



## Secondary Publication

Detemple, Jonas; Wicht, Alexandra

### Uncovering regional inequalities in digitalization : A multifaceted measurement for Germany

Date of secondary publication: 10.03.2026

Version of Record (Published Version), Article

Persistent identifier: urn:nbn:de:bvb:473-irb-114211x

#### Primary publication

Detemple, Jonas; Wicht, Alexandra (2024): Uncovering regional inequalities in digitalization : A multifaceted measurement for Germany, in: Measurement instruments for the social sciences, Trier: PsychOpen GOLD, Vol. 6, No. e13387, pp. 1–13, doi: 10.5964/miss.13387.

#### Legal Notice

This work is protected by copyright and/or the indication of a licence. You are free to use this work in any way permitted by the copyright and/or the licence that applies to your usage. For other uses, you must obtain permission from the rights-holders.

This document is made available under a Creative Commons license.



The license information is available online:

<https://creativecommons.org/licenses/by/4.0/legalcode>

# Uncovering Regional Inequalities in Digitalization: A Multifaceted Measurement for Germany

Jonas Detemple<sup>1,2</sup> , Alexandra Wicht<sup>1,3</sup> 

[1] Federal Institute for Vocational Education and Training (BIBB), Bonn, Germany. [2] Bamberg Graduate School of Social Sciences (BAGSS), University of Bamberg, Bamberg, Germany. [3] Department of Educational Science, University of Siegen, Siegen, Germany.

---

Measurement Instruments for the Social Sciences, 2024, Vol. 6, Article e13387, <https://doi.org/10.5964/miss.13387>

---

**Received:** 2023-12-05 • **Accepted:** 2024-04-26 • **Published (VoR):** 2024-07-03

---

**Handling Editor:** Eldad Davidov, University of Cologne, Cologne, Germany

---

**Corresponding Author:** Jonas Detemple, Friedrich-Ebert-Allee 114-116, 53113 Bonn, Germany. E-mail: [jonas.detemple@bibb.de](mailto:jonas.detemple@bibb.de)

---

**Supplementary Materials:** Data [see [Index of Supplementary Materials](#)]



## Abstract

The ongoing global digital transformation has significant implications for economies and societies, with potential benefits and challenges. This study addresses the critical need for a comprehensive measurement of regional digitalization in Germany to better understand its impact on various aspects of life, including education, employment, and working conditions. Using confirmatory factor analysis (CFA), it introduces a multifaceted regional digitalization measure at the administrative district level (NUTS-3) that incorporates digital infrastructure, culture, technology capacity, high-tech human capital, and digitalization-related innovativeness. Results for 2013 and 2017 are compared. The study reveals that digitalization varies significantly across regions, but hardly over time. Urban regions tend to have higher digitalization levels, which are positively associated with economic productivity and high-skilled labor demand. Our developed measurement of regional digitalization is publicly available.

## Keywords

digitalization, regional, districts, NUTS-3, confirmatory factor analysis, technological change, Germany

In today's world, technological and digital changes are one of the most disruptive upheavals that have taken place globally. Digitalization is relevant in virtually all parts of life and has often been associated with positive outcomes, such as economic growth, technological progress, higher qualifications, and modern lifestyles (Acemoglu, 1998). At



the same time, digitalization also has its widely feared downsides, such as polarization tendencies in the labor market due to the automation of work processes (Acemoglu & Autor, 2011).

We currently lack a comprehensive measure of regional digitalization, which is essential for cross-regional analysis and understanding its impact on individual outcomes such as education, employment, and working conditions. This issue is especially crucial given that existing research consistently highlights the significance of regional disparities in shaping individual life trajectories (e.g., Weßling et al., 2015; Wicht & Nonnenmacher, 2017). This study emphasizes the need for a multifaceted regional digitalization indicator and its connection to upskilling and economic growth. Our focus is primarily on the labor-market implications of digitalization.

