Summary:

Digitalization, including Information and Communication Technologies (ICT) access, digital industries development, and digital empowerment, has important impacts on GDP growth and productivity. Theoretical research interests flourish in analyzing the mechanisms through which digitalization influences the economy. Empirically, correlations are repeatedly found in various regions such as the European Union, India, and Canada. Given that digitalization development does not act as an equal stimulus to all economies, and inequalities in regional digitalization development within a country result in different contributions to the regional GDP, works devoted to digitalization spillover abound.

Japan, whose urban prefectures such as Tokyo and Osaka are more developed than rural prefectures such as Akita and Kagoshima, provides chances for examining spillover effects. Besides, in Japan, digital utilization is becoming more important as it is increasingly difficult to secure a workforce due to the accelerating aging of the population. Investigating the interaction between digitalization and population aging in Japan can bring new insights to countries that would face similar problems in the near future.

Based on Japan's prefecture-level panel data on digitalization development from 2011 to 2019, this paper empirically analyzes impacts of digitalization development and digitalization spillover effects on Japan's prefectural economic activities. I utilize the Principal Component Analysis (PCA) method for constructing the digitalization development index and Directed Acyclic Graphs (DAGs) for measuring the direction of digitalization spillover effects. The results from Ordinary Least Squares (OLS) regressions with Fixed Effects (FE) show that in general, digitalization development positively influences the overall prefectural economic behavior, but the spillover effect negatively impacts overall production and production per capita. Population aging and geographical closeness to countries with advanced digitalization such as China and South Korea worsen the negative influences of the spillover effect, but entertainment and life-related service industry development mitigate instead.

The innovations of this paper to the existing literature are as follows. First, it introduces the application of DAGs for measuring digitalization spillover effects. Second, it estimates the effects of digitalization spillover on overall economic activities and develops two mechanisms for explanation pertaining to population and industrial structures. Lastly, it provides extensible policy implications: For the economy to benefit from the strategic opportunity of digitalization, local governments should take into account other economic perspectives such as population and industrial characteristics.

Does Digitalization Spillover Negatively Influence the Economy? Empirical Evidence from Japan

November 30, 2022

Abstract

Digitalization has long been regarded as a driving force and engine for the promotion of countries' regional and national economy. However, in countries where regional inequalities of digitalization development prevail, the impact of the spillover effect is worth discussing. Based on prefectural panel data of Japan from 2011 to 2019, this paper utilizes the Principal Component Analysis (PCA) method for constructing the digitalization development index and Directed Acyclic Graphs (DAGs) for measuring the direction of digitalization spillover effects, I empirically investigate impacts of digitalization development and digitalization spillover on economic performance. The results from OLS regressions with fixed effects show that in general, digitalization development positively influences the overall prefectural economic behavior, but the spillover effect negatively impacts overall production and production per capita. Population aging and geographical closeness to countries with advanced digitalization such as China and South Korea worsen the negative influences of the spillover effect, but entertainment and life-related service industry development mitigate instead. Therefore, policies on digitalization development should take into account local realities and coordinate with the prefecture's industrial structure, population characteristics, and geographical location to improve economic performance.

Keywords: *Digital economy; spillover effect; industrial structure; population aging.*

1 Introduction

Digitalization, including Information and Communication Technologies (ICT) access, digital industries' development, and digital empowerment, has important impacts on GDP growth (Venturini, 2009) and productivity (CETTE, 2015). Theoretical research interests flourish in analyzing the mechanisms through which digitalization influences the economy (see Miao 2022; Ahmad and Ribarsky 2018). Empirical correlations are repeatedly found in various countries such as the European Union(Alfaro Cortés & Alfaro Navarro, 2011), India (**?**,Maiti, Castellacci, and Melchior 2020), and Canada (Liu, 2021). Given that digitalization development does not act as an equal stimulus to all economies, and inequalities in digitalization development within a country result in different contributions to the regional GDP, works devoted to digitalization spillover abound, leading to the convergence hypothesis (Maiti et al., 2020). However, the literature on the impact of digitalization spillover is limited to specific aspects of the economy, such as the labor market and employment (Karpunina, Petrov, Klimentova, Sozaeva, & Korkishko, 2020), digital manufacturing industry (Miao, 2022), and tax compliance ("Digitalization to improve tax compliance: Evidence from VAT e-Invoicing in Peru", 2022), without equal attention being paid to effects on overall economic activities.

