOs, businesses and local authorities on the impact of digitalisation.

Demographic factors: Variables such as age distribution, gender and other parameters provide insight into how digitalisation might affect population growth, fertility rates and overall demographic composition.

Economic activity: This variable measures the economic vitality of rural areas, reflecting potential shifts in business opportunities, entrepreneurship and local economic growth due to digital infrastructure improvements.

Use of digital services: While not the primary focus of this study, an examination of how the local population engages with digital services, including e-commerce, remote working, and online education, can provide complementary insights into the broader impacts of digitalisation.

Time period (pre- and post-treatment): This variable captures changes over the five-year study period and allows socio-economic indicators to be compared before and after digital infrastructure improvements.

The descriptive statistics

Table 1 presents the descriptive statistics of the data.

Table 1. - The descriptive statistics of the data (key variables for this study)

Variable	Avg Age	Births	Deaths	Dis-placed	If After Treat-ment	If Trea-ted	Immi-grants	N job seekers Graduates	N job seekers Over 12 Months	Popu-lation	Popu-lation 15_64
Mean	42,27	39,64	45,19	90,6	0,5	0,31	92,86	5,17	29,47	3751,23	2424,22
Std.Dev	1,91	101,54	104,13	242,51	0,5	0,46	240,38	11,82	65,12	9007,5	5773,23
Min	36,61	0	0	0	0	0	0	0	0	77	50
Q1	41,01	6	7	13	0	0	14	1	3	538	347
Median	42,28	15	16	36,5	0,5	0	40,5	2	10	1555	1026
Q3	43,55	40	47	82	1	1	89	5	23	4166	2810
Max	49,8	1077	1104	2756	1	1	2565	148	701	94229	61146
MAD	1,88	16,31	17,79	40,77	0,74	0	46,7	2,97	11,86	1605,66	1052,65
IQR	2,53	34	40	68,25	1	1	75	4	20	3624,5	2462,5
CV	0,05	2,56	2,3	2,68	1	1,49	2,59	2,29	2,21	2,4	2,38
Skewness	0,27	8,7	7,9	8,84	0	0,81	8,76	8,29	5,71	8,38	8,37
SE.Skewness	0,11	0,11	0,11	0,11	0,11	0,11	0,11	0,11	0,11	0,11	0,11
Kurtosis	1,06	84,75	73,77	87,72	-2	-1,34	85,41	90,31	47,39	80,27	80,19
N.Valid	482	482	482	482	482	482	482	482	482	482	482
Pct.Valid	100	100	100	100	100	100	100	100	100	100	100

Notes 1: Own analysis in R.

Variable: Each row corresponds to a specific statistical measure for a particular variable of interest.

Mean: The mean value of the variable.

Std.Dev: The standard deviation of the variable.

Min: The minimum value of the variable.

Q1: The first quartile (25th percentile) of the variable.

Median: The median (50th percentile) of the variable.

Q3: The third quartile (75th percentile) of the variable.

Max: The maximum value of the variable.

MAD: The mean absolute deviation of the variable.

IQR: The interquartile range (Q3 - Q1) of the variable.

CV: The coefficient of variation (Std.Dev / Mean) of the variable.

Skewness: A measure of the asymmetry of the distribution of the variable.

SE.Skewness: The standard error of skewness.

Kurtosis: A measure of the "skewness" of the distribution of the variable.

N.Valid: The number of valid observations for the variable.

Pct.Valid: The percentage of valid observations for the variable.

AvgAge: Average age of the population.

Births: Number of births.

Deaths: Number of deaths.

Displaced: Number of displaced persons.

If After Treatment: Dummy variable indicating whether the observation is in the treatment period (1 if after treatment, 0 otherwise).

If Treated: Dummy variable indicating whether the observation is in the treated group (1 if treated, 0 otherwise).

Immigrants: Number of immigrants.

N jobseekers Graduates: Number of jobseekers who are graduates.

