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Global technology cycles and local economic performance

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Global Technology Cycles and Local Economic Performance

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May 2, 2023

Abstract

This paper studies the global synchronicity of technology and its impact on the economy. We employ dynamic factor analysis to decompose patent data in different digital technologies for various countries into global and country-specific factors. Our findings confirm the existence of global and local technology cycles. We further find a significant positive correlation between the estimated global technology index and a country's economic performance. This positive effect is stronger in countries with broad technological exposure. However, a concentration in only few dominant technological fields seems to reduce the positive impact of the global technology cycle on a country's economic performance.

JEL classification: O31, O33, O47, C38, L86

Keywords: innovation index, dynamic factor model, patent data, productivity growth, knowledge diffusion, digitalization, globalization

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1 Introduction

Global inventive activities play a crucial role in the productivity growth of countries, (e.g, Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991; Eaton and Kortum, 1996). Especially, since countries can benefit from knowledge generated elsewhere, for example, through international trade, foreign direct investment (FDI), migration and social networks (see, e.g., Keller, 2010, for an overview). However, while the empirical literature focuses on bilateral relationships to measure the benefits of international knowledge flows (e.g., Coe and Helpman, 1995; Keller, 2002; Branstetter, 2001; Peri, 2005), there is little evidence on multilateral interactions between technological activities worldwide.

This paper proposes an empirical model that accounts for the overall international innovation dynamics simultaneously. Since international knowledge flows happen concurrently between countries, this model can provide new insights compared to models of bilateral knowledge flows. More specifically, we extract global and country-specific technology indices using international patent data for the period from 1980 to 2015. We employ a structural dynamic factor model to decompose percentage changes in patent counts of seven technology fields and across 29 countries into world, country and idiosyncratic components. The world factor represents the co-movement in percentage changes in patent counts at the global level. The country factor captures the joint development that take place across different technologies within a country. The idiosyncratic component measures the technology specific dynamics. To the best of our knowledge, there are no previous applications of a dynamic factor model to account for (international) innovation dynamics. The closest attempt to ours appears to be an effort by Blackman Jr., Seligman and Sogliero (1973) who used three independent factor models creating an innovation index from multiple variables at the industry level from the first factor for three calendar years. In our analysis, we focus on the development of digital technologies, which is extensive in our sample period.

In a further step, we use the estimated factors and each country's exposure to these factors to study the effects of global and country-specific technology cycles on economic performance. More specifically, we regress gross value added, employment, wages and labour productivity in each country's ICTs industry on the world and country factor. We adjust for exposure to these factors, which we derive from a variance decomposition of the patent count data based on our

dynamic factor model. In addition, we include a Gini coefficient measuring the breadth of technological exposure to the global and domestic factor.

Our empirical findings suggest that the global technology index plays an important role in various digital technologies across countries. The world factor explains a large total fraction of the variance in patents in, for example, the U.S., Canada, Germany and France. Moreover, in several countries digital communication and computer technologies load strongly on the global technology index, whereas fluctuations in the audio-visual technologies are rather country-specific. Further, we find that our world factor is highly correlated with past international knowledge flows measured by international citation counts. This suggests that current global dynamics in invention activities rely strongly on the concurrent flow of knowledge between countries.

We additionally find a significant and positive correlation between our global technological index and the economic performance of the ICT sectors. We further see that increased dependence on international knowledge flows without respective domestic invention activities reduces this positive correlation. However, the positive performance effect increases if a country's technological global exposure is broad, i.e. if the development of as many digital technologies as possible is synchronised globally and benefits from international knowledge flows. The selective exposure of individual technological areas, on the other hand, reduces the positive influence of an internationally synchronous digital technology cycle. Thus, countries appear to benefit most from participating in international innovation efforts when their ICT sector is technologically diverse. Countries that rely on expertise in only a few technologies gain less from the global technology cycles, even when their few technologies are strongly associated with the global factor.

Our contribution to the existing literature is twofold. The results highlight the characteristics of multilateral international technological knowledge flows and their economic implications. We document the economic consequences related to the connectedness of a country's activities in various digital technologies to the global and country specific knowledge dynamics. This extends the findings from the aforementioned literature on innovation and growth (e.g., Eaton and Kortum, 1996; Peri, 2005), where the exchange of innovative ideas covers exclusively bilateral knowledge flows. Moreover, our method allows to distinguish between global and local dynamics of technological activities, accounting for complex in-

teractions between countries. In this way, we are able to independently identify the contribution of global and local invention activities on the performance of domestic ICT industries. One important condition for positive performance effects are broad domestic invention activities. This is a precondition to successfully absorb international knowledge for imitation activities or the generation of new inventions (see, e.g., Cohen and Levinthal, 1990).

Further, we contribute to the literature on measuring aggregate technological innovation by estimating global and country-specific innovation indices. Previous research in this area has focused on using patent text similarity (e.g., Kelly et al., 2021), estimated patent market value (e.g., Kogan et al., 2017), per capita patent counts (e.g., Shea, 1999), and is restricted to only one country, i.e., the United States. To the best of our knowledge, we are the first to compute a time series innovation index at the global level distinct from the dynamics at the country level.

The paper is structured as follows. Section 2 specifies the dynamic factor model and describes the resulting world and country indices. Section 3 introduces the econometric analysis and describes the respective results. Section 4 concludes the paper. The appendix contains robustness checks for regression analyses and further results from the dynamic factor model.

2 Measuring Global and Local Technological Innovation

To decompose patent dynamics in various ICT technologies of a large group of countries into global, country-specific and idiosyncratic technology components, we suggest a dynamic factor model in the spirit of Sargent and Sims (1977) and Geweke (1977). Kose, Otrok and Whiteman (2003) apply a similar model to study business cycle co-movements across countries, regions and the world. The global technology factor captures the patent fluctuations that are common across the different technologies and countries. The country-specific technology factor measures the co-movement between the patents for various technologies within a country. The idiosyncratic technology factor picks up only the technology specific movements.

Thus, percentage changes in patent counts at time t , in country i and for technology j for $t = 1, 2, \dots, T$, for $i = 1, 2, \dots, N$ and $j = 1, 2, \dots, M$ can be expressed as

$$p_{i,j,t} = \alpha_{i,j} + \beta_{i,j}^{world} \kappa_t^{world} + \beta_{i,j}^{country} \kappa_{i,t}^{country} + \epsilon_{i,j,t}, \quad (1)$$

where the percentage changes in patent counts $p_{i,j,t}$ are computed using the first difference of log levels of patent counts, κ_t^{world} is the world technology factor, $\kappa_{i,t}^{country}$ represent the country-specific technology factors, $\beta_{i,j}^{world}$ and $\beta_{i,j}^{country}$ are factor loadings that link the world and country-specific technology factors to the particular patent counts and $\epsilon_{i,j,t}$ are i.i.d. normally distributed errors with mean zero and variance $\sigma_{i,j}^2$.

For the technology factors κ_t^{world} and $\kappa_{i,t}^{country}$ we assume the following AR(q) processes

$$\kappa_t^{world} = \phi_1 \kappa_{t-1}^{world} + \dots + \phi_q \kappa_{t-q}^{world} + \eta_t^{world}, \quad (2)$$

$$\kappa_{i,t}^{country} = \phi_{i1} \kappa_{i,t-1}^{country} + \dots + \phi_{iq} \kappa_{i,t-q}^{country} + \eta_{i,t}^{country}, \quad (3)$$

where η_t^{world} and $\eta_{i,t}^{country}$ are i.i.d. and follow a normal distribution with zero mean and variance $(\sigma^{world})^2$ and $(\sigma_i^{country})^2$. In the empirical application, we set $q = 2$.

Before moving on to the estimation procedure, we first have to address some identification issues that are present in the dynamic factor model described above.¹ These are summarized by the sign, scale and rotational indeterminacy. We solve the sign and scale indeterminacy of the model by restricting the factor loadings of the first $N + 1$ factors to be positive and the variance in the factor equation to be equal to one. Moreover, the number of zero restrictions on the factor loading matrix that is implied by the global and country-specific decomposition fixes the rotational indeterminacy.

We estimate the model using Bayesian methods.² To obtain draws from the posterior distribution, we make use of the Gibbs sampling algorithm (see, e.g. Gelfand and Smith, 1990 and Kim and Nelson, 1999 for a textbook treatment). Our Gibbs sampler consists of two blocks. In the first block, conditional on the

¹See, e.g., Bai and Wang, 2015, for a more detailed discussion of the identification in Bayesian dynamic factor models.

²The R Code for the estimation procedure is available upon request.

data and the factors we draw the parameters from a Normal-Gamma distribution. In the second block, conditional on the data and parameters we draw the factors using the efficient simulation smoothing approach of Chan and Jeliazkov (2009). We specify diffuse priors for the parameters of the model.

2.1 Data

This work is primarily based on patent statistics from the global patent dataset PATSTAT (spring 2019 edition) and industry statistics from the STAN database by the OECD (2020 edition). To decompose patenting behavior for specific technological fields into global and country-specific innovations, we depend on country level location information for each priority filing. We obtain this information by using inventor fractional counts, meaning that a patent is accounted to countries according to its share of inventors from this specific country.

We use an imputation strategy for inventor locations suggested by Rassenfosse et al. (2013), including locations provided by de Rassenfosse, Kozak and Seliger (2019). Accordingly we prioritize inventor location over applicant location and patent office location and impute information from the patent family in respective order, if the preferred data is not available in the first filing itself. Additionally, we impute missing location information from the additional data made available through the above cited global geocoding effort.

We select seven ICT related technologies out of 35 technological fields defined by the World Intellectual Property Organization (WIPO): digital communication, audio-visual technology, telecommunications, basic communication processes, computer technology, IT methods for management and semiconductors. Our decomposition into global and country-specific technological innovations is based on 29 countries for the years 1980 to 2015.