Japan, whose urban prefectures such as Tokyo and Osaka are more developed than rural prefectures such as Akita and Kagoshima (LÃ-RodrÃguez and Nakamura n.d.; Porter 2000), provides chances for examining the spillover effect. Besides, in Japan, digital utilization is becoming more important as it is increasingly difficult to secure a workforce due to the accelerating aging of the population (Institute for International Monetary Affairs, 2019). Furthermore, studies about the digital divide and information gap in the digital technology between the benefited young and the excluded senior can be dated back to the 2000s (Japanese Ministry of Public Management & Telecommunications, 2002). Studying the interaction between digitalization and the population structure in Japan can bring new insights to countries that would face similar problems in the near future. Based on Japan's prefecture-level panel data on digitalization development from 2011 to 2019, this paper empirically analyzes impacts of digitalization development and digitalization spillover effects on Japan's prefectural economic activities.

The Innovations of this paper are as follows. First, it introduces the application of Directed Acyclic Graphs (DAGs) for measuring digitalization spillover effects. Second, it estimates the effects of digitalization spillover on overall economic activities and develops two mechanisms for explanation with regard to population and industrial structures. Lastly, it provides extensible policy implications: For economic wellbeing to benefit from the strategic opportunity of digitalization, local governments should take into account other economic perspectives such as population and industrial characteristics.

2 Data, models, and variables

2.1 Data

Based on the status quo of digitalization development in Japan, I analyze annual, prefectural panel data of Japan from 2011 to 2019. Data are from the Ministry of Internal Affairs and Communication, Annual Report on National Accounts, White Paper on Local Public Finance, Annual Report on the Internal Migration in Japan derived from the Basic Resident Registration, Investigations and Indicators of Social Lives, Consumer Confidence Survey, and Administrative Investment Performance Reports.

For explanatory variable construction, I select the numbers of corporations and enterprises, numbers of employees engaged in the industry, proportions of the selling and added values in the digital industry of the overall production from the macroeconomic perspective, capabilities to gain access to the network measured by the Internet availability rate from the individual and household perspective, family Internet availability rate, and personal smartphone and computer availability rates. Range of variables covers hardware availability and exposure to the Internet, as well as the development of the digitalization-related industries, to depict the situation of digitalization in a certain prefecture.

2.2 Models

2.2.1 DAG model

I use Directed Acyclic Graphs (DAGs) to addresses the notion of spillovers, which offers systematic representations of causal relationships (Textor, van der Zander, Gilthorpe, Liśkiewicz, & Ellison, 2016). Composing of nodes, representing variables, and arrows, representing direct causal effects of one variable on another, DAGs can be used to illustrate concepts such as confounding, selection bias, and the distinction between total, direct, and indirect effects (Nilsson, Bonander, Strömberg, & Björk, 2021). Following Awokuse and Bessler 2003, DAGs can be used to represent conditional independence as implied by the recursive product decomposition, and z statistic is used to test estimated sample correlations and conditional correlations against zero. In this research, I stepwise test correlations of undirected edges, that is, the correlations of digitalization extent indicator of every two prefectures in the variable set, and remove those with 0 correlation or partial correlation in each step, the remaining edges are 'directed' according the concept of sepset.

This section addresses the notion of spillover in terms of Directed Acyclic Graphs (DAGs), which offers systematic representations of causal relationships (Textor et al., 2016). Composing of nodes, variables and arrows, DAGs can be used to represent direct causal effects of one variable on another, or illustrate confounding and selection bias, and distinctions between total, direct, and indirect effects (Nilsson et al., 2021). Following Awokuse and Bessler 2003, DAGs can be used to represent conditional independence as implied by the recursive product decomposition:

$$P(v_1, v_2, v_3..., v_n) = Pr(v_i|p_{ai}) \tag{1}$$

where Pr is the probability of variables v1,v2,v3 ... , vn, and p_{ai} is the realization of some subset of the variables that precede (come before in a timely or causal sense) v_i in order $(v_1, v_2, v_3..., v_n)$. In this paper, the PC algorithm presented in Spirtes et al. (2000), which was developed to apply the concept of d-separation to observational data and to build DAGs is applied to draw the timely manner of changes in items. The PC algorithm and its more refined extensions are available in the software TETRAD II.