N jobseekers over 12 months: Number of jobseekers over 12 months.

Population: Total population.

Population 15-64: Population aged 15-64.

Table 1 shows the total output for the whole dataset, not just the matched values (see Equation 1).

Rationale for the choice of variables

The core variables of the technological optimism approach, as highlighted by Brynjolfsson & McAfee (2013) and Hilbert (2016), are IfAfterTreatment and IfTreated. These variables indicate improvements in digital service options (treatment; variable: IfTreated) and the period before or after such improvements (IfAfterTreatment).

A number of studies suggest positive outcomes of such ICT treatments, for example, Azu et al. (2021) and Kummer et al. (2020) propose the concept that treatment should reduce unemployment, highlighting the importance of variables related to population statistics.

Furthermore, McKnight (2016) suggests that treatment should increase opportunities for highly educated individuals.

However, Adema et al. (2021) and Poutvaara et al. (2022) argue not only for overall population dynamics, but also for changes in demographic indicators for the treated group, highlighting the urgency of comprehensive demographic statistics.

Methodology

Our study employs a rigorous methodology, centred on paired balanced propensity score matching (Holland, 1986; Quandt, 1972; Roy, 1951; Rubin, 1974) [equation 1], to unravel the complex relationship between improved internet and technology infrastructure and rural development in the Czech Republic. Through meticulous survey data collected from local municipal administrations, non-governmental organisations and businesses, we have carefully curated a dataset covering a crucial five-year period up to 2021-2022. Using paired balanced propensity score matching, we identified 60 rural areas (with 74 key stakeholders) that received significant digital infrastructure improvements and matched them with an equivalent number of untreated areas for a comprehensive comparison. This technique ensures a balanced and meaningful comparison by taking into account a number of pre-treatment covariates, such as respondent type, regional technological resources and proximity to urban centres.

$$\begin{cases} Y_{CZ} = \mu_{CZ}(X) + U_{CZ} \\ Y_{Not\_CZ} = \mu_{Not\_CZ}(X) + U_{Not\_CZ} \end{cases} \qquad (1)$$

Notes: The variable Y_{CZ} denotes the hypothetical outcome if a stakeholder (and therefore a municipality) increased the number of digital service options by implementing an infrastructure project (as mentioned by a stakeholder (NGO, company or municipality)). Similarly, Y_{Not_CZ} denotes the hypothetical outcome if a stakeholder mentioned no enhance in the number of digital service options. The parameter μ encapsulates the underlying non-linear process that generates the data based on the pre-treatment covariates represented by X. U denotes random errors associated with the two different types of cities.

