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Regional technological systems in transition – Dynamics of relatedness and techno-economic matches in China

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Abstract

Based on a newly compiled set of Chinese data, this paper puts established assumptions on the role of technological variety in perspective. It does so from two main angles. First, by documenting whether, in China, technological variety has played a similar role for regional development as in Western economies. Second, by exploring how, more recently, this may change as China transitions towards an innovation driven economy. In summary, its findings suggest that, while technological variety has indeed so far mattered differently for China's regional development, more recently, first traces of systemic change can be identified in the both evolution of related variety and its emerging impact on aspects of regional development.

1 Introduction

In recent years, the degree of variety and relatedness in regions' industrial and technological portfolios has received increasing attention as a determinant of techno-economic pathways and thus, ultimately, options and rationales for regional development (Boschma et al, 2017; Isaksen and Trippl, 2016; Grillitsch et al. 2018). Since Frenken et al. (2007) first proposed the notion of *related variety*, various methodologies to capture technological diversity and relatedness have been put forward and arrived at a notable level of sophistication (Hidalgo et al., 2018; Balland et al., 2018). In this context, an in many respects beneficial effect of related variety has become accepted as common ground (Content and Frenken, 2016).

Empirically, however, most research in this area has remained based on evidence from Europe or the United States. Accordingly, it remains uncertain if even its more fundamental propositions will apply to the same extent under emerging economy conditions. Although some studies have empirically transferred some aspects of its methodology to the Chinese context (Guo et al., 2015; He et al., 2015; Guo and He, 2017), it is conceptually unclear whether its accepted findings will self-evidently hold in economies whose economic development is shaped by very different types of agency and institutions. Accordingly, most of the existing literature has not make active claims towards universality. As Boschma et al. (2017) reiterated, differences in agency plays a key role for regional development. Empirically, Boschma and Capone (2015) demonstrated notable impacts of institutional differences on technological diversity even when comparing established Western economies. Thus, an exploration of existing assumptions' relevance in the Chinese context appears timely as the world's second largest economy, with its alternative economic model, transitions from an externally to an internally driven mode of development. Despite the specificity of the Chinese situation, such transformations do not affect China alone. Hence, an improved understanding of their impact on regional diversity should also help inform future studies of regional development in institutionally diverse economic contexts at large.

Against this background, this paper will analyse the role of established, basic aspects of regional technological variety under the framework conditions of China. Different from earlier studies that consider patent activities as a variable dependent on variety in the industrial or product space (Castaldi et al., 2015; Kogler et al., 2013), this study follows the recommendation put forward by Content and Frenken (2016) by measuring *variety in the technological space*, to then consider their impact on regional economic development more broadly.

Intentionally, it seeks to analyse those effects for an economy that remains differently positioned in global value chains (Fu et al., 2012; Liefner and Wei, 2014) and, over the past two decades, has experienced fundamental economic and institutional transformation (Breznitz and Murphree, 2011; Peyman, 2018). In this distinct yet dynamic context, technological variety may have (had) very different origins and thus implications than in established market economies. At the same time, other factors like the pronounced differences in regional "fit" between technological and industrial activities (Liu et al., 2018) may have played a more central role for regional development than elsewhere. More recently, finally, more and more provinces shifted towards innovation-driven development models (Liu et al., 2018) - which will have affected ongoing shifts in the spatial configuration of the national innovation system (Fan, 1995; Liu et al., 2018; Liu and White, 2001; Kroll, 2016),

Overall, there are thus two main reasons why China constitutes a relevant study case justifying this paper’s contribution to the literature. First, China's past trajectory suggests a stronger role of external and macro-level agency (FDI & industrial policy) than in established economies and thus different relations between technological variety and economic development. Second, recent literature on China seems to imply that precisely this will be changing as - in the country's process of technological upgrading - new, different sources of technological variety are increasingly emerging.

With a view to the first aspect, differences should result from the fact that most of China's initial technological capacity was infused from the outside when its planned economy was transformed through foreign investment and became the world's workshop in the 1990s. At that time, most evidence of "technological specialisation" was in fact a reflection of foreign-investment driven islands of capacity in an otherwise fairly fragmented innovation system (Liefner and Wei, 2014; Liu et al., 2018; Wei, 2014). At the same time, various provincial governments "created" specialisation actively, if not artificially, by encouraging local concentrations of technologically related firms (Barbieri et al., 2012; Liefner and Wei, 2014; Liu et al., 2018). Moreover, most of its early hotspots of indigenous technological development emerged drawing on scientific expertise in electronics and computing (Kroll and Schiller, 2010; Segal, 2003). Eventually, all three trends taken together led to an above average level of technological specialisation not only at national but, often, also at regional level (Liefner and Wei, 2014; Wang et al., 2015).