2.2.2 Regression model

The following basic models are created around the digitalization spillover index to explore the impact of digitalization development spillover on the overall economic performance.

$$lnProduction_{i,t} = \alpha_i + \beta_t + \gamma Spillover_{i,t} + \Sigma_{j=0}^{n} \phi_j lnX_{j,i,t} + \epsilon_{i,t} \tag{2}$$

where the subscript i refers to the i^{th} prefecture, t refers to the t^{th} year.

$Production_{i,t}$ refers to the production of prefecture i in year t, and X refers to other control variables. This model takes the logarithms of relevant variables to eliminate the influence of heteroskedasticity.

$Spillover$ is a binary variable indicating the spillover effect driven from the direction of the DAGs. γ is the coefficient of interest, which measures impacts of digitalization spillover on production.

α, β and ϕ are control variable coefficients, where α_i refers to the time-invariant, prefecture-specific fixed effect for each prefectures i, β_t refers to the time-variant, not prefecture-specific shock for each period t, and ϕ_j measures influences of the $j - th$ controlled variables on the explained variable.

Finally, ϵ is a random error term, measured for each prefecture i in each time period t.

2.2.3 Hypothesis

Based on the regression model, I develop the null hypothesis

$$H0 : \gamma = 0$$

which indicates that digitalization spillover has no relationship with production.

Conversely, the alternative hypothesis

$$H1 : \gamma \neq 0$$

indicates that digitalization spillover has relationship with production. I expect the γ to be non-zero and negative. As digitalization development is a costly investment for the prefecture economy, we may expect that digitalization spillover reveal that the extent of digitalization exceed the demands, and hence, spill over to other prefectures. As a result, $Spillover$ has a negative effect on $Production$, resulting in a negative γ.

3 Variables

3.1 Explained variables

Overall GDP (***GDP***): The overall gross domestic income measured by the production of a prefecture, adjusted based on GDP on year 2010 and annual inflation rate. Data resource: Japan National Bureau of statistics.

GDP per capita (***GDPperc***): The prefecture's gross production value (adjusted) divided by the prefecture's population. Data resource: Japan National Bureau of statistics.

3.2 Explanatory variables

To construct a digitalization extent index that describes the extent of overall digitalization development in the society, I first use the Principal Component Analysis (PCA) method. The p-value of 0.000 from Bartlett test shows that variables are intercorrelated, and the Kaiser-Meyer-Olkin Measure of sampling Adequacy is 0.886. The statistically significant correlations and high collinearity indicate that using the PCA method is appropriate. All factors with eigenvalues greater than 1 retain 82.8% variation in the original data. Factor 1 includes numbers of enterprises, proportions of employees, and selling amounts of digitalization-related industries. Factor 2 includes the internet, smartphone, and computer availability rates. Factor Loadings range from 0.6496 to 0.9517 after using the Matrix Rotation Method with Kaiser Normalization.

Then, using three continuous years for calculating the direction of directed arrows in the base year and the Peter and Clark (PC) algorithm (Spirtes & Glymour, 1991), I create annual prefecture digitalization spillover index from 2013 to 2019. For each combination (i, t), the binary variable digitalization spillover index $Spillover_{i,t}$ is given value 1 if the prefecture i experiences digitalization spillover in year t, and prefectures with either spill-in effects or without effects are given value -1. I only keep directed arrows statistically significant at 1%.

3.2.1 Control variables

I select six macroeconomic variables that contribute to the GDP, including prefectural employment rate, prefectural average consumption, prefectural public life investment, prefectural public agricultural investment, and prefectural public security investment as control variables. All consumption and investment data are in the per capita term, calculated by dividing the total monetary amount to the population.

3.2.2 Further mechanism testing

I further explore mechanisms of population aging (measured by the difference between two proportions: people more than 80 years old to the total population in the prefecture and in the region) and industrial structure (measured by the ratio of their production to the GDP). Population aging may influence the development of regional digital industries and the efficiency of digitalization. Seniors meet difficulties adapting to digital technologies and are reluctant to welcome the spread of digitalization.

Meanwhile, the development of digitalization may rely on the industrial structure. An example is the manufacturing industry which is closely related to the development of digitalization, as higher-level digitalization encourages the manufacturing industry to flourish, while advanced manufacturing technologies are the prerequisite for digitalization development. On the other hand, the effects of digitalization on the quality of life may coincide with those on entertainment and life-related service industries to some extent.