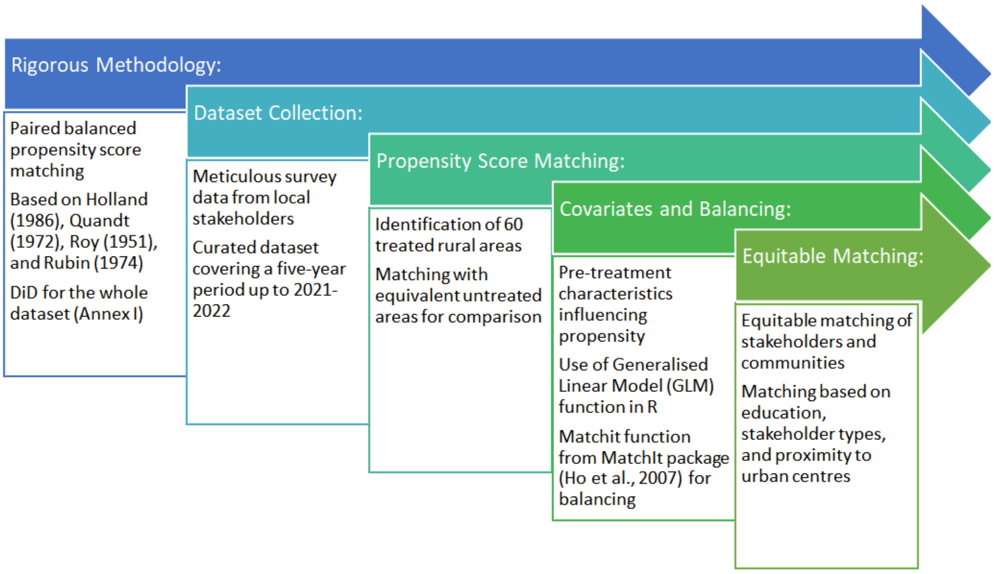

Fig. 4: Methodology overview

Notes: Authors' work.

This similarity is determined by a statistical measure of distance calculated using the Generalised Linear Model (GLM) function in R. The X covariates (Equation 1) include a number of pre-treatment characteristics that influence the propensity of a rural area and local stakeholders to undertake an infrastructure project to increase the number of digital service options. This balancing process is facilitated by the use of the matchit function from the MatchIt package (Ho et al., 2007), which incorporates enhancements suggested to improve the robustness of the method.

The result of this meticulous process is a dataset in which the number of stakeholders and communities is equitably matched with stakeholders and communities that closely match them in terms of respondents' education, types of stakeholders participating in a survey, and time to the nearest local (ORP) and regional (KRM) centres.

The paired balanced propensity score matching technique allows us to carefully compare the treated and untreated rural areas, thus shedding light on the true causal impact of digitisation. This approach mitigates potential bias and enhances the credibility of our findings. By juxtaposing the socio-economic indicators of these matched pairs, our analysis goes beyond mere correlation to delve into causation, allowing for a more nuanced understanding of the impact of digital infrastructure improvements. Through this method, we seek to determine whether the expected benefits of technological optimism are being realised, or whether a more complex narrative is emerging, one that encompasses a myriad of factors shaping rural development in response to digitalisation.

4. Results

Figures 5 and 6 show the main results of this research.

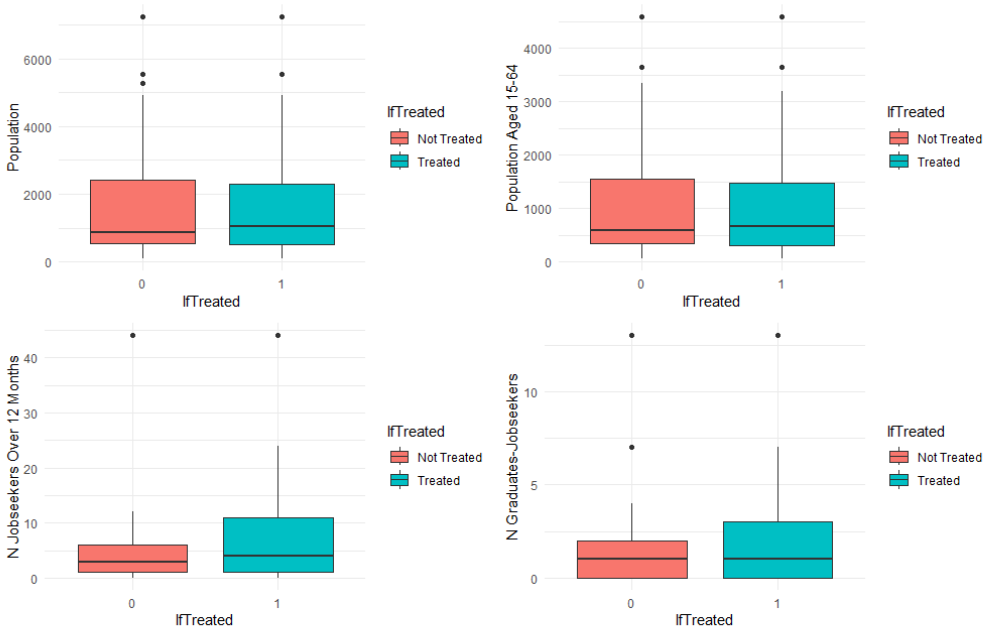

Fig. 5: Differences in population and unemployment after the increase in the number of digital service options in the selected Czech rural areas, 2021-2022

Notes: Own elaboration in R.