2.2 Global and Local Technology Indices

Figure 1 shows the global technological index for the years 1980 to 2015. At the beginning of the observation period there are strong fluctuations without a clear trend, which could be related to the relatively low patent activities in some of the analysed areas of digital technologies (e.g. audio-visual technologies, digital communication, IT management). Only with the liberalisation of telecommunications markets towards the end of the 1990s in many OECD countries the

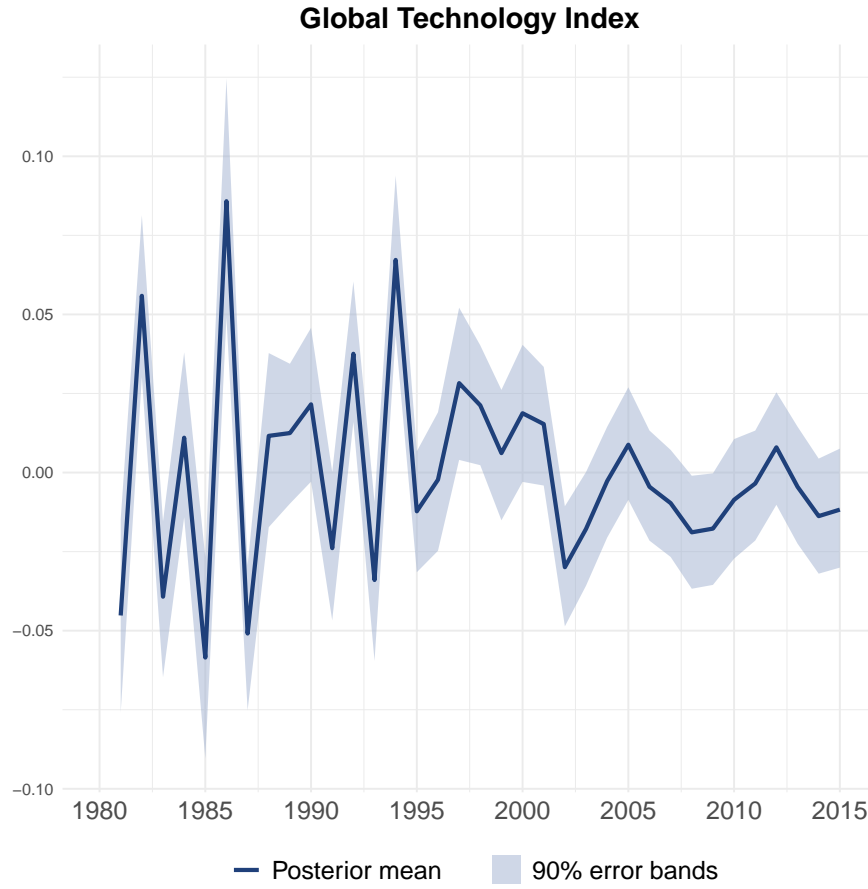


Figure 1: Global ICT technology index. The blue solid line represents the posterior mean and the shaded area contains 90% of the posterior probability.

incentives to innovate and to patent new developments in the field of digital technologies increased (see Polemis and Tselekounis, 2021). Consequently, we start to observe a clearer pattern. The global technological index implies a growth in global patent activity until 2001 and then drops significantly as a consequence of the ICT crisis in 2001. Subsequently, we notice an overall downward tendency including minor moments of growth. For example, there is no clear increase in the technology index immediately after the great financial crisis in 2008 and a decline during the crisis. Moreover, after the liberalisation of telecommunication markets in most OECD countries, the fluctuations are much smaller than before. Overall, it is interesting to see that there is a global cycle for the development of digital technologies.

Table B4 reports the share of the variance in changes in patent counts explained

by to the global technology index for each technology field and country.³ The global technology index explains a significant fraction in a couple of technology fields in many countries. The fraction of variance explained by the world factor in the fields of computer technology and digital communication is exceptionally high in various countries. These high shares indicate a strong international linkage of invention activity in these fields.

The local technological indices are different across countries (see Figure 2 and Figure 3).⁴ However, there are also some commonalities: We see a significant drop in technological activity related to the 2008 financial crisis (USA, Germany, Japan). In other countries, like the UK, this connection can hardly be observed. Also common to the countries shown is the significant decline in technological development activities as a consequence of the ICT-driven economic downturn in 2001. The variance decomposition in Table B4 reveals that a large fraction of the patent count dynamics can be explained by the country-specific factors. Especially, the technology fields in various countries in audio-visual and IT management seem to be driven locally by the country factors, mostly isolated from the international innovation developments.

2.3 Innovation Dynamics and Knowledge Flow

To comprehend the mechanism leading to the observed common innovation dynamics, we analyze them from a perspective of invention and imitation behaviour. While overall technological progress depends on the leading innovative countries pushing the technological frontier, follower countries benefit from the possibility of comparably cheaper imitation. This leads to patterns of joint innovation and imitation activities, resulting in convergence of growth between innovating and imitating countries (Barro and Sala-i-Martin, 1995). According to the empirical literature, flows of ideas from innovative countries help to stimulate growth elsewhere (e.g., Coe and Helpman, 1995; Keller, 2002; Branstetter, 2001; Peri, 2005). Peri (2005) shows that accessible inbound knowledge flows can have an effect on innovation 50% to 80% as large as the domestic R&D stock. Further,

³Given orthogonal factors, the variance of each patent in technology field j and country i can be described as

$$var(p_{i,j,t}) = (\beta_{i,j}^{world})^2 var(\kappa_t^{world}) + (\beta_{i,j}^{country})^2 var(\kappa_{i,t}^{country}) + var(\epsilon_{i,j,t}).$$

Thus, the share of variance due to, for example, the global technology index is $\frac{(\beta_{i,j}^{world})^2 var(\kappa_t^{world})}{var(p_{i,j,t})}$.

⁴See also the additional figures in Appendix A.

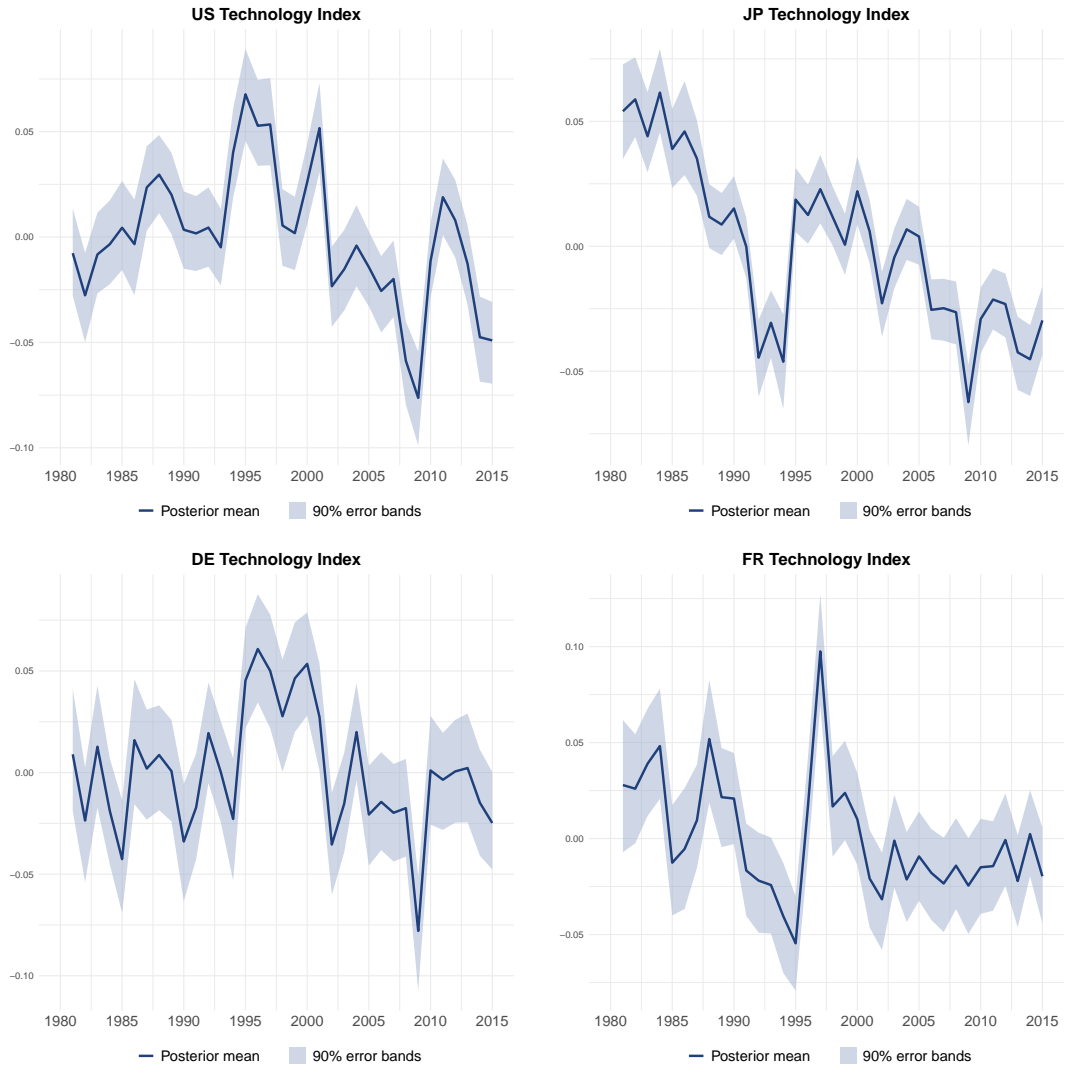


Figure 2: ICT technology indices for the U.S. (upper-left panel), Japan (upper-right panel), Germany (lower-left panel), and France (lower-right panel). The blue solid line represents the posterior mean and the shaded area contains 90% of the posterior probability.

Eaton and Kortum (1996) find that countries' domestic productivity growth is to a large extent affected by ideas originating abroad. However, there are significant differences regarding this effect with technological leaders being less dependent on foreign knowledge input.

Our data shows that the United States and Japan have a substantially higher share in domestic knowledge sourcing (around 70% of citations are domestic) compared to the other countries in our sample. Germany, China, and South

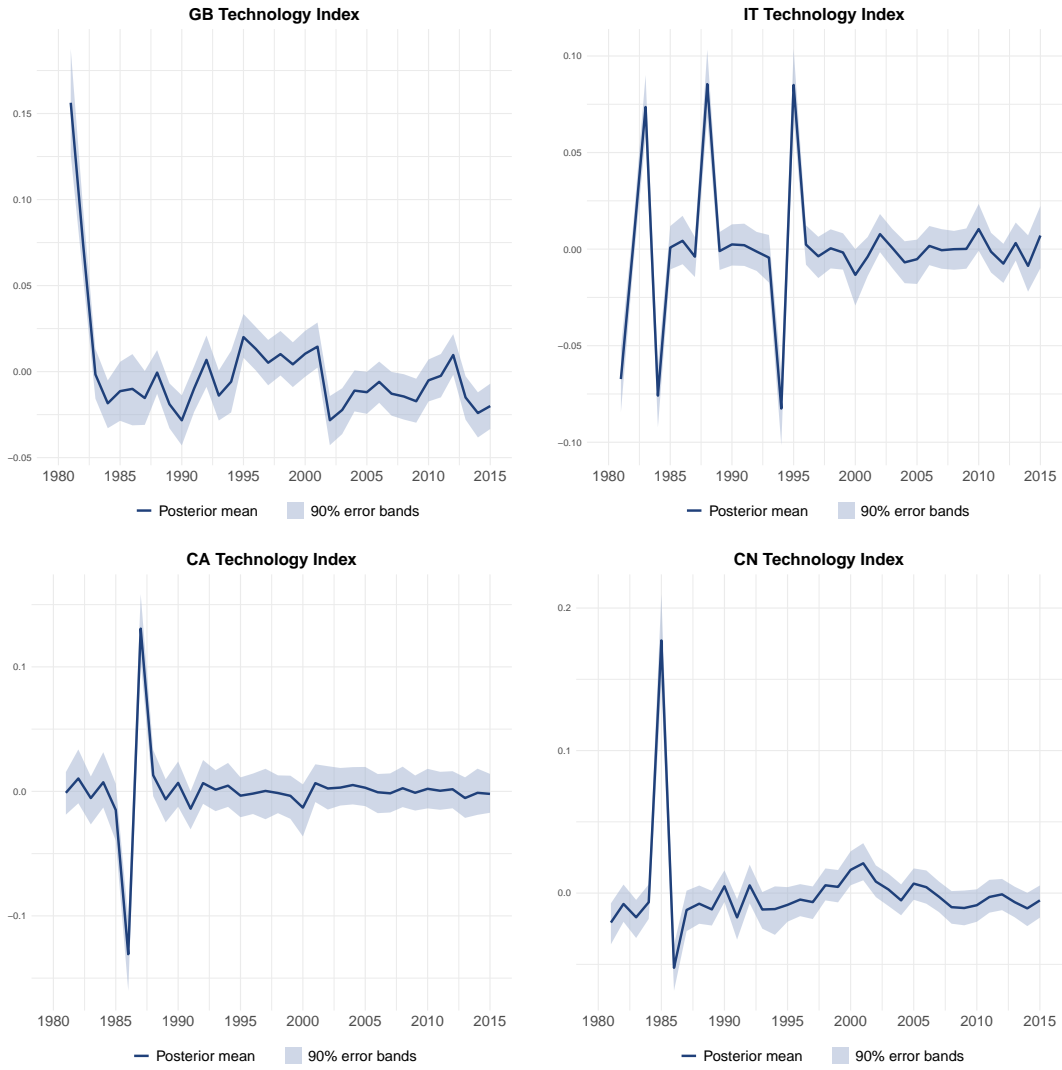


Figure 3: ICT technology indices for Great Britain (upper panel), Italy (lower-left panel), Canada (lower-right panel), and China (lower-right panel). The blue solid line represents the posterior mean and the shaded area contains 90% of the posterior probability.