4 Empirical Analysis

4.1 Descriptive statistics

Table 1 shows the sample mean descriptive statistics of the main variables.

Table 1: Descriptive statistics of variables.

VARIABLES	N	mean	sd	min	max
software industry enterprise	282	0.128	0.152	0.0147	1.111
information processing and provision service industry enterprise	282	0.0853	0.0945	0.0146	0.732
internet-associated service industry enterprise	282	0.0322	0.0437	0.00505	0.322
software industry employee	282	28.47	60.43	0	430.9
information processing and provision service industry employee	282	2.039	5.172	0.0298	41.61
internet-associated service industry employee	282	0.720	1.746	0	13.62
software industry selling to prefectural GDP	282	1.436	2.861	0	23.58
information processing and provision service industry selling	282	1.117	2.341	0.00997	13.40
prefectural internet-associated service industry selling	282	0.643	1.648	0	12.37
software industry added value	282	0.530	0.897	0	6.075
information processing and provision service industry added value	282	0.328	0.586	0.00578	4.494
internet-associated service industry added value	282	0.237	0.600	0	3.828
Internet availability rate	282	0.800	0.0559	0.671	0.957
personal computer availability rate	282	0.314	0.0562	0.158	0.468
digitalization index ***Digital***	282	0.124	0.783	-0.438	5.247

Notes: Numbers are counted per 1000 population.
Proportions are calculated by dividing by the prefecture's total GDP.

4.2 Analysis of digitalization spillover in Japanese prefectures

Figure 1 shows the DAGs used to construct the explanatory variable of 2013-2019, drawn from the statistics of the continuous 3 years. I find that constant spill-over prefectures are Tokyo (in 7 of 7 years), Yamaguchi (in 6 of 7 years), and Tochigi (in 5 of 7 years), while constant spill-in prefectures are Yamanashi (in 7 of 7 years), Shiga and Wakayama (both in 5 of 7 years). The spillover effect is most obvious in the year 2016 and least obvious in the year 2013. Based on the DAGs, I construct the main variable, spillover. Take subgraph (1) as an example, in the year 2013, the variable spillover of Aichi, Akita, and other variables with an arrow pointing to other prefectures is given value 1 (in bold), and the variable Spillover of all other prefectures, both with the arrow pointed in, and without arrows, are given value -1.