Interpreting the box plots involves understanding the distribution and central tendencies of the data within different categories. The box in each plot represents the interquartile range (IQR), which encapsulates the middle

50% of the data, while the line within the box marks the median. The 'whiskers' extend to the range of data within 1.5 times the IQR, highlighting potential outliers. Points beyond the whiskers are considered outliers.

Comparison of the box plots across categories reveals variations in the central tendencies, ranges and potential outliers of the data, and helps to visually assess differences and similarities between treated and untreated rural areas in terms of key socio-economic indicators.

Municipalities with more than 7500 inhabitants are not included in this plot.

Figure 5 illustrates the four key indicators: population, labour force aged 15-64, total unemployment and unemployment among highly skilled professionals; the pattern shows remarkable similarity after treatment, adjusted for pre-treatment covariates. The medians, marked by their central lines, converge in both the treated and non-treated groups, which are matched in the pre-treatment period. This visualisation shows the absence of significant disparities in these indicators, further confirming the complex interplay between digital infrastructure improvements and socio-economic dynamics within the perfectly matched communities.

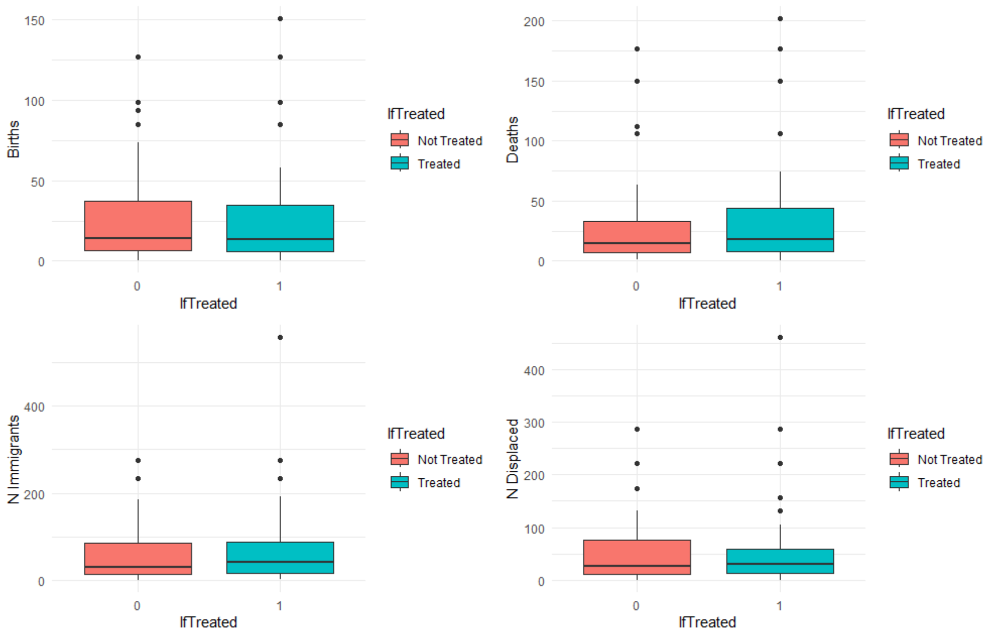

Figure 6: Differences in population and demographic parameters after the increase in the number of digital service options in the selected Czech rural areas, 2021-2022

Notes: Own elaboration in R.