Korea follow with 38%, 25%, and 19% domestic knowledge sourcing, respectively. Tracking the flow of knowledge between countries via patent citations, we see that past international knowledge flows, measured by backward citations between patents, are highly correlated with current global innovation dynamics (see Figure 4).⁵ Shifting the world factor backwards we see that the correlation to the citation time series peaks after a five year lag with a correlation coefficient of .78. Using

⁵We use backward citations between patent families using the same sample as to compute the dynamic factor model.

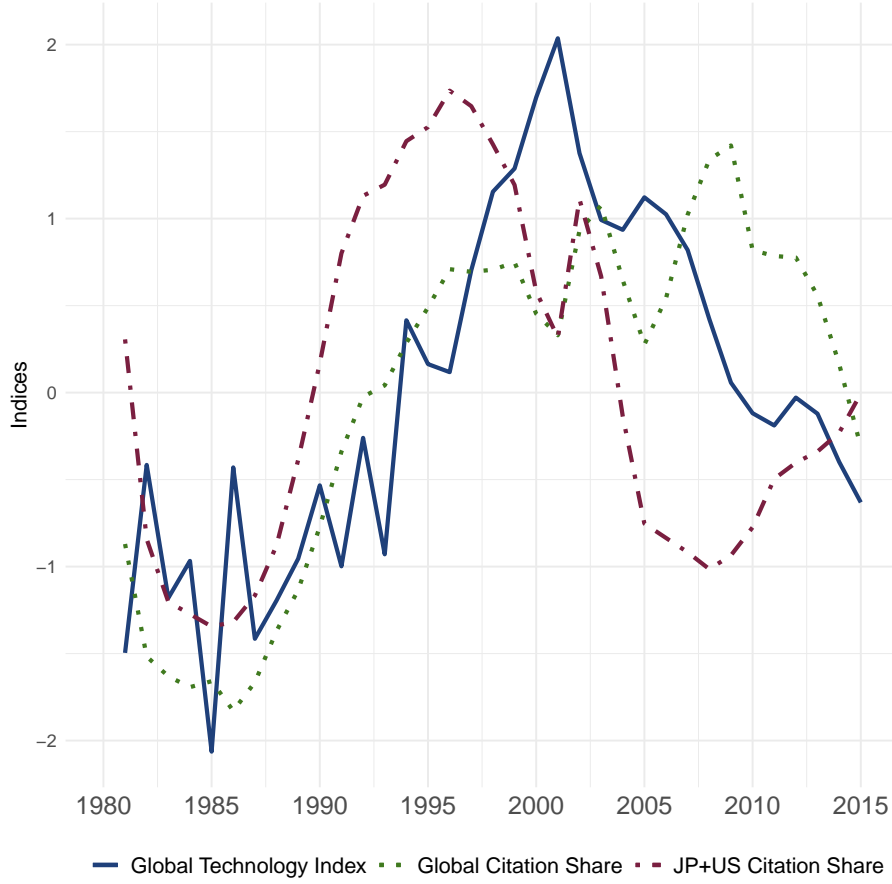


Figure 4: World latent ICT technology index and demeaned international share of patent citations. The blue solid line represents the cumulative sum of the world index. The green dotted line represents the international citation share of all countries. The read dashed line represents the share of international citations of the Japan and the United States.

the same approach, the correlation between the world factor and the international citation shares of the United States and Japan reaches almost exactly the same coefficient, but only after a -6 year shift. This suggests that the two technology leaders source their inbound knowledge earlier than the other countries. The joint global activity captured by the dynamic factor model might therefore arise due to simultaneous imitation behaviour, as a result of knowledge absorption from technological leaders by follower countries. The adoption and imitations of specific technology additionally leads to growth in product market size for the respective technology, potentially benefiting the leading countries. The empirical insight into the strong correlation between past knowledge flows and the global innovation dynamics establishes a strong connection to the theory on innovation

and economic growth. This constitutes the basis for the interpretation of our subsequent analysis regarding innovation dynamics and economic growth.

3 Common Innovation Dynamics and Economic Growth

In this section we analyze the economic implications of global and domestic innovation dynamics in three parts. First, we analyze the overall effect of world and country-specific technology factors on performance of ICT producing industries. Second, we shed light on the economic implications regarding the differences in exposure to the world and domestic innovation dynamics. Third, we investigate the role of technological specialization with regard to global and domestic exposure. By using the Gini coefficient to measure concentration among technological fields within a country's ICT industry, we analyze the role of technological breadth with regard to global and domestic innovation dynamics.

3.1 The Impact of Global and Local Innovation Dynamics

In the previous section, we decomposed technological activities in the ICT industries into global and domestic dynamics and broke down the variance in patents explained by the respective components. In this section, we investigate the relationship between the global and domestic innovation activities and the economic performance of the country level ICT industries.⁶ We regress the growth rate of economic performance y in the ICT industry of a specific country i at time t on the lagged world and country-specific innovation indices κ^{world} and $\kappa^{country}$, respectively:

$$y_{it} = b_0 + b_1\kappa_{t-1}^{world} + b_2\kappa_{it-1}^{country} + c_i + e_{it} \quad (4)$$

where c_i are fixed effects for the country-specific ICT-industries and e_{it} are iid error terms.^{7,8} We assume that the ICT producing industries are the main driving force for the development of digital technologies in a country. They are thus responsible for the potential correlation between economic performance and the global and domestic innovation indices.

For the econometric panel analysis we use the above mentioned PATSTAT and STAN databases. We apply deflators provided by the OECD to adjust variables

⁶According to the OECD definition the ICT industries comprise ISIC rev. 4 codes 26, 61, 62-63.

⁷We do not include time fixed effects due to multicollinearity with the world index

⁸We present heteroscedasticity robust standard errors in all estimations.

where necessary. We use the variables value added in volumes (Value Added; growth rate), full-time equivalents - total engaged (Employment), wages and salaries (Wage), and value added per full-time equivalent (Labor Productivity) from the STAN database.⁹ We provide basic statistics for this set of variables in Table A3 and Table A2. The performance variables are highly correlated. The correlation coefficients vary between 0.497 and 0.779. The average growth rates also fluctuate considerably for the different dependent variables. Value added grows on average by 6.5%, employment by 2.1% and wages by 5.1%. Labour productivity grows by only 2.4% on average for all countries and years observed. In our main estimation we observe the technological and economic development of 17 countries over a period of 35 years (1982 to 2016).

Table 1: Baseline Regressions

	(1) Value Added b/se	(2) Employment b/se	(3) Wage b/se	(4) Labor Productivity b/se
L.World Factor	0.764*** (0.193)	0.433*** (0.116)	0.683*** (0.167)	0.290* (0.139)
L.Country Factor	-0.005 (0.005)	0.005 (0.003)	-0.006 (0.005)	-0.004 (0.003)
Constant	0.064*** (0.000)	0.021*** (0.000)	0.050*** (0.000)	0.023*** (0.000)
N	357	164	329	162
Countries	14.00	8.00	14.00	7.00
F	23.32***	8.38**	14.76***	3.09
r^2	0.05	0.05	0.05	0.02

Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating Equation (4) using OLS. The sample contains country-level ICT industry indicators, where the respective industry performance measures are used as dependent variables. The independent variables, world and country factor, are derived from the dynamic factor model described in Section 2. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

Table 1 shows that global digital technological activities are significantly and positively related with the growth in value added. A 1% increase in the world index in t-1 increases value added growth by 0.76%-points. We also see similar growth effects for wages and lower growth effects for employment and labor

⁹For more information about the STAN database and the construction of the variables, see Horvát and Webb (2020).

productivity.¹⁰ Independent of the lag structure, country-specific digital technological cycles tend to be unimportant for economic growth in the ICT industries of a country. These results indicate that the domestic ICT industries benefits from joint dynamics in global technological developments. The domestic technology cycles, capturing the activity decoupled from international development only measuring within country dynamics, do not appear to be related with the economic performance indicators at hand. In line with the above reasoning on innovation-imitation and adoption dynamics we argue that the positive influence of joint global activity are possibly due to the adoption of technologies developed by technological leaders, the benefits of less costly imitation by follower countries, as well as the overall growth in markets for the respective technologies.

3.2 Global vs. Local Technological Exposure

In our second analytical step, we shed light on the role of relative exposure to global and domestic innovation dynamics. We exploit the results from the variance decomposition, which attributes the share of variance in a country's technological activities (patenting) explained by the world factor (global technology index), the country factors (domestic technology index), and an idiosyncratic term. By building the ratio ξ_i between the variance explained by the global and the domestic index, we obtain a measure of country's relative exposure to global and domestic technological activities.

$$y_{ijt} = b_0 + b_1\kappa_{t-1}^{world} + b_2\kappa_{t-1}^{world} \times \xi_i + b_3\kappa_{it-1}^{country} + b_4\kappa_{it-1}^{country} \times \xi_i + c_i + e_{it} \quad (5)$$

Here again y indicates the economic performance of the ICT industry in a specific country i at a specific point in time t and κ^{world} and $\kappa^{country}$ indicate the world and the domestic technological index. Additionally, we interact the innovation indicators with the relative technological exposure to world and country factors ξ_i . Similar to the previous section e_{it} is the error term. Regression results are contained in Table 2.

Our results show that the global over domestic exposure ratio qualifies the results of the global and domestic innovation dynamics. Inspecting the global dynamics, we see that the contribution of global technology dynamics to growth decreases

¹⁰The dependent variables measure the growth between t and $t+1$. The significant relationship between the growth rates and the world factor remains even without a time lag, i.e. when we measure the world factor in t (see Table C5 in appendix section C.1.)