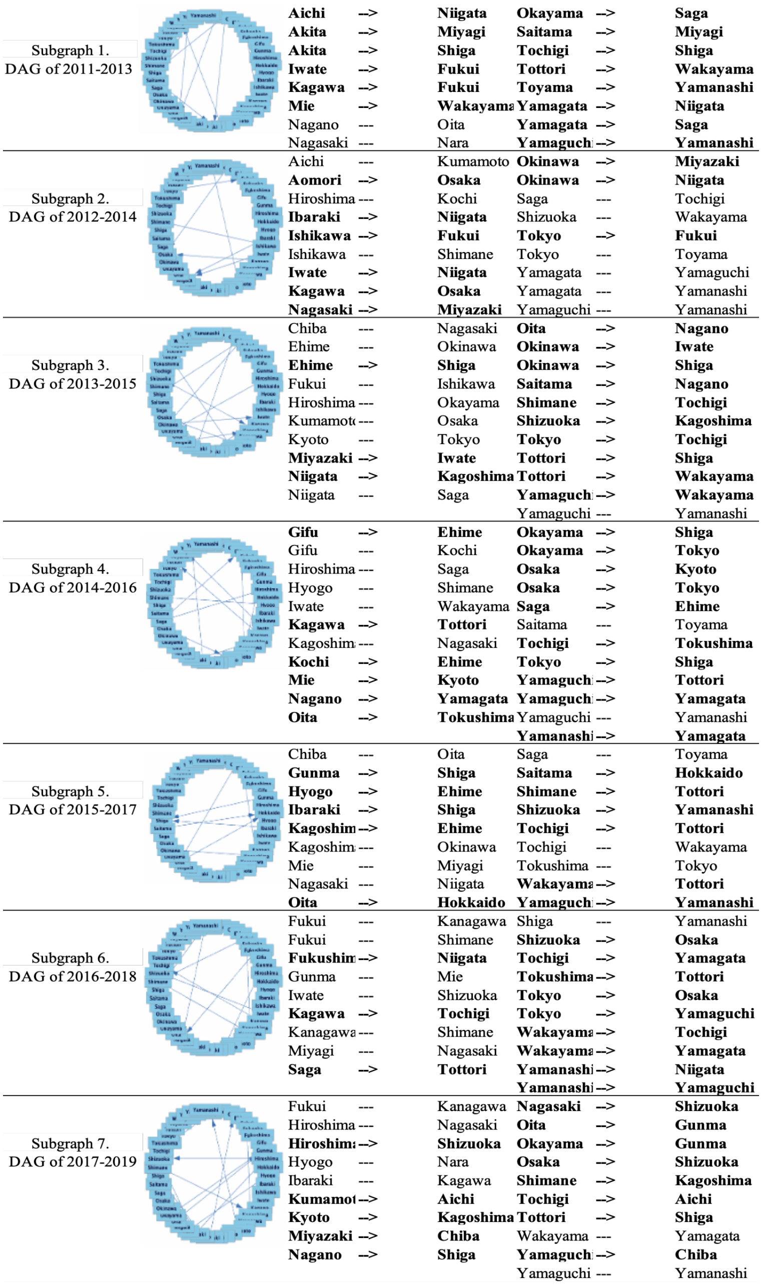

Figure 1: Directed Acyclic Graphs (DAGs) of year 2013-2019.

4.3 Benchmark regression analysis

The empirical estimation results of the model are shown in Table 2. The per capita GDP of the prefectures with digitalization spillover is 0.4% lower than the prefectures without spillover effects. It shows that the spillover of digitalization development harms the local economy.

Despite the negative impact of digitalization spillover on GDP per capita, indicating that digitalization spillover is not conducive to the local GDP per capita improvement, impacts of digitalization development on GDP per capita are positive, which is consistent with the existing literature, according to the examination of the original digitalization development index. One positive explanation is overdevelopment. When digitalization development exceeds the reasonable application level, the positive benefits are unable to compensate for the construction and operation costs.

Table 2: Baseline regression: the effects of digitalization spillover and digitalization development on GDP per capita.

	Spillover	***Digital***
	GDPperc	***GDPperc***
Spillover	-0.004**	
	(0.002)	
Digital		0.100***
		(0.010)
control variables	Y	Y
_cons	3.967***	3.769***
	(0.104)	(0.089)
N	282	282
r2_a	0.097	0.370

Notes: * p <0.1, ** p <0.05, *** p <0.01. Standard errors are reported in parentheses.

4.4 Robustness and endogeneity tests

4.4.1 Robustness test

I change the explained variable to the overall GDP for robustness testing. As shown in Table 3, the coefficients of the core explanatory variables are statistically significant and in accordance with the benchmark regression model. The spillover effect has a negative impact on total production, while digitalization development has a positive impact. The total GDP of the prefectures with digitalization spillover is 0.4% lower than the prefectures without the spillover effect.

Table 3: Robustness test: the effects of digitalization spillover and digitalization development on total GDP.

	Spillover *GDP*	*Digital* *GDP*
Spillover	-0.003**	
	(0.002)	
Digital		0.082***
		(0.008)
control variables	Y	Y
_cons	7.026***	6.863***
	(0.089)	(0.077)
N	282	282
r2_a	0.054	0.319

Notes: * p <0.1, ** p <0.05, *** p <0.01. Standard errors are reported in parentheses.

4.4.2 Endogeneity test

To test the endogeneity, the instrumental variable should directly introduce changes in the explanatory variable but does not directly influence the explained variable, and is only indirectly correlated with the explained variable through the explanatory variable.

I select the availability rate of high-speed Internet in primary schools to test the endogeneity for two reasons. First, since the time range of this paper is 2011-2019, the contribution of primary students to the GDP is ignorable. Second, in a region where digitalization development level is high, its education sector is likely to catch up with its industry and life-related services in terms of digitalization.

After controlling for the endogenous variable and conducting the fixed effects regression test again, the negative impact of the spillover effect on GDP is still statistically significant, as shown in Table 4.

Table 4: Endogeneity test.