Fig. 6 provides a comprehensive visual representation of four key demographic indicators: the number of births, deaths, immigrants and displaced persons. This insightful analysis complements our earlier visualisation by delving into surrogate measures of demographic dynamics within rural regions. In particular, the alignment of the medians across the box plots indicates a remarkable consistency in these indicators, suggesting that there are no immediate demographic shifts directly attributable to the treatment - i.e. the introduction of enhanced digital service offerings.

Furthermore, the results of the difference-in-differences regressions for the whole (not just PSM-matched) dataset (see Annex I) show that none of the coefficients for the interaction term between 'IfTreated' and 'IfAfterTreatment' are statistically significant across the different dependent variables, as indicated by their p-values greater than 0.1. Therefore, there is no clear evidence that the treatment (the increase in digital service options) had a significant effect on the outcomes of interest. In addition, the adjusted R-squared values for the regressions are generally low, indicating that the models explain very little of the variance in the dependent variables. Therefore, on the basis of these results, it appears that the treatment did not have a significant effect on the outcomes examined.

Fig. 7: Main research findings: Population and demographic differences due to increase in digital service options (ICT infrastructure)

Notes: Own elaboration.

However, it's important to recognise the potential for latent, longer-term effects. The immediacy of the post-treatment snapshot, as visually captured in Figure 6 (and partially in Figure 5), is limited by the time constraints of our current research. Unravelling the intricacies of these persistent effects remains a prospect for future investigation in this area. This conundrum is compounded by the interplay between protracted demographic processes and the rapid evolution of ICT technologies, which makes the findings presented in Figure 6 complementary in nature. Their purpose is to enrich the broader panorama of the rapid socio-economic transformations taking place in these municipalities and to unravel the intriguing interplay between persistent demographic dynamics and the rapidly evolving digital landscape.

5. Discussion

Among the most ardent proponents of technological optimism, Brynjolfsson & McAfee (2013) assert an unprecedented increase in global population over the last two centuries, attributing this remarkable phenomenon to technological advances. Their holistic assessment, ranging from prehistory to the modern era, underscores the central role of technology, in particular the emergence of information and communication technologies (ICTs) as a harbinger of the impending transition from Technology 1.0 to Technology 2.0.

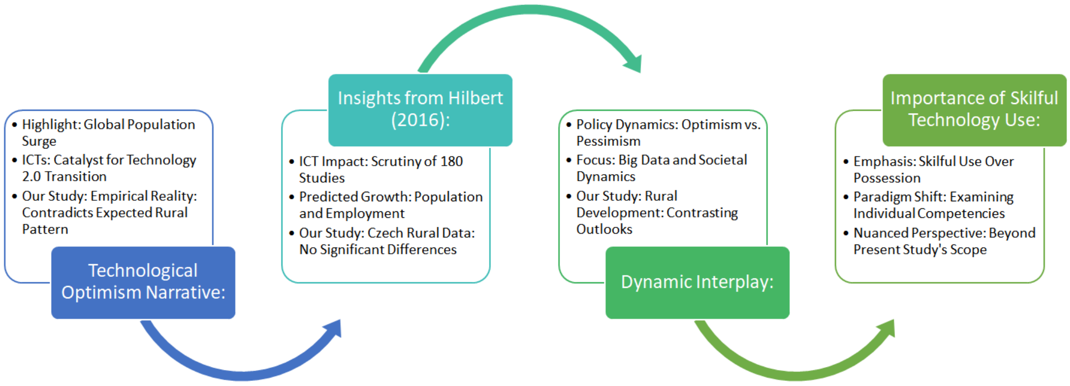

Fig. 8: Perspectives on technological optimism in rural contexts: theoretical background

Notes: Own elaboration.

However, our empirical analysis reveals a contrasting narrative in the context of rural areas. While the trajectory of technological progress has historically driven population growth, our data reveal a nuanced reality in which rural regions, despite embracing ICT growth, do not reflect the general population surge. This disjuncture invites a nuanced discussion about the applicability of this overarching trend to rural contexts, and challenges the assumed direct link between ICT expansion and rural population dynamics, a cornerstone of progress as advocated by these scholars.