Table 2: Regressions with Ratio ξ_i

	(1)	(2)	(3)	(4)
	Value Added b/se	Employment b/se	Wage b/se	Labor Productivity b/se
L.World Factor	1.414*** (0.316)	0.646*** (0.162)	1.190*** (0.208)	0.735** (0.297)
L.World Factor \times W/C	-1.031*** (0.280)	-0.310 (0.199)	-0.835*** (0.175)	-0.599* (0.283)
L.Country Factor	-0.024** (0.008)	-0.005 (0.005)	-0.018* (0.010)	-0.000 (0.005)
L.Country Factor \times W/C	0.026*** (0.006)	0.013** (0.005)	0.016* (0.008)	-0.004 (0.005)
Constant	0.064*** (0.000)	0.021*** (0.000)	0.050*** (0.000)	0.023*** (0.000)
N	357	164	329	162
Countries	14.00	8.00	14.00	7.00
F	20.66***	19.36***	12.77***	10.37***
r^2	0.08	0.06	0.06	0.03

Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating Equation (5) using OLS. The sample contains country-level ICT industry indicators, where the respective industry performance measures are used as dependent variables. The independent variables extend the base model by two interaction terms, consisting of the ratio ξ_i between the variance explained by the global and the domestic index with the world and country factors, respectively. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

when the global technological exposure of the particular country is relatively high. This could be related to knowledge outflows and consequently to increasing global competition; however, the net effect remains positive. The contribution and exposure to the global technological cycle thus increases the performance of the domestic ICT industry.

The opposite mechanism can be observed for the domestic dynamics where the contribution to growth increases with a comparatively strong international exposure. We see a similar result for wage growth. This suggests that domestic ICT industries benefit more from domestic innovation cycles when their world technology exposure is relatively large. The reason for this positive effect is likely related to knowledge inflows from global technological developments, as we observe strong correlations between world dynamics and previous international

knowledge flows.¹¹

3.3 Technological Specialization and Economic Growth

In our third analytical step, we use the Gini coefficient to measure the technological concentration of countries regarding their exposure to the world and domestic factor. Technological fields based on patent classifications are used to differentiate seven distinct technology fields within ICT. We calculate the ratio γ_i of the concentration of world exposure over the concentration of domestic exposure (Gini ratio). We then investigate whether the performance effect of exposure to the world and country factors is related to the concentration of the respective exposure. A high value of this ratio indicates a high concentration of the world exposure on individual technologies, combined with a broad country exposure involving diverse technological fields. A low ratio indicates just the opposite, i.e. country exposure is more concentrated on individual technologies compared to global exposure.

$$y_{ijt} = b_0 + b_1\kappa_{t-1}^{world} + b_2\kappa_{t-1}^{world} \times \gamma_i + b_3\kappa_{it-1}^{country} + b_4\kappa_{it-1}^{country} \times \gamma_i + c_i + e_{it} \quad (6)$$

In Equation (6), y indicates the economic performance of the ICT industry in a given country i at a given time t . κ^{world} and $\kappa^{country}$ denote world and domestic technology indices. In addition, the equation contains an interaction term combining technology indicators with the just described ratio of Gini coefficients γ_i . e_{it} denotes the error term.

Table 3 shows the results of these estimates. While we still see the significant and positive impact of the world index, we also find that the interaction effect between this indicator and the Gini ratio is significant and negative for all performance variables except for employment growth. This indicates that the positive effect of global innovation dynamics decreases with relatively concentrated exposure to individual technologies, but increases with comparatively broader exposure to the global technology dynamics. Thus, we can add to the above result that it is not only the relative extent of exposure that matters, but also whether the global exposure includes a broader range of technologies. The results regarding

¹¹The relationship between the growth rates and the factors remains qualitatively similar without a time lag. However, the accuracy of the measured relationships is lower (see Table C6 in appendix section C.1)

the breadth of exposure suggest that a country's ICT industry being at the global technological frontier in several digital technologies can benefit more from technological synergies than it loses from potential diffusion of its own knowledge. Thus, there are advantages for first mover countries when technological activity is broad and its ICT industry contributes strongly to the world technological cycle.

Table 3: Regressions with Ratio γ_i

	(1)	(2)	(3)	(4)
	Value Added	Employment	Wage	Labor Productivity
	b/se	b/se	b/se	b/se
L.World Factor	1.852*** (0.383)	1.194* (0.520)	1.516*** (0.460)	1.143* (0.575)
L.World Factor \times Gini W/C	-0.859*** (0.264)	-0.677 (0.401)	-0.681* (0.332)	-0.755 (0.488)
L.Country Factor	-0.032* (0.016)	0.001 (0.006)	-0.025 (0.018)	-0.013** (0.004)
L.Country Factor \times Gini W/C	0.020** (0.009)	0.002 (0.006)	0.014 (0.010)	0.008 (0.004)
Constant	0.064*** (0.000)	0.021*** (0.000)	0.050*** (0.000)	0.023*** (0.000)
N	357	164	329	162
Countries	14.00	8.00	14.00	7.00
F	22.82***	13.42***	10.67***	3.76*
r^2	0.08	0.06	0.07	0.03

Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating Equation (6) using OLS. The sample contains country-level ICT industry indicators, where the respective industry performance measures are used as dependent variables. The independent variables extend the base model by two interaction terms, consisting of the ratio γ_i between the Gini concentration of world exposure over the Gini concentration of domestic exposure, at the level of seven distinct technological fields. The exposures are derived from the variance decomposition above. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

If a country's technological activities exposed to the domestic cycle are less concentrated than technological activities exposed to the global cycle, then we see a less negative impact of a country's technological activities on value added and employment growth. This suggests that, regardless of whether the domestic ICT industry is primarily exposed to global or domestic cycles, it should be diverse rather than concentrated. This allows a country to benefit from the synergies between the different areas of digital technologies. However, it can be seen that stronger exposure to the global technology cycles is preferable to stronger ex-

posure to the country-specific technology cycle. With additional time lags the effects for the ICT industries of a country get weaker.¹²

3.4 Robustness Checks

We conduct a series of robustness checks using model specifications including three types of additional control variables, namely patent stocks, economic conditions, knowledge flows. We also check for the sensitivity regarding our lag-structure. All results are provided in Appendix B. First, regarding robustness of temporal shifts, models including all independent variables at $t = 0$ show that results remain mostly similar to those of the models including time lags. However, regarding the influence of country factor-based variables, we see a tendency to a more immediate effect.

Second, we adjusting our three main estimations by including patent stocks as lagged independent variable. We derive the knowledge stock on patent counts, applying a 15% depreciation rate. Overall, our results appear robust regarding the coefficients and statistical significance of the three variables value added, employment, and wage. However, patent stocks appear explain a significant share of labor productivity, reducing the explanatory power of our factor related variables.

Third, extending our models by a global economic conditions index (Baumeister, Korobilis and Lee, 2022), as well as country-level GDP, we see that those economic indicators explain some variance in our performance indicators, partially reducing our effect size and statistical certainty. However, there remains strong explanatory power regarding our factor indicators. Given the literature on the cyclicity of innovation activity (see, e.g., Barlevy, 2007) documenting , it appears intuitive that previous economic conditions explain some of the variance else explained by our innovation dynamics indicators.

Fourth, including lagged knowledge flow indicators based on patent citations (see Section 2.3) into our models, we see that our results remain largely robust. We use two different aggregations of knowledge inflow. One for only Japan and the United States, and the other for the remaining counties in our sample. We see that knowledge flows towards Japan and the US has on average negative implica-

¹²The relationship between the growth rates and the factors remains qualitatively similar without a time lag (see Table C7 in appendix section C.1).

tions for the countries in our sample, while the implications is positive for inflows into the remaining countries. This is strongly in line with the discussed literature, stating the positive implications of inbound knowledge flows. Unfortunately, it is not possible to estimate the implication of knowledge flows originating from Japan and the US onto the two countries performance metrics.

Finally, combining all additional indicators as controls into our main models, we see that still a modest share of our factor-based variables yield significant results. However, it is mostly variables related to the world-factor remaining statistically significant. We can see that in the combined models the long-run effects of six year lagged knowledge flows remains. This result agrees with the high time-series correlation of international knowledge flows and the world factor. It is also in line with the regression results in Table C23, where we use the world and country factors as dependent variables, including all the indicators used in our robustness checks as independent variables.

4 Conclusion

Using a dynamic factor model, we identify a single world factor measuring the joint technological activities at the global level in the ICT sectors. In addition to the world factor, we also identify multiple country level factors that capture the local technological activities. We find that the global factor is highly correlated with past inbound international knowledge flows measured by backward patent citations. Therefore, current global technology dynamics appear to be strongly related to previous knowledge sourcing. Our regression results show that current global technology dynamics are positively associated with most of our local (country) economic performance indicators for the ICT sectors. This can be explained by the knowledge inflow from innovation leaders allowing for imitation of technology (e.g., Coe and Helpman, 1995; Keller, 2002; Branstetter, 2001; Peri, 2005), which benefits the technological development and performance in the focal industry. At the same time, the exposure to the global cycle tends to increase market competition, which has the potential to deteriorate the positive performance effects from knowledge inflows (e.g., Bloom, Schankerman and Van Reenen, 2013). However, our results show that the positive knowledge effect outperforms the negative competition effect.

We further scrutinize the relation by analyzing the role of international and do-

mestic innovation exposure based on a variance decomposition of patent activity. Here we see that the degree of international openness of innovation activities, which we define as the relationship between global and domestic exposure, is important. High global innovation dynamics have negative economic implications in countries with a tendency towards international innovation exposure. In contrast, the country specific innovation dynamics do have positive economic implications in more internationally oriented countries.

These results suggest that a strong exposure to the world factor - and related knowledge flows - essentially leads to positive performance effects if the "absorptive capacity" of the local industry is relatively large. Absorptive capacity is usually high if there is a strong local technological development. This is a necessary prerequisite for being able to effectively process international knowledge flows and to develop new, internationally competitive technologies (Cohen and Levinthal, 1990). Therefore, the technological dynamics of the domestic industry is crucial for the positive relationship of the world factor to the performance indicators. At the same time, however, the results show that a strongly domestically oriented technological development, which is independent of the international knowledge flows or the previously generated knowledge of other countries, has no performance effects.

The results derived from the global over domestic exposure ratio can be further qualified by our insights on country level specialization, using a ratio of global and domestic Gini coefficients over technological fields. Overall, the results show that increased technological specialization in combination with a tendency towards international exposure has mostly negative economic implications. This is probably due to a lack of positive synergies resulting from a technologically diversified ICT industry. A technologically diverse ICT industry seems to be necessary to be able to process the flow of knowledge from abroad comprehensively and to develop internationally competitive technologies in the individual areas. Products and services based on such technologies are more difficult to imitate due to their technological complexity. This leads to sustainable competitive advantages and the observed positive relationship between diverse technological activities in the context of a strong exposure to the world factor, and the performance of the local ICT industry.

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Appendix

A Descriptive Statistics

Table A1: Variable Descriptions

Name	Description
Value Added	Value added in volumes
Employment	Full-time equivalents - total engaged
Wage	Wages and salaries
Labor Productivity	Value added per full-time equivalent
World Factor	First component of the dynamic factor model
Country Factor	Second component of the dynamic factor model
W/C	Ratio of world variance over country variance explained by a variance decomposition of the respective factors.
Gini W/C	Gini coefficient of the W/C Ratios at the technology field level.
Patent Stock	We derive the knowledge stock on patent counts, applying a 15% depreciation rate.
Global GDP	Global economic conditions index by Baumeister, Korobilis and Lee (2022).
Country GDP	Country level GDP.
Knowledge Inflow excl. JP & US	Aggregated international knowledge inflow into sample countries, excluding Japan and the United States as receiver countries
Knowledge Inflow JP & US	Aggregated international knowledge inflow into Japan and the United States only.

Table provides a brief description of the variables used in the main estimations, as well as additional variables used in robustness checks.