	First-Stage *Spillover*	**2SLS** *GDPperc*
IV	-1.939***	
	(0.552)	
Spillover		-0.062**
		(0.027)
control variables	Y	Y
_cons	3.162***	3.612***
	(1.000)	(0.095)
N	282	282
r2_a	0.125	

Notes: * p <0.1, ** p <0.05, *** p <0.01. Standard errors are reported in parentheses.

4.4.3 Further mechanism testing

According to the results above, impacts on per capita GDP are positive for digitalization development while negative for digitalization spillover. From the perspectives of population aging and industrial structures, I examine the mechanisms through which digitalization spillover imposes negative impacts on GDP.

4.4.3.1 Population aging perspective

One major challenge in digital transformation is to ensure its spread to target populations. As elder meet barriers using technology (Vaportzis, Clausen, & Gow, 2017), population aging can largely influence the extent of digitalization, thus, I estimate the degree of population aging with the variable Diff80, the difference between the over-80-year-old population proportions of the prefecture and the regional average. Results in Table 5 show that the negative impacts of population aging on production per capita are statistically significant.

Initially aiming at increasing regional productivity, large investments go to the digital industry. However, the aging population discourages digitalization and forbids it to reach expected outcomes by impeding the spread of digital technologies, and hence, digital industries spill over to other regions, which in turn negatively affects their economic performances.

4.4.3.2 Industrial structure perspective

Service sectors are identified as the heaviest users of ICT, which is to be seen as a natural consequence of the increasing digitalization of many services (Greif & Hannes, 2015). As the aims and functions of the service sector have some overlap with digitalization, I construct the variable, service, the ratio of entertainment and life-related service industry production to total GDP. Results in Table 6 show that the positive impacts of the service industry on the production per capita are statistically significant.

The development of the service industry mitigates the negative effect of digitalization spillover on production. As digitalization improves the quality of life by providing convenience and creating additional value, the effects of digitalization may overlap with entertainment and life-related service industries.

Table 5: Mechanism test of population aging and industrial structure.

	Population Aging	**Industrial Structure**
	GDP	***GDP***
Spillover	-0.006***	-0.007***
	(0.002)	(0.003)
Diff80	-1.318**	
	(0.511)	
*Spillover*Diff80*	-0.288***	
	(0.084)	
Service		-30.265***
		(10.019)
*Spillover*Service*		10.642**
		(4.682))
control variables	Y	Y
_cons	3.939***	3.879***
	(0.102)	(0.112)
N	282	282
r2_a	0.137	0.147

Notes: * p <0.1, ** p <0.05, *** p <0.01. Standard errors are reported in parentheses.

4.4.4 Heterogeneity analysis

The emergence of e-commerce technology has had an important impact on firms' export marketing (Gregory, Karavdic, & Zou, 2007). However, limited knowledge exists on whether increased access to countries with different levels of digitalization affects the extent of digitalization development. Therefore, I divide the observations into two types: prefectures that directly face the Sea of Japan, such as Hokkaido, Aomori, and Nagasaki, indicating their geographical closeness to countries such as China and Korea, and those that do not. With this binary division, I carry out interregional heterogeneity analyses. Results in Table 7 show that the negative effects of digitalization spillover to GDP per capita in prefectures that directly face the Sea of Japan are statistically significant while they are not in the prefectures that do not.

Prefectures that directly face the Sea of Japan may develop a higher degree of digitalization. On the other hand, excessive supplies of digitalization that exceed demands of the prefecture's population spill over to other prefectures, and hence, negatively influence the GDP per capita.

Table 6: Heterogeneity test with geographic division: geographical closeness to countries with advanced digitalization

	Not facing Sea of Japan	**Facing Sea of Japan**
	GDPperc	***GDPperc***
spillover	-0.001	-0.010***
	(0.002)	0.003
Sea	NO	YES
control variables	Y	Y
_cons	3.793***	4.935***
	(0.120)	(0.191)
N	186	98
r2_a	0.054	0.561

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are reported in parentheses.

5 Discussion

This research may have the limitations of omitted variables bias. Specifically, besides six selected controlled macroeconomic variables, external shocks such as the financial crisis may influence the GDP from another perspective. But since this paper utilizes the investment as the main influence of digitalization development, the external shocks are not the main focus. Moreover, the possibility that GDP growth further influences the Digitalization and spillover effect exists, but as the change is second-order, the issue is neither the main topic of the research.