We find significant disparities in regional digitalization between eastern and western regions and between federal states (e.g., BMWK, 2023; Opiela et al., 2023). Our goal, however, is to offer a more detailed perspective by examining regional differences at the administrative district level (NUTS-3). This approach provides a nuanced understanding of digitalization inequalities, which are pertinent to various research fields such as sociology, economics, and human geography. In addition to studying regional disparities, our indicator can also be used in combination with survey data providing regional merging identifiers. The developed measurement of regional digitalization is publicly available for the time points 2013 and 2017 and can be accessed in the Supplementary Materials (see Detemple & Wicht, 2024a).

## Theoretical Background

The relevance of discussing digitalization stems from technology's growing importance in both the economy and daily life, a trend that began with the Industrial Revolution (Häußling, 2019). Today, technological development is reflected in the trends of digitalization and computerization. While digitalization has received widespread scholarly attention, its precise meaning remains open to interpretation. In contrast to digitization, which involves converting physical data into digital format (codification), digitalization represents a broader social and economic phenomenon driven by technological change and the introduction of new digital technologies.

While there is no overarching definition and theory of digitalization (Kraus et al., 2022), traditional economic approaches to skill- and routine-biased technological change emphasize the role of labor market-related technological innovations that lead to the automation of routine tasks and an increasing demand for highly skilled workers with non-routine tasks complementing robots and machines (Acemoglu, 1998; Acemoglu & Autor, 2011; Autor et al., 2003). Moreover, there is a common understanding that digitalization represents a multifaceted construct that encompasses multiple aspects of technological change in the economy (e.g., Archibugi et al., 2009; Kraus et al., 2022).

Previous research on digitalization and technological change has mainly focused on the country level (e.g., Archibugi et al., 2009; Katz et al., 2014; Mammadli & Klivak, 2020), global time trends (e.g., Hornstein et al., 2005), or the occupation and firm level (e.g., Kristal, 2013; Spitz-Oener, 2006). For developing a regional measurement of digitalization, country-level research serves as a valuable reference point. Katz et al. (2014) developed a digitalization index for 184 countries, considering indicators such as affordability, infrastructure investment, network access, capacity, usage, and human capital. Building on this, Mammadli and Klivak (2020) measured digitalization in OECD countries based on infrastructure, mathematics education, and ICT skills. For Germany, BMWK (2023) and Opiela et al. (2023) developed digitalization measurements at the level of federal states. BMWK (2023) focused on internal (reflecting on processes, products, business models, further education, research, and innovation activities) and external company indicators (such as technical infrastructure, administrative-legal framework, and society), while Opiela et al. (2023) emphasized infrastructure, living conditions, economy, and administration. Archibugi et al. (2009) noted that although various approaches exist for measuring digitalization as a multifaceted index, the results tend to align and be comparable. However, country-specific measurements mask regional differences and assume that digitalization is uniform at the country level.

Efforts were made to consider regional disparities in digitalization, with a focus on potential adverse effects such as job automation and robotization (Acemoglu & Restrepo, 2020; Dauth et al., 2017; Leigh & Kraft, 2018), or substitution risks due to locally concentrated workers with routine tasks (Autor et al., 2013; Kropp & Dengler, 2019). While the automation and substitution risks of jobs are potential consequences of digitalization, they may be less useful for predicting a certain degree of digitalization. First, automation is only one possible consequence of digitalization alongside the increasing demand for non-routine, highly skilled workers. Given the strong regional differences in occupational structures (e.g., Kleinert et al., 2018), it is not necessary or even unlikely that both phenomena occur simultaneously in one region. Second, empirical studies often do not use measures of actual automation, but rather measures of substitution risks in terms of the share of routine tasks prone to automation at the occupation level. However, studies suggest that it is less likely that entire occupations will be replaced by robots and machines, but that the skill and task profiles within occupations will change instead (Dauth et al., 2017; Dengler & Matthes, 2018).

For Germany, regional studies examined specific aspects of digitalization, such as internet broadband coverage at the municipality level (Falck et al., 2014), digital innovativeness measured by technology-related patent applications (Berger et al., 2017), or digital culture in terms of registered website domains per capita at the district level (Lechner et al., 2017; Wicht et al., 2021). However, it can be assumed that digitalization as a broader social and economic phenomenon is difficult to depict drawing on one single

facet. Instead, it is advisable to combine the strengths of several indicators in a new, reflective measurement.