Table A2: Correlation Table - Main Variables

Variables	Value Added	Employment	Wage	Labor Productivity	World Factor	Country Factor	W/C	Gini W/C
Value Added	1.000							
Employment	0.497 (0.000)	1.000						
Wage	0.779 (0.000)	0.763 (0.000)	1.000					
Labor Prod.	0.713 (0.000)	-0.255 (0.001)	0.157 (0.067)	1.000				
World Factor	0.207 (0.000)	0.369 (0.000)	0.258 (0.000)	-0.009 (0.915)	1.000			
Country Factor	0.044 (0.417)	0.139 (0.084)	0.012 (0.836)	0.026 (0.751)	0.073 (0.180)	1.000		
W/C	0.081 (0.134)	-0.015 (0.848)	-0.039 (0.492)	0.214 (0.007)	0.013 (0.807)	-0.004 (0.941)	1.000	
Gini W/C	-0.064 (0.239)	-0.047 (0.558)	-0.203 (0.000)	0.133 (0.099)	0.010 (0.847)	0.018 (0.736)	0.475 (0.000)	1.000

Correlation coefficients for the variables used in our main models. Standard errors in brackets.

Table A3: Summary Statistics - Main Variables

	mean	sd	p50	min	max	count
Value Added	0.065	0.081	0.053	-0.241	0.520	343
Employment	0.021	0.040	0.020	-0.106	0.132	155
Wage	0.051	0.079	0.039	-0.136	0.531	311
Labor Productivity	0.024	0.050	0.020	-0.097	0.179	155
World Factor	0.000	0.021	-0.005	-0.033	0.068	343
Country Factor	-0.045	0.724	-0.036	-4.509	2.694	343
W/C	0.647	0.427	0.477	0.156	1.571	343
Gini W/C	1.307	0.502	1.184	0.635	2.403	343

Table provides a summary statistics for the variables used in our main models. It contains the mean, standard deviation, median, minimum, maximum, and count of observations.

B Country Factors

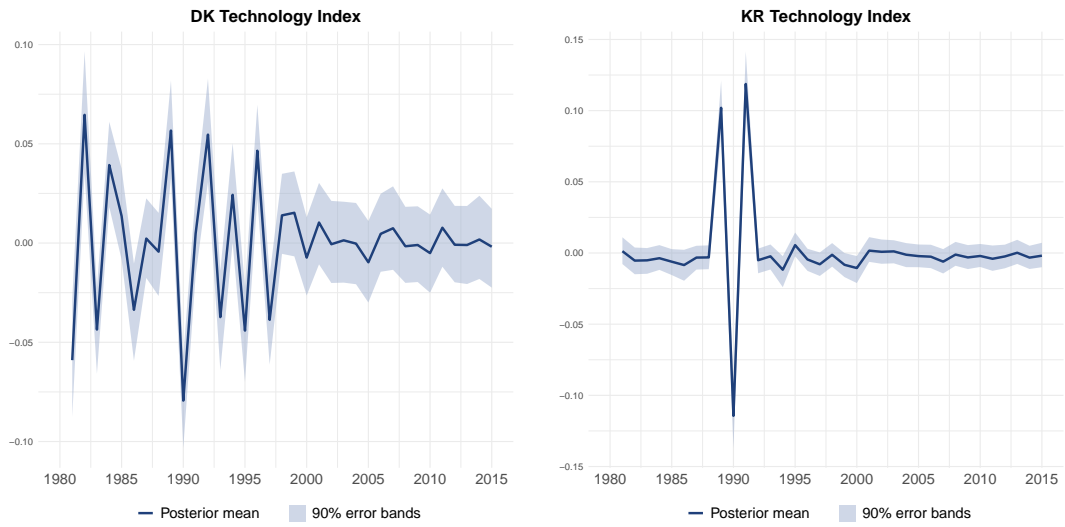


Figure B1: ICT technology indices for Denmark (left) and Korea (right). The blue solid line represents the posterior mean and the shaded area contains 90% of the posterior probability.



Figure B2: ICT technology indices for Poland (upper-left), Hungary (upper-right), Finland (middle-left), Ireland (middle-right), Spain (lower-left), and New Zealand (lower-right). The blue solid line represents the posterior mean and the shaded area contains 90% of the posterior probability.



Figure B3: ICT technology indices for India (upper-left), Romania (upper-right), Israel (middle-left), Austria (middle-right), Norway (lower-left), and Belgium (lower-right). The blue solid line represents the posterior mean and the shaded area contains 90% of the posterior probability.

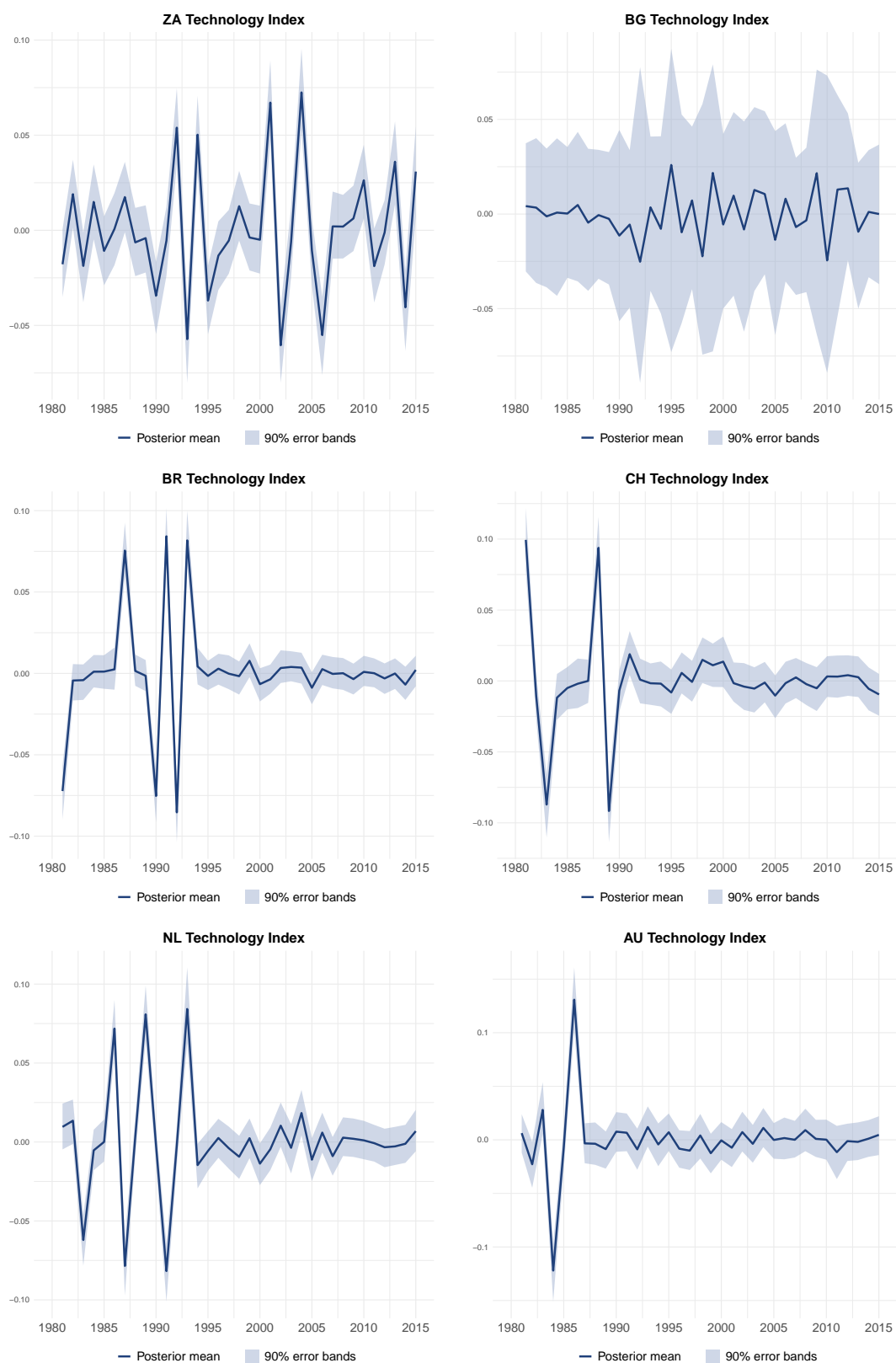


Figure B4: ICT technology indices for South Africa (upper-left), Bulgaria (upper-right), Brazil (middle-left), Switzerland (middle-right), the Netherlands (lower-left), and Australia (lower-right). The blue solid line represents the posterior mean and the shaded area contains 90% of the posterior probability.

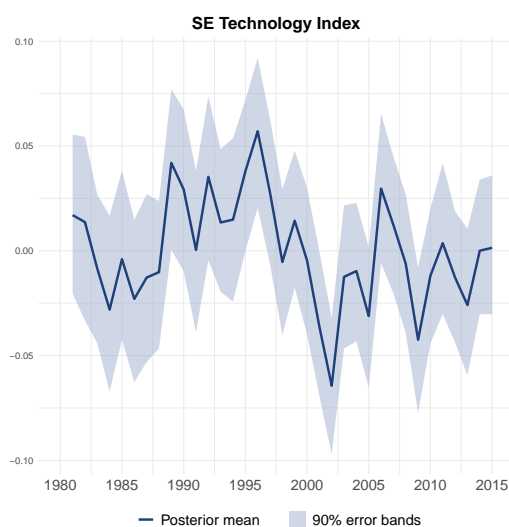


Figure B5: ICT technology indices for Sweden. The blue solid line represents the posterior mean and the shaded area contains 90% of the posterior probability.