In a comprehensive study, Hilbert (2016) delved into the realm of technological optimism by scrutinising 180 social science studies investigating the impact of ICT technologies, including big data, on fundamental social processes. His findings posited an extraordinary surge, akin to the transformative influence of microscopes in biology or telescopes in astronomy.

These findings, which have profound implications, imply that the trajectory of progress is poised for an even more pronounced upswing, predicting substantial growth in various areas, including population and employment.

However, our careful examination of Czech rural data differs from this expected pattern. Despite the optimistic projections, our study reveals no statistically significant differences between the treated (ICT-improved) and control groups within precisely matched scenarios, calling into question the assumed trajectory of rapid escalation in aspects such as population growth and employment levels, and prompting a re-evaluation of the expected correlations in the context of rural areas.

A thought-provoking perspective suggests (Vydra & Klievink, 2019) that optimism about the potential of technology is counterbalanced by technological pessimism in the realm of policy-making.

While this juxtaposition highlights a dynamic interplay, it falls short of offering concrete solutions or calibrated approaches. In particular, this study maintains a clear focus beyond rural areas, exploring the complex relationship between technology (big data) and societal dynamics, and leaving open the question of how these contrasting outlooks manifest themselves in the context of rural development.

A contingent of scholars argue (Matli & Ngoepe, 2020; Pupillo et al., 2018) that the central concern is not simply the possession of technologies, but their skilful use (Hanushek & Woessmann, 2016; Hanushek & Woessmann, 2020). This paradigm shift underlines the importance of examining individuals' competencies and their skilful use of technologies. However, it is pertinent to note that this nuanced perspective, which delves into the realm of skills and technology use, is beyond the scope of the present study and lies outside the ambit of the formulated research questions, thus warranting a separate exploration.

Theoretical expectations and contrasting realities: Implications of COVID-19 for rural ICT infrastructure

The COVID-19 pandemic should theoretically have favoured the theory of technological optimism and increased the significance of the results of our study. Our previous research (Shemetev et al., 2021) provided strong evidence of a pattern of increased remote work or preference for quiet environments during the pandemic. Therefore, if individuals had better infrastructure in rural areas, they would theoretically have been able to work from home or enjoy a peaceful rural environment, which could additionally provide maximum security in terms of COVID-19 (with fewer personal contacts compared to urban areas [lower risk of infection], better family life, more space and less stress (Wirth, 1969; Woods, 2011)). Consequently, one would expect significant demographic changes in the short term.

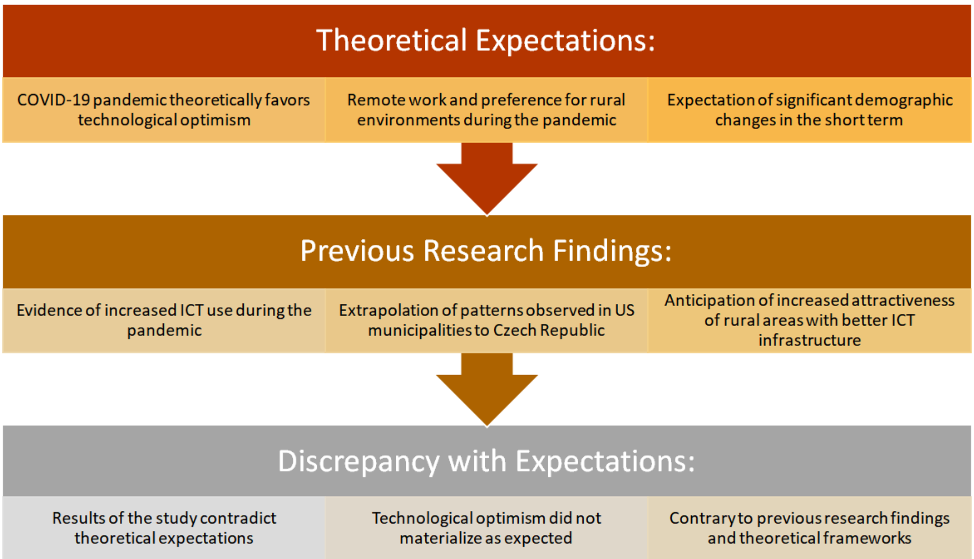

Fig. 9: Technological Optimism and the COVID-19 Pandemic: A Reality Check

Notes: Own elaboration.