While regional studies on digitalization acknowledge the need to consider regional heterogeneity, they have yet to employ comprehensive, multifaceted measurements. This study aims to expand on the analytical strategies used in prior country and regional studies (e.g., Katz et al., 2014; Mammadli & Klivak, 2020), by providing a multifaceted assessment of regional digitalization. The measure includes various aspects of digitalization pertinent to education, employment, and work, encompassing digital infrastructure, culture, technology capacity, high-tech human capital, and digitalization-related innovativeness.

## Data

In order to assess regional digitalization as a multifaceted construct, we built on various administrative data sources at the NUTS-3 level, namely the Federal Statistical Office, EU Klems, the Federal Office for Building and Regional Planning, the Federal Employment Agency, and the German Economic Institute (BA, 2023; BBSR, 2022; Destatis, 2023; IW, 2023; Stehrer et al., 2019). This dataset covered two measurement time points, 2013 and 2017, for a comprehensive analysis of regional digitalization across all 401 administrative districts in Germany over time. The dataset encompassed five key facets of regional digitalization: digital infrastructure, digital culture, digital technology capacity, high-tech human capital, and digitalization-related innovativeness.

- Digital infrastructure: This facet reflects the availability of fast internet connections in a region (Falck et al., 2014). It was measured by a region's broadband coverage and captures the proportion of households that are equipped with internet connections of at least 50 Mbit/s, thus reflecting the accessibility of high-speed internet infrastructure (BBSR, 2022).
- Digital culture: This facet captures insights into the digital engagement of a region's residents (Lechner et al., 2017; Wicht et al., 2021). It was quantified by the ratio of registered German website domains to the resident population (Destatis, 2023).
- Digital technology capacity: This facet targets the capacity that firms in a region have, on average, for digital technology software and devices. It is reflected in firms' average IT capital, which we measured by nationwide, industry-specific capital in IT software and programs (Stehrer et al., 2019), weighted by the corresponding regional employment figures (BA, 2023).
- High-tech human capital: This facet highlights technological skills and knowledge that are manifested in the region's high-tech industry. It was captured by the proportion of employees in scientific IT and service occupations (BBSR, 2022).
- Digitalization-related innovativeness: This facet reflects the extent to which firms invest in technology- and digitalization-related research and innovation. It was

measured by the share of registered patents that are settled in the field of technology (Berger et al., 2017), weighted by the resident population of the region (Destatis, 2023).

Comparing differences in the indicators over time, we found that regional characteristics were relatively stable between 2013 and 2017 (see Supplementary Materials; Figure S1, Table S1–S2, Detemple & Wicht, 2024b). The largest differences emerged in broadband coverage, where regions in 2017 were about one standard deviation higher than in 2013. Otherwise, the differences were small to non-existent, which is why temporal comparisons between regions are not very meaningful for our digitalization indicators.

## Method

Confirmatory factor analysis (CFA) was used to gauge how well the data aligned with the theoretical model of digitalization. We posited one overarching, latent factor consisting of multiple indicators to best represent regional digitalization. This factor was assumed to have a linear relationship with the observed indicators. CFA calculates factor loadings, reflecting the strength of the association between digitalization and each indicator while accounting for indicator-specific error terms. Unlike formative composite measures, CFA does neither require equal nor subjective weighting of the indicators (Archibugi et al., 2009). Moreover, CFA offers the advantage of assessing the model's goodness of fit using statistical criteria, such as RMSEA (Root Mean Square Error of Approximation), CFI (Comparative Fit Index), and SRMR (Standardized Root Mean Squared Residual) (e.g., Hoyle, 1995).

To handle extreme outliers in certain indicators (regional digital culture, high-tech human capital, and digitalization-related innovativeness), we grouped the top 1% into a single category. To relax CFA's statistical requirements for metric and normally distributed variables, we used Satorra-Bentler standard errors (Kolenikov, 2009). Given our standardized latent factor ( $M = 0$ ,  $SD = 1$ ), a one standard deviation increase in the level of digitalization corresponds, on average, to an increase in an indicator by its factor loading.