Table B4: Variance Decomposition

	World	Country	Idiosyncratic
Denmark Digital comm.	0.08	0.65	0.27
Denmark Audio-visual	0.00	0.41	0.58
Denmark Telecomm.	0.03	0.45	0.52
Denmark Basic comm.	0.05	0.54	0.41
Denmark Computer tech.	0.22	0.10	0.68
Denmark IT manag.	0.01	0.17	0.82
Denmark Semicond.	0.03	0.18	0.79
Korea Semicond.	0.05	0.01	0.93
Korea Audio-visual	0.02	0.77	0.21
Korea Telecomm.	0.01	0.03	0.96
Korea Digital comm.	0.07	0.59	0.34
Korea Basic comm.	0.02	0.27	0.72
Korea Computer tech.	0.04	0.24	0.72
Korea IT manag.	0.06	0.75	0.19
Poland Computer tech.	0.05	0.21	0.74
Poland Audio-visual	0.07	0.57	0.36
Poland Telecomm.	0.04	0.07	0.89
Poland Digital comm.	0.21	0.45	0.34
Poland Basic comm.	0.02	0.23	0.76

Poland IT manag.	0.08	0.68	0.24
Poland Semicond.	0.04	0.04	0.92
Hungary Digital comm.	0.31	0.42	0.27
Hungary Audio-visual	0.19	0.52	0.30
Hungary Telecomm.	0.16	0.01	0.83
Hungary Basic comm.	0.03	0.13	0.84
Hungary Computer tech.	0.04	0.02	0.94
Hungary IT manag.	0.13	0.57	0.30
Hungary Semicond.	0.24	0.01	0.74
Finland Digital comm.	0.18	0.06	0.75
Finland Audio-visual	0.02	0.60	0.37
Finland Telecomm.	0.01	0.22	0.77
Finland Basic comm.	0.07	0.06	0.87
Finland Computer tech.	0.03	0.04	0.93
Finland IT manag.	0.04	0.52	0.44
Finland Semicond.	0.03	0.02	0.95
Ireland Computer tech.	0.34	0.30	0.36
Ireland Audio-visual	0.01	0.34	0.65
Ireland Telecomm.	0.03	0.08	0.89
Ireland Digital comm.	0.11	0.03	0.87
Ireland Basic comm.	0.01	0.04	0.96
Ireland IT manag.	0.03	0.07	0.90
Ireland Semicond.	0.07	0.15	0.78
Spain Computer tech.	0.16	0.11	0.72
Spain Audio-visual	0.08	0.57	0.35
Spain Telecomm.	0.21	0.04	0.76
Spain Digital comm.	0.20	0.24	0.56
Spain Basic comm.	0.02	0.04	0.94
Spain IT manag.	0.02	0.60	0.38
Spain Semicond.	0.03	0.03	0.94
New Zealand Computer tech.	0.01	0.46	0.54
New Zealand Basic comm.	0.04	0.47	0.49
New Zealand Audio-visual	0.04	0.04	0.92
New Zealand Telecomm.	0.01	0.21	0.77
New Zealand Digital comm.	0.08	0.15	0.77
New Zealand IT manag.	0.02	0.54	0.44

New Zealand Semicond.	0.01	0.21	0.78
India Computer tech.	0.01	0.10	0.89
India Audio-visual	0.03	0.37	0.60
India Telecomm.	0.02	0.07	0.91
India Digital comm.	0.15	0.02	0.83
India Basic comm.	0.07	0.01	0.92
India IT manag.	0.01	0.28	0.71
India Semicond.	0.14	0.20	0.66
China Computer tech.	0.01	0.25	0.74
China Audio-visual	0.11	0.02	0.87
China Telecomm.	0.14	0.47	0.38
China Digital comm.	0.24	0.40	0.36
China Basic comm.	0.02	0.33	0.65
China IT manag.	0.17	0.23	0.61
China Semicond.	0.11	0.37	0.52
Romania Computer tech.	0.03	0.02	0.95
Romania Audio-visual	0.03	0.26	0.70
Romania Telecomm.	0.01	0.05	0.94
Romania Digital comm.	0.03	0.36	0.61
Romania Basic comm.	0.01	0.03	0.96
Romania IT manag.	0.08	0.30	0.62
Romania Semicond.	0.07	0.01	0.91
Isreal Computer tech.	0.03	0.21	0.76
Isreal Audio-visual	0.03	0.36	0.61
Isreal Telecomm.	0.03	0.10	0.87
Isreal Digital comm.	0.57	0.03	0.40
Isreal Basic comm.	0.08	0.06	0.86
Isreal IT manag.	0.15	0.30	0.55
Isreal Semicond.	0.11	0.03	0.86
Austria Computer tech.	0.05	0.01	0.94
Austria Audio-visual	0.03	0.22	0.75
Austria Telecomm.	0.03	0.02	0.95
Austria Digital comm.	0.23	0.22	0.54
Austria Basic comm.	0.05	0.05	0.90
Austria IT manag.	0.03	0.24	0.73
Austria Semicond.	0.01	0.08	0.91

Norway Computer tech.	0.19	0.04	0.77
Norway Audio-visual	0.05	0.01	0.93
Norway Telecomm.	0.01	0.12	0.87
Norway Digital comm.	0.08	0.03	0.89
Norway Basic comm.	0.01	0.16	0.83
Norway IT manag.	0.01	0.03	0.96
Norway Semicond.	0.03	0.04	0.94
Belgium Digital comm.	0.01	0.02	0.97
Belgium Audio-visual	0.01	0.16	0.83
Belgium Telecomm.	0.03	0.08	0.88
Belgium Basic comm.	0.06	0.08	0.87
Belgium Computer tech.	0.04	0.05	0.91
Belgium IT manag.	0.04	0.14	0.83
Belgium Semicond.	0.01	0.08	0.91
South Africa Audio-visual	0.01	0.03	0.96
South Africa Semicond.	0.08	0.28	0.65
South Africa Telecomm.	0.09	0.11	0.80
South Africa Digital comm.	0.02	0.25	0.74
South Africa Basic comm.	0.11	0.46	0.43
South Africa Computer tech.	0.10	0.25	0.65
South Africa IT manag.	0.07	0.45	0.49
Bulgaria Computer tech.	0.02	0.06	0.92
Bulgaria Telecomm.	0.00	0.13	0.87
Bulgaria Audio-visual	0.01	0.08	0.91
Bulgaria Digital comm.	0.00	0.06	0.94
Bulgaria Basic comm.	0.01	0.02	0.97
Bulgaria IT manag.	0.05	0.17	0.78
Bulgaria Semicond.	0.00	0.03	0.97
Brazil Telecomm.	0.05	0.07	0.88
Brazil Audio-visual	0.07	0.24	0.69
Brazil Digital comm.	0.03	0.14	0.83
Brazil Basic comm.	0.01	0.06	0.93
Brazil Computer tech.	0.19	0.21	0.60
Brazil IT manag.	0.11	0.16	0.73
Brazil Semicond.	0.05	0.07	0.89
Switzerland Computer tech.	0.14	0.06	0.81

Switzerland Audio-visual	0.01	0.27	0.72
Switzerland Telecomm.	0.09	0.18	0.73
Switzerland Digital comm.	0.07	0.26	0.67
Switzerland Basic comm.	0.08	0.10	0.82
Switzerland IT manag.	0.01	0.36	0.64
Switzerland Semicond.	0.02	0.02	0.96
Italy Computer tech.	0.11	0.10	0.79
Italy Audio-visual	0.04	0.27	0.69
Italy Telecomm.	0.09	0.04	0.88
Italy Digital comm.	0.03	0.23	0.75
Italy Basic comm.	0.02	0.19	0.79
Italy IT manag.	0.04	0.20	0.77
Italy Semicond.	0.03	0.02	0.95
Netherlands Computer tech.	0.08	0.01	0.91
Netherlands Audio-visual	0.11	0.09	0.80
Netherlands Telecomm.	0.03	0.17	0.80
Netherlands Digital comm.	0.12	0.07	0.81
Netherlands Basic comm.	0.01	0.02	0.97
Netherlands IT manag.	0.07	0.14	0.79
Netherlands Semicond.	0.01	0.02	0.97
Australia Computer tech.	0.27	0.03	0.70
Australia Audio-visual	0.04	0.08	0.88
Australia Telecomm.	0.01	0.08	0.91
Australia Digital comm.	0.01	0.08	0.91
Australia Basic comm.	0.45	0.01	0.53
Australia IT manag.	0.13	0.14	0.73
Australia Semicond.	0.05	0.02	0.93
Canada Computer tech.	0.06	0.06	0.88
Canada Audio-visual	0.24	0.10	0.66
Canada Telecomm.	0.02	0.03	0.94
Canada Digital comm.	0.25	0.04	0.72
Canada Basic comm.	0.10	0.03	0.87
Canada IT manag.	0.06	0.10	0.84
Canada Semicond.	0.12	0.02	0.86
Germany Audio-visual	0.05	0.09	0.86
Germany Telecomm.	0.12	0.11	0.77

Germany Digital comm.	0.01	0.16	0.83
Germany Basic comm.	0.01	0.15	0.84
Germany Computer tech.	0.17	0.17	0.66
Germany IT manag.	0.32	0.02	0.66
Germany Semicond.	0.15	0.16	0.68
France Computer tech.	0.45	0.11	0.43
France Audio-visual	0.01	0.22	0.77
France Telecomm.	0.01	0.26	0.73
France Digital comm.	0.32	0.05	0.63
France Basic comm.	0.12	0.03	0.85
France IT manag.	0.09	0.02	0.89
France Semicond.	0.01	0.04	0.95
Great Britain Computer tech.	0.01	0.05	0.94
Great Britain Audio-visual	0.01	0.12	0.87
Great Britain Telecomm.	0.01	0.09	0.90
Great Britain Digital comm.	0.03	0.07	0.89
Great Britain Basic comm.	0.01	0.10	0.88
Great Britain IT manag.	0.01	0.01	0.98
Great Britain Semicond.	0.05	0.11	0.84
Japan Audio-visual	0.01	0.14	0.85
Japan Telecomm.	0.00	0.17	0.82
Japan Digital comm.	0.03	0.05	0.92
Japan Basic comm.	0.08	0.12	0.80
Japan Computer tech.	0.01	0.10	0.89
Japan IT manag.	0.01	0.02	0.97
Japan Semicond.	0.06	0.08	0.86
Sweden Telecomm.	0.16	0.10	0.74
Sweden Audio-visual	0.03	0.04	0.93
Sweden Digital comm.	0.03	0.05	0.92
Sweden Basic comm.	0.02	0.05	0.93
Sweden Computer tech.	0.03	0.05	0.93
Sweden IT manag.	0.04	0.01	0.95
Sweden Semicond.	0.01	0.06	0.94
United States Telecomm.	0.15	0.00	0.85
United States Computer tech.	0.10	0.06	0.84
United States Audio-visual	0.05	0.08	0.88

United States Digital comm.	0.04	0.07	0.89
United States Basic comm.	0.09	0.07	0.84
United States IT manag.	0.12	0.05	0.83
United States Semicond.	0.05	0.09	0.86

Fraction of variance explained by the world factor, country factor and idiosyncratic component. The variance decomposition is based on the posterior mean of the parameters. See Footnote 3 for more details on the calculation of the variance decompositions.