6 Conclusion

Through a case study of Japanese prefectures, this paper finds that digitalization development and spillover have important impacts on overall economic performance. In general, digital development positively influences the overall production and production per capita of the prefecture, but the spillover effect brings negative influences. Furthermore, the spillover effect is worsened by population aging, which negatively influences digitalization development. However, entertainment and life-related service industry development mitigate the negative effect of spillover. Moreover, for prefectures that directly face the Sea of Japan and are geographically close to countries with advanced digitalization such as China and South Korea, the negative impacts of spillover are more severe. Therefore, to maximize the role of the digital economy in promoting economic growth, the digital industries and digitalization development in the prefectures should coordinate with their industrial structures and population characteristics. Lastly, as Japan is stepping ahead with respect to the issue of population aging, the evidence from Japan may bring insights to other societies which would face similar problems in the near future.

References

Ahmad, N., & Ribarsky, J. (2018). Towards a framework for measuring the digital economy.

Alfaro Cortés, E., & Alfaro Navarro, J.-L. (2011, Feb 01). Do ict influence economic growth and human development in european union countries? *International Advances in Economic Research*, *17*(1), 28-44.

Awokuse, T., & Bessler, D. (2003). Vector autoregressions, policy analysis, and directed acyclic graphs: An application to the u.s. economy. *Journal of Applied Economics*, *6*, 1-24.

CETTE, G. (2015, 4th quart). Which Role for ICTs as a Productivity Driver Over the Last Years and the Next Future? *Communications & Strategies*, *1*(100), 65-83.

Digitalization to improve tax compliance: Evidence from vat e-invoicing in peru. (2022). *Journal of Public Economics*, *210*, 104661.

Gregory, G., Karavdic, M., & Zou, S. (2007, 2022/11/08/). The effects of e-commerce drivers on export marketing strategy. *Journal of International Marketing*, *15*(2), 30-57. (Full publication date: 2007)

Greif, W., & Hannes, L. (2015). *Effects of digitalisation on service industries and employment*. European Economic and Social Committee.

Japanese Ministry of Public Management, P., Home Affairs, & Telecommunications. (2002). *Information and communications in japan, white paper 2002*.

Karpunina, K., E, Petrov, V., I, Klimentova, A., E, Sozaeva, A., J, & Korkishko, V., I. (2020). Mechanisms of self-development of subsidized regions. *Proceedings of the 35rd International Business Information Management Association Conference*.

LÃ-RodrÃguez, J. A., & Nakamura, D. (n.d.). Mind the Remoteness!: Income disparities across Japanese Prefectures. *Estudios de economÃa*.

Liu, H. (2021). Economic performance associated with digitalization in canada over the past two decades.

Maiti, D., Castellacci, F., & Melchior, A. (2020). Digitalisation and development: Issues for india and beyond. In *Digitalisation and development: Issues for india and beyond* (pp. 3–29). Singapore: Springer Singapore.

Miao, Z. (2022, Jan 01). Industry 4.0: technology spillover impact on digital manufacturing industry. *Journal of Enterprise Information Management*, *35*(4/5), 1251-1266.

Nilsson, A., Bonander, C., Strömberg, U., & Björk, J. (2021, Apr 01). A directed acyclic graph for interactions. *International Journal of Epidemiology*, *50*(2), 613-619.

Porter, M. E. (2000, Feb 01). Location, competition, and economic development: Local clusters in a global economy. *Economic Development Quarterly*, *14*(1), 15-34.

Spirtes, P., & Glymour, C. (1991). An algorithm for fast recovery of sparse causal graphs. *Social Science Computer Review*, *9*(1), 62-72.

Spirtes, P., Glymour, C., Scheines, R., Kauffman, S., Aimale, V., & Wimberly, F. (2000). Constructing bayesian network models of gene expression networks from microarray data.

Textor, J., van der Zander, B., Gilthorpe, M. S., Liśkiewicz, M., & Ellison, G. T. (2016, Dec 01). Robust causal inference using directed acyclic graphs: the r package 'dagitty'. *International Journal of Epidemiology*, *45*(6), 1887-1894.

Vaportzis, E., Clausen, M. G., & Gow, A. J. (2017, October). Older adults perceptions of technology and barriers to interacting with tablet computers: A focus group study. *Front Psychol*, *8*, 1687.

Venturini, F. (2009, December). The long-run impact of ICT. *Empirical Economics*, *37*(3), 497-515.