## Quality Criteria

### Objectivity

Drawing on data from administrative data sources and relying on complete surveys helps to minimize objectivity concerns. Nonetheless, it should be noted that administrative data may still be susceptible to errors in data preparation and data collection.

## Reliability

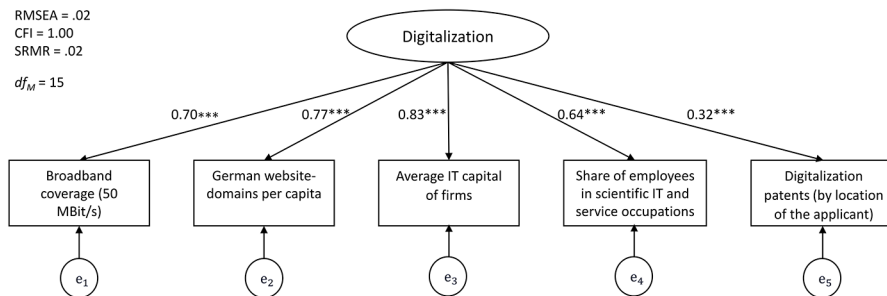
The scale reliability of our set of regional indicators was acceptably good, as indicated by measures of McDonald's Omega (.79 for 2013 and .80 for 2017), suggesting that the regional indicators have high internal consistency (McNeish, 2018).

## Factorial Validity

The results of the CFA for the year 2017 are shown in Figure 1 (for more detailed results of the two time points 2013 and 2017, see Supplementary Material; Table S1–S2, Detemple & Wicht, 2024b). Digitalization as a latent factor is highly associated with all five regional indicators, as demonstrated by the significance levels of the factor loadings ( $p < .001$ ). Comparing the size of the factor loadings, it can be concluded that regional IT capital is associated most strongly with digitalization (0.83), followed by website domains (0.77), broadband coverage (0.70), and employees in scientific IT and service occupations (0.64). Digitalization patents are relatively less important (0.32). With RMSEA = .02, CFI = 1.00, and SRMR = .02, the fit indices indicate that the data fit the postulated digitalization model acceptably well. Based on the CFA results, we identified and predicted a pattern of digitalization (standardized with  $M = 0$  and  $SD = 1$ ).

**Figure 1**

*Confirmatory Factor Analysis Model of Digitalization (2017)*



*Note.* All indicators are z-standardized ( $M = 0$  and  $SD = 1$ ). Satorra-Bentler standard errors used.  $N = 401$ .

\* $p < .05$ . \*\* $p < .01$ . \*\*\* $p < .001$ .