C Robustness Checks Regression Estimations

C.1 Main Estimations – Contemporary Time

Table C5: Baseline Regressions at Contemporary Time

	(1)	(2)	(3)	(4)
	Value Added	Employment	Wage	Labor Productivity
	b/se	b/se	b/se	b/se
World Factor	0.770*** (0.250)	0.850*** (0.214)	0.950*** (0.258)	-0.077 (0.172)
Country Factor	0.002 (0.005)	0.010** (0.004)	-0.002 (0.004)	0.003 (0.004)
Constant	0.065*** (0.000)	0.022*** (0.000)	0.051*** (0.000)	0.024*** (0.000)
N	343	156	316	155
Countries	14.00	8.00	14.00	7.00
F	11.43***	11.98***	9.80***	0.71
r^2	0.05	0.17	0.08	0.00

Results from adjusted baseline model (Table 1) with removed temporal lags from the independent variables, estimating coefficients at current time. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

Table C6: Regressions with Ratio ξ_i at Contemporary Time

	(1)	(2)	(3)	(4)
	Value Added b/se	Employment b/se	Wage b/se	Labor Productivity b/se
World Factor	1.186* (0.567)	1.593*** (0.248)	1.389** (0.483)	0.321* (0.164)
World Factor \times W/C	-0.654 (0.557)	-0.917*** (0.230)	-0.676 (0.490)	-0.488*** (0.122)
Country Factor	-0.008 (0.009)	0.007 (0.007)	-0.003 (0.008)	0.005 (0.013)
Country Factor \times W/C	0.014 (0.008)	0.004 (0.006)	0.003 (0.009)	-0.002 (0.011)
Constant	0.065*** (0.000)	0.022*** (0.000)	0.051*** (0.000)	0.024*** (0.000)
N	343	156	316	155
Countries	14.00	8.00	14.00	7.00
F	7.30***	40.84***	6.61***	13.60***
r^2	0.06	0.19	0.09	0.01

Results from adjusted ratio ξ_i model (Table 2) with removed temporal lags from the independent variables, estimating coefficients at current time. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

Table C7: Regressions with Ratio γ_i at Contemporary Time

	(1) Value Added b/se	(2) Employment b/se	(3) Wage b/se	(4) Labor Productivity b/se
World Factor	2.206*** (0.569)	1.867* (0.792)	2.144** (0.714)	1.492* (0.754)
World Factor \times Gini W/C	-1.129** (0.434)	-0.830 (0.614)	-0.955* (0.444)	-1.322* (0.589)
Country Factor	-0.028* (0.015)	-0.020** (0.008)	-0.008 (0.011)	0.003 (0.030)
Country Factor \times Gini W/C	0.023** (0.009)	0.025*** (0.007)	0.006 (0.007)	-0.002 (0.023)
Constant	0.065*** (0.000)	0.022*** (0.000)	0.051*** (0.000)	0.024*** (0.000)
N	343	156	316	155
Countries	14.00	8.00	14.00	7.00
F	13.54***	36.40***	9.57***	8.94**
r^2	0.09	0.19	0.10	0.02

Results from adjusted ratio γ_i model (Table 3) with removed temporal lags from the independent variables, estimating coefficients at current time. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

C.2 Patent Stocks as Control Variable

Table C8: Baseline Regressions Including Patent Stocks

	(1)	(2)	(3)	(4)
	Value Added	Employment	Wage	Labor Productivity
	b/se	b/se	b/se	b/se
L.World Factor	0.760** (0.293)	0.482*** (0.110)	0.777** (0.276)	0.075 (0.149)
L.Country Factor	-0.007 (0.005)	0.006* (0.003)	-0.007 (0.006)	-0.007* (0.004)
L2.Patent Stock	0.152 (0.217)	-0.031 (0.047)	0.009 (0.208)	0.261*** (0.039)
Constant	0.054*** (0.014)	0.023*** (0.003)	0.049*** (0.014)	0.006* (0.003)
N	343	160	317	158
Countries	14.00	8.00	14.00	7.00
F	17.89***	8.70***	19.94***	21.37***
r^2	0.08	0.06	0.06	0.13

Results from extended baseline model (Table 1), adding country-industry level patent stocks to control for possible level effects. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

Table C9: Regressions with Ratio ξ_i Including Patent Stocks

	(1)	(2)	(3)	(4)
	Value Added	Employment	Wage	Labor Productivity
	b/se	b/se	b/se	b/se
L.World Factor	1.462*** (0.423)	0.648*** (0.174)	1.368*** (0.344)	0.580* (0.289)
L.World Factor \times W/C	-1.072*** (0.302)	-0.240 (0.246)	-0.950*** (0.225)	-0.680 (0.356)
L.Country Factor	-0.024** (0.009)	-0.004 (0.005)	-0.021* (0.011)	0.000 (0.004)
L.Country Factor \times W/C	0.024** (0.009)	0.014** (0.005)	0.020* (0.011)	-0.009** (0.003)
L2.Patent Stock	0.131 (0.217)	-0.036 (0.051)	-0.004 (0.210)	0.266*** (0.041)
Constant	0.055*** (0.014)	0.024*** (0.003)	0.050*** (0.014)	0.005 (0.003)
N	343	160	317	158
Countries	14.00	8.00	14.00	7.00
F	20.63***	279.64***	13.10***	51.25***
r^2	0.10	0.07	0.08	0.14

Results from adjusted ratio ξ_i model (Table 2), adding country-industry level patent stocks to control for possible level effects. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

Table C10: Regressions with Ratio γ_i Including Patent Stocks

	(1) Value Added b/se	(2) Employment b/se	(3) Wage b/se	(4) Labor Productivity b/se
L.World Factor	2.004*** (0.641)	1.186* (0.517)	1.786** (0.684)	0.893 (0.791)
L.World Factor \times Gini W/C	-0.972** (0.375)	-0.622 (0.426)	-0.817* (0.425)	-0.748 (0.617)
L.Country Factor	-0.030* (0.016)	-0.002 (0.008)	-0.023 (0.019)	0.003 (0.006)
L.Country Factor \times Gini W/C	0.018 (0.011)	0.006 (0.008)	0.013 (0.012)	-0.010 (0.006)
L2.Patent Stock	0.134 (0.210)	-0.035 (0.050)	-0.002 (0.204)	0.265*** (0.042)
Constant	0.055*** (0.014)	0.023*** (0.003)	0.050*** (0.013)	0.005 (0.003)
N	343	160	317	158
Countries	14.00	8.00	14.00	7.00
F	19.09***	13.56***	19.69***	11.05***
r^2	0.10	0.07	0.08	0.14

Results from adjusted ratio γ_i model (Table 3), adding country-industry level patent stocks to control for possible level effects. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

C.3 World and Country GDP as Control Variable

Table C11: Baseline Regressions Including GDP

	(1)	(2)	(3)	(4)
	Value Added	Employment	Wage	Labor Productivity
	b/se	b/se	b/se	b/se
L.World Factor	0.342** (0.156)	0.160* (0.077)	0.312*** (0.084)	0.185 (0.155)
L.Country Factor	-0.008 (0.005)	0.002 (0.003)	-0.010 (0.006)	-0.004 (0.003)
L2.Global GDP	0.023* (0.011)	0.015** (0.006)	0.026** (0.009)	-0.014 (0.009)
L2.Country GDP	-0.000*** (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.000** (0.000)
Constant	0.155*** (0.026)	0.049*** (0.009)	0.113*** (0.024)	0.061*** (0.014)
N	329	156	306	154
Countries	14.00	8.00	14.00	7.00
F	8.02***	3.74*	4.86**	4.83**
r^2	0.20	0.11	0.14	0.08

Results from extended baseline model (Table 1), adding the global economic conditions index, as well as country-level GDP, to control for economic conditions at levels corresponding to our factors. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

Table C12: Regressions with Ratio ξ_i Including GDP

	(1)	(2)	(3)	(4)
	Value Added	Employment	Wage	Labor Productivity
	b/se	b/se	b/se	b/se
L.World Factor	0.995*** (0.293)	0.118 (0.210)	0.893*** (0.182)	0.745* (0.353)
L.World Factor \times W/C	-0.951*** (0.294)	0.014 (0.258)	-0.902*** (0.219)	-0.699* (0.340)
L.Country Factor	-0.017** (0.006)	-0.010** (0.004)	-0.018** (0.007)	-0.001 (0.005)
L.Country Factor \times W/C	0.014*** (0.004)	0.017*** (0.004)	0.012 (0.007)	-0.002 (0.004)
L2.Global GDP	0.020* (0.011)	0.015** (0.006)	0.025** (0.009)	-0.016 (0.009)
L2.Country GDP	-0.000*** (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.000** (0.000)
Constant	0.153*** (0.025)	0.050*** (0.009)	0.112*** (0.024)	0.060*** (0.014)
N	329	156	306	154
Countries	14.00	8.00	14.00	7.00
F	9.28***	357.96***	10.27***	69.10***
r^2	0.21	0.12	0.15	0.09

Results from adjusted ratio ξ_i model (Table 2), adding the global economic conditions index, as well as country-level GDP, to control for economic conditions at levels corresponding to our factors. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

Table C13: Regressions with Ratio γ_i Including GDP

	(1)	(2)	(3)	(4)
	Value Added	Employment	Wage	Labor Productivity
	b/se	b/se	b/se	b/se
L.World Factor	1.470*** (0.436)	0.701 (0.685)	1.399** (0.508)	1.363 (0.820)
L.World Factor \times Gini W/C	-0.848** (0.311)	-0.472 (0.556)	-0.857* (0.425)	-1.029 (0.596)
L.Country Factor	-0.018 (0.012)	0.002 (0.009)	-0.018 (0.013)	-0.005 (0.003)
L.Country Factor \times Gini W/C	0.009 (0.007)	-0.000 (0.009)	0.008 (0.008)	0.000 (0.003)
L2.Global GDP	0.020 (0.012)	0.015* (0.006)	0.025** (0.009)	-0.015 (0.009)
L2.Country GDP	-0.000*** (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.000** (0.000)
Constant	0.153*** (0.025)	0.049*** (0.009)	0.112*** (0.024)	0.061*** (0.013)
N	329	156	306	154
Countries	14.00	8.00	14.00	7.00
F	23.54***	14.60***	4.95***	138.04***
r^2	0.22	0.11	0.16	0.09

Results from adjusted ratio γ_i model (Table 3), adding the global economic conditions index, as well as country-level GDP, to control for economic conditions at levels corresponding to our factors. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

C.4 Knowledge Inflow as Control Variable

Table C14: Baseline Regressions Including Knowledge Inflow, omitting US and JP

	(1) Value Added b/se	(2) Employment b/se	(3) Wage b/se	(4) Labor Productivity b/se
L.World Factor	0.375** (0.146)	0.127 (0.102)	0.299** (0.101)	0.203 (0.131)
L.Country Factor	-0.007 (0.005)	0.002 (0.004)	-0.008* (0.005)	-0.005 (0.003)
L6.Knowledge Inflow excl. JP & US	0.563** (0.218)	0.359* (0.160)	0.548** (0.244)	0.101 (0.087)
Constant	-0.075 (0.054)	-0.065 (0.038)	-0.084 (0.060)	-0.002 (0.021)
N	357	164	329	162
Countries	14.00	8.00	14.00	7.00
F	12.83***	6.44**	8.86***	2.15
r^2	0.16	0.15	0.16	0.03

Results from extended baseline model (Table 1), adding aggregated knowledge inflows measured by patents' backward citations (see, Section 2.3) for all countries in the sample, besides Japan and the United States. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

Table C15: Baseline Regressions Including Knowledge Inflow to US and JP only

	(1) Value Added b/se	(2) Employment b/se	(3) Wage b/se	(4) Labor Productivity b/se
World Factor	0.394* (0.198)	0.686*** (0.171)	0.633*** (0.186)	-0.370*** (0.082)
Country Factor	-0.005 (0.005)	0.008** (0.003)	-0.007 (0.004)	-0.000 (0.003)
L5.Knowledge Inflow JP & US	-1.114*** (0.221)	-0.302*** (0.084)	-0.867*** (0.252)	-0.537*** (0.100)
Constant	0.872*** (0.159)	0.240*** (0.061)	0.679*** (0.183)	0.412*** (0.073)
N	343	156	316	155
Countries	14.00	8.00	14.00	7.00
F	30.69***	10.86***	5.10**	40.99***
r^2	0.23	0.21	0.20	0.11

Results from extended baseline model (Table 1), adding aggregated knowledge inflows measured by patents' backward citations (see, Section 2.3) for Japan and the United States only. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