In addition, our other previous research highlights the increase in ICT use, especially during official orders to stay at home (Shemetev & Pelucha, 2022). Given that the Czech Republic has also implemented such orders, we could extrapolate from the patterns observed in US municipalities (Shemetev & Pelucha, 2022) and expect a similar increase in ICT use, making rural areas with better ICT infrastructure even more attractive.

However, the results of our study show that this expected scenario did not materialise in the Czech Republic. The results of our study show that technological optimism did not work, as theoretically expected (Adema et al., 2022; Azu et al., 2021; Brynjolfsson & McAfee, 2013; Brynjolfsson & Saunders, 2013; Hilbert, 2016; Kummer et al., 2020; McKnight et al., 2016; Poutvaara et al., 2022).

6. Conclusion

In conclusion, our empirical investigation into the impact of enhanced internet and technological infrastructure on Czech rural areas challenges the prevailing paradigm of technological optimism. Despite significant advancements in digitalization within the treatment group, our comprehensive analysis (utilizing Propensity Score Matching) reveals a nuanced reality. The absence of substantial differences in socio-economic indicators between treated and untreated rural areas defies the anticipated direct correlation between improved digital services and positive outcomes. Our findings underscore the intricate and multifaceted nature of rural development, suggesting that technological enhancements alone may not guarantee socio-economic growth.

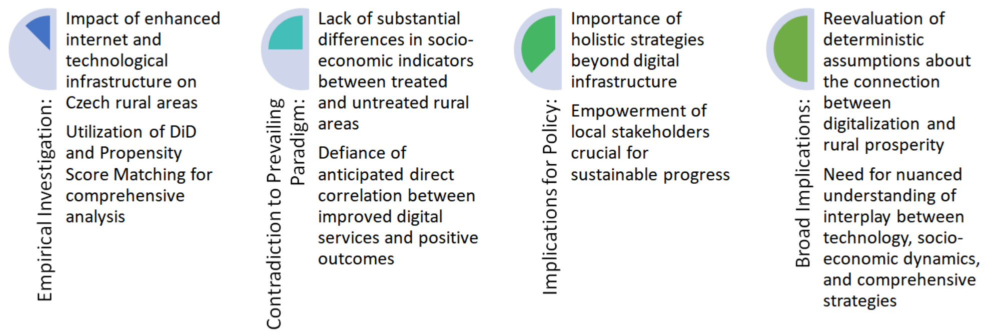

Fig. 10: Technological Optimism and the COVID-19 Pandemic: A Reality Check

Notes: Own elaboration.

Annex II contains suggestions on the possible applicability of the results of this study to other countries of the European Union.

Policymakers should heed the lesson that holistic strategies, encompassing not only digital infrastructure but also empowering local stakeholders to leverage these advancements effectively, are imperative for fostering sustainable progress. While this study delves into the context of Czech rural regions, its implications resonate beyond borders, calling for a reevaluation of deterministic assumptions about the unassailable connection between digitalization and rural prosperity. In the pursuit of equitable and thriving rural communities, a nuanced understanding of the interplay between technology, socio-economic dynamics, and comprehensive strategies becomes paramount.

Acknowledgments

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Annex I: DiD Regression Results

See Table A.