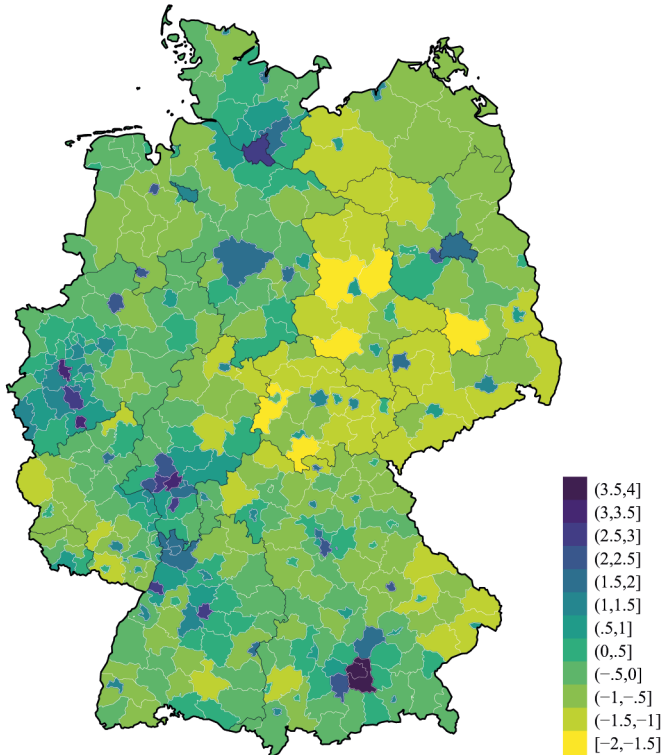
## Construct Validity

Figure 2 illustrates the distribution of digitalization in Germany and shows considerable regional variance across the country. Urban regions, often characterized by smaller district sizes, tended to have higher levels of digitalization. Additionally, the distribution is right-skewed, implying that most regions have a basic level of digitalization, while a few regions reach relatively high levels. The regions with the highest digitalization levels were Munich (both city and county districts), Frankfurt, and Dusseldorf. The estimated

digitalization levels for all districts are available as a CSV file in the Supplementary Materials (see Detemple & Wicht, 2024a).

**Figure 2**

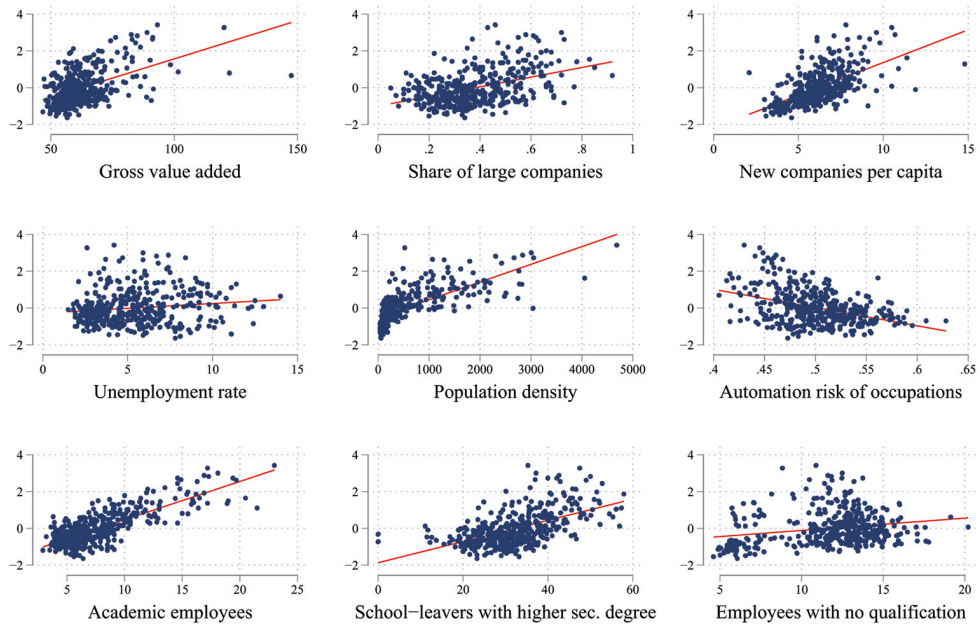
*Distribution of Digitalization Across Administrative Districts in Germany (2017), © GeoBasis-DE/BKG, 2023*



Previous research has pointed out that digitalization does not exist independently of other regional characteristics (such as urbanity, local labor market conditions, and economic welfare) (Jerzmanowski & Tamura, 2019; Mammadli & Klivak, 2020). To further validate our measurement of regional digitalization, bivariate associations with common regional indicators were evaluated. As shown in Figure 3, we found that regional digitalization is positively associated with gross value added, the share of large companies, the share of new companies, population density, the share of academic employees, and the share of school leavers with a higher secondary degree (which is equivalent to a university-entrance qualification). In line with previous research, these findings suggest that digitalization is associated with higher economic productivity and a higher demand for high-skilled labor. It also shows that digitalization is higher in urban regions.

Figure 3

*Bivariate Associations Between Digitalization and Further Regional Indicators (2017)*



The automation risk of occupations is negatively correlated with regional digitalization, indicating that occupations with a high automation risk (primarily jobs with routine tasks and lower skill requirements) are more prevalent in comparatively less digitalized regions. There is no correlation between unemployment and digitalization. On average, however, regions with higher levels of digitalization do not have lower shares of employees without (formally recognized) qualifications (if anything, the shares are slightly higher). Considering that the share of academic employees increases with regional digitalization suggests that there is a slight region-specific polarization in terms of employee qualifications rather than a general trend towards higher qualified employees.