Table C16: Regressions with Ratio ξ_i Including, omitting US and JP

	(1)	(2)	(3)	(4)
	Value Added	Employment	Wage	Labor Productivity
	b/se	b/se	b/se	b/se
L.World Factor	0.960*** (0.298)	0.261 (0.249)	0.750*** (0.183)	0.634* (0.295)
L.World Factor \times W/C	-0.898*** (0.277)	-0.200 (0.218)	-0.725*** (0.180)	-0.570* (0.278)
L.Country Factor	-0.020*** (0.006)	-0.007 (0.004)	-0.016** (0.007)	-0.001 (0.005)
L.Country Factor \times W/C	0.018*** (0.005)	0.013** (0.005)	0.011 (0.006)	-0.004 (0.005)
L6.Knowledge Inflow excl. JP & US	0.541** (0.222)	0.357* (0.162)	0.538** (0.247)	0.094 (0.089)
Constant	-0.069 (0.055)	-0.064 (0.039)	-0.081 (0.060)	0.000 (0.021)
N	357	164	329	162
Countries	14.00	8.00	14.00	7.00
F	27.13***	10.68***	8.14***	22.19***
r^2	0.18	0.16	0.16	0.04

Results from adjusted ratio ξ_i model (Table 2), adding aggregated knowledge inflows measured by patents' backward citations (see, Section 2.3) for all countries in the sample, besides Japan and the United States. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

Table C17: Regressions with Ratio ξ_i Including Knowledge Inflow to US and JP only

	(1)	(2)	(3)	(4)
	Value Added b/se	Employment b/se	Wage b/se	Labor Productivity b/se
L.World Factor	0.859*** (0.281)	0.353* (0.166)	0.750*** (0.132)	0.349 (0.323)
L.World Factor \times W/C	-0.773** (0.278)	-0.164 (0.204)	-0.680*** (0.179)	-0.406 (0.301)
L.Country Factor	-0.021*** (0.006)	-0.007 (0.004)	-0.015* (0.008)	-0.003 (0.007)
L.Country Factor \times W/C	0.015*** (0.004)	0.013** (0.004)	0.007 (0.007)	-0.004 (0.006)
L5.Knowledge Inflow JP & US	-1.082*** (0.213)	-0.353*** (0.090)	-0.893*** (0.266)	-0.464*** (0.123)
Constant	0.849*** (0.155)	0.277*** (0.065)	0.698*** (0.193)	0.359*** (0.089)
N	357	164	329	162
Countries	14.00	8.00	14.00	7.00
F	9.48***	326.47***	7.89***	18.00***
r^2	0.24	0.12	0.19	0.11

Results from adjusted ratio ξ_i model (Table 2), adding aggregated knowledge inflows measured by patents' backward citations (see, Section 2.3) for Japan and the United States only. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

Table C18: Regressions with Ratio γ_i Including Knowledge Inflow, omitting US and JP

	(1)	(2)	(3)	(4)
	Value Added	Employment	Wage	Labor Productivity
	b/se	b/se	b/se	b/se
L.World Factor	1.370*** (0.268)	0.836 (0.522)	1.100*** (0.338)	1.049 (0.610)
L.World Factor \times Gini W/C	-0.771*** (0.235)	-0.640 (0.401)	-0.646* (0.340)	-0.746 (0.480)
L.Country Factor	-0.026** (0.011)	0.009 (0.007)	-0.021 (0.013)	-0.012** (0.004)
L.Country Factor \times Gini W/C	0.014** (0.006)	-0.007 (0.009)	0.010 (0.007)	0.005 (0.003)
L6.Knowledge Inflow excl. JP & US	0.546** (0.215)	0.360* (0.162)	0.541** (0.242)	0.096 (0.088)
Constant	-0.070 (0.053)	-0.065 (0.039)	-0.082 (0.059)	-0.000 (0.021)
N	357	164	329	162
Countries	14.00	8.00	14.00	7.00
F	15.03***	11.82***	9.13***	2.29
r^2	0.18	0.16	0.17	0.04

Results from adjusted ratio γ_i model (Table 3), adding aggregated knowledge inflows measured by patents' backward citations (see, Section 2.3) for all countries in the sample, besides Japan and the United States. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

Table C19: Regressions with Ratio γ_i Including Knowledge Inflow to US and JP only

	(1)	(2)	(3)	(4)
	Value Added	Employment	Wage	Labor Productivity
	b/se	b/se	b/se	b/se
L.World Factor	1.180*** (0.315)	0.900 (0.500)	1.031** (0.361)	0.751 (0.606)
L.World Factor \times Gini W/C	-0.632** (0.244)	-0.583 (0.391)	-0.561 (0.324)	-0.630 (0.492)
L.Country Factor	-0.019 (0.013)	0.004 (0.004)	-0.015 (0.015)	-0.010 (0.008)
L.Country Factor \times Gini W/C	0.007 (0.007)	-0.002 (0.006)	0.004 (0.008)	0.003 (0.006)
L5.Knowledge Inflow JP & US	-1.088*** (0.205)	-0.352*** (0.086)	-0.897*** (0.252)	-0.469*** (0.126)
Constant	0.853*** (0.148)	0.276*** (0.062)	0.701*** (0.183)	0.362*** (0.092)
N	357	164	329	162
Countries	14.00	8.00	14.00	7.00
F	9.49***	10.46***	8.17***	9.51***
r^2	0.24	0.12	0.19	0.11

Results from adjusted ratio γ_i model (Table 3), adding aggregated knowledge inflows measured by patents' backward citations (see, Section 2.3) for Japan and the United States only. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

C.5 Combined Control Variable Model

Table C20: Baseline Regressions Including all Controls

	(1)	(2)	(3)	(4)
	Value Added	Employment	Wage	Labor Productivity
	b/se	b/se	b/se	b/se
L.World Factor	0.200 (0.137)	0.085 (0.104)	0.164* (0.077)	0.082 (0.170)
L.Country Factor	-0.010* (0.005)	0.003 (0.004)	-0.011** (0.005)	-0.008 (0.004)
L2.Patent Stock	-0.054 (0.235)	-0.124** (0.050)	-0.178 (0.250)	0.153** (0.050)
L2.Global GDP	0.011 (0.011)	0.011 (0.006)	0.015** (0.007)	-0.015 (0.010)
L2.Country GDP	0.000* (0.000)	-0.000 (0.000)	0.000** (0.000)	0.000 (0.000)
L6.Knowledge Inflow excl. JP & US	0.755** (0.293)	0.417** (0.149)	0.758** (0.286)	0.015 (0.058)
L6.Knowledge Inflow JP & US	-0.952*** (0.290)	-0.127 (0.081)	-0.987** (0.341)	-0.560** (0.190)
Constant	0.542*** (0.162)	0.026 (0.065)	0.542** (0.198)	0.393** (0.128)
N	329	156	306	154
Countries	14.00	8.00	14.00	7.00
F	13.81***	14.57***	3.85**	.
r^2	0.30	0.20	0.27	0.18

Results from extended baseline model (Table 1), adding all the above introduced control variables on patent stocks, economic conditions and knowledge flow. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

Table C21: Regressions with Ratio ξ_i Including all Controls

	(1)	(2)	(3)	(4)
	Value Added	Employment	Wage	Labor Productivity
	b/se	b/se	b/se	b/se
L.World Factor	0.753** (0.276)	-0.067 (0.328)	0.626** (0.212)	0.581 (0.336)
L.World Factor \times W/C	-0.802** (0.293)	0.145 (0.386)	-0.713** (0.265)	-0.604 (0.320)
L.Country Factor	-0.017*** (0.005)	-0.012*** (0.003)	-0.019** (0.007)	-0.001 (0.005)
L.Country Factor \times W/C	0.010** (0.004)	0.020*** (0.004)	0.012* (0.006)	-0.008 (0.005)
L2.Patent Stock	-0.059 (0.234)	-0.129** (0.052)	-0.183 (0.250)	0.158** (0.054)
L2.Global GDP	0.009 (0.011)	0.011 (0.006)	0.014* (0.007)	-0.016 (0.010)
L2.Country GDP	0.000* (0.000)	-0.000 (0.000)	0.000** (0.000)	0.000 (0.000)
L6.Knowledge Inflow excl. JP & US	0.741** (0.292)	0.425** (0.154)	0.746** (0.286)	0.001 (0.052)
L6.Knowledge Inflow JP & US	-0.927*** (0.291)	-0.117 (0.104)	-0.966** (0.344)	-0.546** (0.207)
Constant	0.529*** (0.161)	0.019 (0.072)	0.531** (0.197)	0.386** (0.138)
N	329	156	306	154
Countries	14.00	8.00	14.00	7.00
F	10.40***	.	4.07**	.
r^2	0.31	0.22	0.28	0.19

Results from adjusted ratio ξ_i model (Table 2), adding all the above introduced control variables on patent stocks, economic conditions and knowledge flow. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

Table C22: Regressions with Ratio γ_i Including all Controls

	(1)	(2)	(3)	(4)
	Value Added b/se	Employment b/se	Wage b/se	Labor Productivity b/se
L.World Factor	1.144*** (0.323)	0.432 (0.840)	1.127*** (0.331)	0.863 (0.886)
L.World Factor \times Gini W/C	-0.705** (0.246)	-0.296 (0.687)	-0.756** (0.321)	-0.676 (0.649)
L.Country Factor	-0.015 (0.010)	-0.001 (0.012)	-0.015 (0.012)	-0.009 (0.010)
L.Country Factor \times Gini W/C	0.005 (0.007)	0.003 (0.011)	0.005 (0.007)	0.000 (0.009)
L2.Patent Stock	-0.059 (0.227)	-0.128** (0.053)	-0.183 (0.241)	0.146** (0.052)
L2.Global GDP	0.009 (0.011)	0.010 (0.006)	0.015* (0.007)	-0.015 (0.010)
L2.Country GDP	0.000* (0.000)	-0.000 (0.000)	0.000** (0.000)	0.000 (0.000)
L6.Knowledge Inflow excl. JP & US	0.740** (0.284)	0.410** (0.146)	0.747** (0.277)	-0.000 (0.064)
L6.Knowledge Inflow JP & US	-0.926*** (0.276)	-0.124 (0.083)	-0.962** (0.329)	-0.549** (0.214)
Constant	0.529*** (0.154)	0.027 (0.065)	0.529** (0.192)	0.392** (0.139)
N	329	156	306	154
Countries	14.00	8.00	14.00	7.00
F	28.09***	.	26.37***	.
r^2	0.31	0.21	0.29	0.19

Results from adjusted ratio γ_i model (Table 3), adding all the above introduced control variables on patent stocks, economic conditions and knowledge flow. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. Sample and variables remain the same as in the main model. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.

C.6 Dynamic Factor Model Outcomes as Dependent Variable

Table C23: World and Country Factor as Dependent Variables

	(1)	(2)
	World	Country
	b/se	b/se
L.Patent Stock	-0.000 (0.010)	0.219 (1.173)
L.Global GDP	0.018*** (0.000)	0.296** (0.103)
L.Country GDP	-0.000*** (0.000)	0.000 (0.000)
L5.Knowledge Inflow excl. JP & US	0.065*** (0.009)	0.400 (0.832)
L5.Knowledge Inflow JP & US	-0.100*** (0.016)	-6.339** (2.624)
Constant	0.064*** (0.011)	4.119** (1.880)
N	408	408
Countries	18.00	18.00
F	1997.12***	3.09**
r^2	0.21	0.07

Results from two regression model using world and country factors as dependent variables. All indicators used for robustness checks are included as independent variables. Coefficient estimates, standard errors (in brackets) and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) from estimating the adjusted model using OLS. The estimation includes country-specific fixed effects. Reported standard errors are heteroscedasticity robust.