Table A. DiD Regression Results

Difference-in-Differences Regression Results

	Dependent variable:								
	Population (1)	Births (2)	Population15 (3)	NjobseekersOver12Months (4)	NjobseekersGraduates (5)	Deaths (6)	Immigrants (7)	Displaced (8)	AvgAge (9)
IfTreated	864.288	10.671	561.150	5.991	1.264	9.696	18.714	18.023	-0.001
	(1,255.863)	(14.157)	(804.888)	(8.809)	(1.636)	(14.507)	(33.508)	(33.820)	(0.260)
IfAfterTreatment	-16.458	0.747	-121.295	-30.711***	-2.627**	6.934	-0.964	-0.952	0.833***
	(990.785)	(11.169)	(634.998)	(6.950)	(1.291)	(11.445)	(26.435)	(26.682)	(0.205)
IfTreated:IfAfterTreatment	29.164	-1.014	1.722	-3.302	-0.880	2.000	12.551	5.218	-0.075
	(1,776.058)	(20.021)	(1,138.283)	(12.458)	(2.314)	(20.516)	(47.387)	(47.829)	(0.368)
Constant	3,485.952***	36.102***	2,309.970***	43.476***	6.229***	38.398***	85.566***	84.657***	41.863***
	(700.591)	(7.897)	(449.011)	(4.914)	(0.913)	(8.093)	(18.692)	(18.867)	(0.145)
Observations	482	482	482	482	482	482	482	482	482
Adjusted R2	-0.004	-0.004	-0.004	0.055	0.010	-0.003	-0.004	-0.005	0.039
Residual Std. Error (df = 478)	9,026.479	101.751	5,785.107	63.315	11.758	104.268	240.836	243.081	1.870
Note:									*p<0.1; **p<0.05; ***p<0.01

Notes: Own elaboration in R. Formula: Y ~ IfTreated + IfAfterTreatment + IfTreated:IfAfterTreatment produced by the code:

```
dependent_variables <- c("Population", "Births", "Population15_64", "NjobseekersOver12Months", "NjobseekersGraduates", "Deaths", "Immigrants", "Displaced", "AvgAge")

regression_models <- list() # List to store regression models

# Perform DiD regression for each dependent variable

for (variable in dependent_variables) {

formula <- as.formula(paste(variable, "~ IfTreated + IfAfterTreatment + IfTreated:IfAfterTreatment"))
```

```
model <- lm(formula, data = BigStartPANEL)

regression_models[[variable]] <- model

}

# Print regression output using stargazer (*library(stargazer) is already running)

stargazer::stargazer(regression_models, type = "text", title = "Difference-in-Differences Regression Results",

          dep.var.labels = dependent_variables, keep.stat = c("n", "adj.rsq", "ser"), align = TRUE)
```

As the results for the interaction term are statistically insignificant in all regressions, there is no need for robust standard errors. Robust standard errors are normally used to correct for heteroscedasticity or other violations of the assumptions of ordinary least squares (OLS) regression. However, in this case, using robust standard errors would likely increase the standard errors, potentially leading to larger errors and possibly obscuring the interpretation of the results.

Therefore, using the usual standard errors is sufficient to confirm the insignificance of the coefficients in the interaction term. This decision simplifies the analysis and interpretation of the results by avoiding introducing unnecessary complexity.

This Table A shows the total output for the whole dataset, not just the matched values (see Equation 1).

Annex 2: Conclusions for other countries in the European Union

On the basis of our paper alone, it could be argued that the conclusion regarding the digital paradox in the Czech Republic could also apply to other countries in Europe, especially those with similar rural contexts and challenges.

However, without considering additional sources or data from other European countries, it would be speculative to generalise the findings of this paper to the wider European context. Factors such as different levels of digital infrastructure development, socio-economic conditions and policy environments in different European countries could significantly influence the manifestation of the digital paradox.

Therefore, without additional evidence from comparative studies or empirical research conducted in other European countries, it would be difficult to state with confidence whether the conclusions drawn from this paper are applicable beyond the Czech Republic.