According to the theories of skill- and routine-biased technological change (Acemoglu, 1998; Acemoglu & Autor, 2011; Autor et al., 2003) digitalization includes both the automation of routine tasks and a higher demand for non-routine tasks and thus high-skilled labor. In line with Acemoglu and Restrepo (2020), our results suggest that upskilling and automation processes represent two distinct factors of digitalization. Whereas the demand for high-skilled labor is linked to our measurement, there are good reasons to argue that automation processes would be better reflected by measures on robotization, which appeared to be distinct from other technology innovations (Acemoglu & Restrepo, 2020).

## Test Fairness

As shown earlier, digitalization is more pronounced in urban regions with high population density. To determine whether a region's urbanity makes a difference in CFA's modeling of digitalization, we tested measurement invariance by comparing rural and urban regions. The test shows that the null hypothesis of invariance in factor loadings, intercepts, and error terms between urban and rural regions must be rejected. This suggests that digitalization operates differently in rural and urban regions (see Supplementary Material; Table S3, Detemple & Wicht, 2024b).

## Conclusions

Our study contributes to the literature on technological and digital change by providing a measure of digitalization at a small-scale regional level that maps digitalization processes concerning increasing demand for highly skilled workers and economic growth. The strength of our measurement lies in the fact that it encompasses the commonalities of several individual proxies of digitalization used so far and thus maps digitalization more accurately. Depending on the research context, researchers may consider using our measurement on digitalization together with a valid measure of robotization to additionally reflect on polarization and automation processes.

---

**Funding:** This article was written as part of the work conducted by the junior research groups “Regional (infra-)structure and processes of occupational segmentation in vocational education and training” and “Career orientations and their realization: young people’s transitions to vocational education and training in a spatial context,” based at the Federal Institute for Vocational Education and Training (BIBB). The work of the research groups is funded by the German Federal Ministry of Education and Research (BMBF).

---

**Acknowledgments:** We are grateful to the anonymous reviewer for valuable comments and suggestions on an earlier version of this article. We also thank Per Kropp and Barbara Schwengler from the Institute for Employment Research (IAB) for their feedback on the conceptual framework of our study. We would also like to thank Klara Kaufmann from the IAB for supporting us in calculating an indicator based on sensitive employment data. We further thank Helen Hickmann from the Federal Institute for Vocational Education and Training (BIBB) for valuable feedback in the writing process.

---

**Competing Interests:** The authors have declared that no competing interests exist.

---

**Data Availability:** The data used are regional data at the NUTS-3 level from the following sources: Regional data on broadband coverage, the share of employees in scientific IT and service occupations, and the number of inhabitants are available online and upon request from the Federal Office for Building and Regional Planning (BBSR). Regional data on German website domains are available online at the Federal Statistical Office. Regional data on the average IT capital of firms are available online at EU Klems. Regional data on employment figures by industry branches are available upon request from the Federal Employment Agency (BA). Regional data on digitalization patents are available upon request from the German Economic Institute (IW).

---

## Supplementary Materials

For this article, the following Supplementary Materials are available:

- Estimated digitalization levels for all German districts (2013 and 2017; see Detemple & Wicht, 2024a)
- Supplementary tables and figures (see Detemple & Wicht, 2024b)

### Index of Supplementary Materials

Detemple, J., & Wicht, A. (2024a). *Supplementary materials to "Uncovering regional inequalities in digitalization: A multifaceted measurement for Germany"* [Estimates]. PsychOpen GOLD. <https://doi.org/10.23668/psycharchives.15025>

Detemple, J., & Wicht, A. (2024b). *Supplementary materials to "Uncovering regional inequalities in digitalization: A multifaceted measurement for Germany"* [Supplementary tables and figures]. PsychOpen GOLD. <https://doi.org/10.23668/psycharchives.15024>

## References

- Acemoglu, D. (1998). Why do new technologies complement skills? Directed technical change and wage inequality. *The Quarterly Journal of Economics*, *113*(4), 1055–1089. <https://doi.org/10.1162/003355398555838>
- Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In D. Card & O. Ashenfelter (Eds.), *Handbook of labor economics* (Vol. 4, pp. 1043–1171). Elsevier. [https://doi.org/10.1016/S0169-7218\(11\)02410-5](https://doi.org/10.1016/S0169-7218(11)02410-5)
- Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, *128*(6), 2188–2244. <https://doi.org/10.1086/705716>
- Archibugi, D., Denni, M., & Filippetti, A. (2009). The technological capabilities of nations: The state of the art of synthetic indicators. *Technological Forecasting and Social Change*, *76*(7), 917–931. <https://doi.org/10.1016/j.techfore.2009.01.002>
- Autor, D. H., Dorn, D., & Hanson, G. H. (2013). *Untangling trade and technology: Evidence from local labor markets* [NBER Working Paper No. 18938]. <http://www.nber.org/papers/w18938>
- Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333. <https://doi.org/10.1162/003355303322552801>
- BA. (2023). *Statistik der Bundesagentur für Arbeit: Sozialversicherungspflichtig Beschäftigte am Arbeitsort, Bearbeitung IAB*. Federal Employment Agency (BA). <https://statistik.arbeitsagentur.de>
- BBSR. (2022). *INKAR - Indikatoren und Karten zur Raum- und Stadtentwicklung*. Federal Office for Building and Regional Planning. <https://www.inkar.de/>
- Berger, S., Koppel, O., & Röben, E. (2017). *Deutschlands Hochburgen der Digitalisierung* [IW Kurzberichte No. 42/2017]. German Economic Institute. <https://www.iwkoeln.de/studien/sarah-berger-oliver-koppel-enno-roeben-deutschlands-hochburgen-der-digitalisierung-340150.html>
- BMWK. (2023). *Digitalisierung der Wirtschaft in Deutschland: Digitalisierungsindex 2022*. Federal Ministry for Economic Affairs and Climate Action. <https://www.de.digital/DIGITAL/Navigation/DE/Lagebild/Digitalisierungsindex/digitalisierungsindex.html>
- Dauth, W., Findeisen, S., Südekum, J., & Wößner, N. (2017). *German robots: The impact of industrial robots on workers* [IAB-Discussion Paper No. 30/2017]. Institute for Employment Research. <https://hdl.handle.net/10419/172894>
- Dengler, K., & Matthes, B. (2018). The impacts of digital transformation on the labour market: Substitution potentials of occupations in Germany. *Technological Forecasting and Social Change*, *137*, 304–316. <https://doi.org/10.1016/j.techfore.2018.09.024>
- Destatis. (2023). *Regionaldatenbank Deutschland*. Federal Statistical Office. <https://www.regionalstatistik.de/genesis/online>
- Falck, O., Gold, R., & Heblich, S. (2014). E-lections: Voting behavior and the internet. *The American Economic Review*, *104*(7), 2238–2265. <https://doi.org/10.1257/aer.104.7.2238>

- Häußling, R. (2019). *Techniksoziologie* (2nd ed.). Barbara Budrich.
- Hornstein, A., Krusell, P., & Violante, G. L. (2005). The effects of technical change on labor market inequalities. In P. Aghino & S. N. Durlauf (Eds.), *Handbook of economic growth* (Vol. 1B, pp. 1275–1370). Elsevier Masson SAS. [https://doi.org/10.1016/S1574-0684\(05\)01020-8](https://doi.org/10.1016/S1574-0684(05)01020-8)
- Hoyle, R. H. (1995). *Structural equation modeling: Concepts, issues, and applications*. Sage.
- IW. (2023). *IW Patent database*. German Economic Institute. <https://www.iwkoeln.de/en/institute/projects/patent-database.html>
- Jerzmanowski, M., & Tamura, R. (2019). Directed technological change & cross-country income differences: A quantitative analysis. *Journal of Development Economics*, 141, Article 102372. <https://doi.org/10.1016/j.jdevec.2019.102372>
- Katz, R., Koutroumpis, P., & Martin Callorda, F. (2014). Using a digitization index to measure the economic and social impact of digital agendas. *Info*, 16(1), 32–44. <https://doi.org/10.1108/info-10-2013-0051>
- Kleinert, C., Vosseler, A., & Blien, U. (2018). Classifying vocational training markets. *The Annals of Regional Science*, 61(1), 31–48. <https://doi.org/10.1007/s00168-017-0856-z>
- Kolenikov, S. (2009). Confirmatory factor analysis using confa. *The Stata Journal*, 9(3), 329–373. <https://doi.org/10.1177/1536867X0900900301>
- Kraus, S., Durst, S., Ferreira, J. J., Veiga, P., Kailer, N., & Weinmann, A. (2022). Digital transformation in business and management research: An overview of the current status quo. *International Journal of Information Management*, 63, Article 102466. <https://doi.org/10.1016/j.ijinfomgt.2021.102466>
- Kristal, T. (2013). The capitalist machine: Computerization, workers' power, and the decline in labor's share within U.S. industries. *American Sociological Review*, 78(3), 361–389. <https://doi.org/10.1177/0003122413481351>
- Kropp, P., & Dengler, K. (2019). The impact of digital transformation on regional labour markets in Germany: Substitution potentials of occupational tasks. In *Proceedings of the Weizenbaum Conference 2019 "Challenges of digital inequality - Digital education, digital work, digital life"* (pp. 1–8). Weizenbaum Institute. <https://doi.org/10.34669/wi.cp/2.8>
- Lechner, C. M., Obschonka, M., & Silbereisen, R. K. (2017). Who reaps the benefits of social change? Exploration and its socioecological boundaries. *Journal of Personality*, 85(2), 257–269. <https://doi.org/10.1111/jopy.12238>
- Leigh, N. G., & Kraft, B. R. (2018). Emerging robotic regions in the United States: Insights for regional economic evolution. *Regional Studies*, 52(6), 804–815. <https://doi.org/10.1080/00343404.2016.1269158>
- Mammadli, E., & Klivak, V. (2020, January 24). *Measuring the effect of the digitalization*. <https://doi.org/10.2139/ssrn.3524823>
- McNeish, D. (2018). Thanks coefficient alpha, We'll take it from here. *Psychological Methods*, 23(3), 412–433. <https://doi.org/10.1037/met0000144>

- Opiela, N., Tiemann, J., Gumz, J. D., Goldacker, G., Weber, M., & Kammer, R. (2023). *Deutschland-Index der Digitalisierung 2023*. Kompetenzzentrum Öffentliche IT.  
<http://www.oeffentliche-it.de/publikationen>
- Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of Labor Economics*, *24*(2), 235–270.  
<https://doi.org/10.1086/499972>
- Stehrer, R., Bykova, A., Jäger, K., Reiter, O., & Schwarzhappel, M. (2019). *Industry level growth and productivity data with special focus on intangible assets*. The Vienna Institute for International Economic Studies. <https://euklems.eu/wp-content/uploads/2019/10/Methodology.pdf>
- Wefßling, K., Hartung, A., & Hillmert, S. (2015). Spatial structure counts: The relevance of regional labour-market conditions for educational transitions to vocational training. *Empirical Research in Vocational Education and Training*, *7*, Article 12. <https://doi.org/10.1186/s40461-015-0024-6>
- Wicht, A., & Nonnenmacher, A. (2017). Modeling spatial opportunity structures and youths' transitions from school to training. *Open Journal of Statistics*, *7*(6), 1013–1038.  
<https://doi.org/10.4236/ojs.2017.76071>
- Wicht, A., Reder, S., & Lechner, C. M. (2021). Sources of individual differences in adults' ICT skills: A large-scale empirical test of a new guiding framework. *PLoS One*, *16*(4), Article e0249574.  
<https://doi.org/10.1371/journal.pone.0249574>