With a view to the latter aspect, however, newer literature suggests that, China's technological portfolio has substantially broadened in line with its overall surge in technological capacities (Kroll, 2009; Kroll and Frietsch, 2014). As world-level capacities spread beyond initial lead sectors, the nation's technological diversification increased to a level more in line with what classical theory would consider fitting for a economy that size (Archibugi and Pianta, 1992). At the same time, most provinces' regional development policies are no longer simplistically based on "building" localised specialisation, but give more room to emergent industrial dynamics (Barbieri et al., 2012; Liu et al., 2018; Wang et al., 2010). As a result of increasing technological activity in further domains, new localised ecosystems have developed internal dynamics across the country, breaking established paths in various provinces and contributing to the national innovation system (Guo and He, 2017; Kroll, 2016). In parallel, many provinces' development begins to provide evidence of branching based on the existing portfolio of local capacities (He et al., 2018). Also, some suggest that in the nation's leading and ever better connected hotspots of innovation (Liu et al., 2018; Zhang, 2013), related variety has become a more relevant factor – even if strongly moderated by others (He et al., 2018).

For the time being, however, most studies remain focused on specific locations and thus insufficient to document the overarching forces of change are undoubtedly at work in China's complex national innovation system (He et al., 2018; Kroll, 2016). Moreover, most current literature focuses on the role of variety in the industrial portfolios of provinces and cities (Wang and Prevezer, 2015; Guo et al., 2015; He et al., 2015; Guo and He, 2017) while a more comprehensive analysis of techno-economic development logics is, to the author's knowledge, not yet available.

Against this background, this paper will pursue a twofold objective. First, it will analyse whether established, fundamental measures of technological variety have displayed relevant implications for economic development in China, compared in particular to the regional fit between technological and economic activities. Second, it will establish whether there are traces of new processes generating or even new implications of related variety in more recent years.

2 Conceptual background

In the past two decades, scholars in economic geography and the adjoining regional sciences have investigated whether technological proximity or distance gives rise to increased innovative activities and, if so, which type of technological relatedness can be found most conducive (e.g. Boschma, 2017; Breschi et al., 2003; Frenken et al., 2007; Miguelez and Moreno, 2018). One finding that this literature has converged towards is that both technological closeness and distance, if taken to the extreme, will limit the generation of innovative solutions (Arts and Veugelers, 2015; Fleming and Sorenson, 2001; ÓhUallacháin and Lee, 2011). For both the industrial and the technological space, diverse studies of patent, industrial and trade data suggest that innovative activities in regions develop best in a situation of "related variety" (Frenken et al., 2007) where there is enough technological distance to allow for new recombinations but at the same time enough closeness that stakeholders with different areas of expertise can productively relate to each other (Boschma, 2017; Boschma and Iammarino, 2009; Content and Frenken, 2016). So far, most of these studies have worked on data reflecting industrial or product spaces rather than the technological space directly - which will be the ambition of this paper.

In any case, most conclusions on the effects of technological variety have been derived from the analysis of European (e.g. Frenken et al., 2007; Miguelez and Moreno, 2018; Balland et al., 2018) or other Western economies' datasets (e.g. Boschma et al., 2015; Castaldi et al., 2015). Consciously or unconsciously, most empirical research thus focuses on situations in which the fundamental framework conditions are more or less constant (Content and Frenken, 2016; Martin and Sunley, 2006) and in which technological variety is a reflection of gradual, evolutionary developments, driven by micro-level agency (Boschma et al., 2017). Implicitly, these premises have become taken for granted in the focus and framing of many studies (Asheim and Gertler, 2005; Asheim et al., 2016). As one example, many 'branching studies' (Content and Frenken, 2016; Frenken and Boschma, 2007; Neffke et al., 2011) focus on the role of technological variety in new path creation or renewal (Grillitsch et al., 2018; Isaksen, 2015; Isaksen and Trippl, 2016; Boschma et al., 2017). Arguably, that approach is most obviously relevant where established paths lose dynamism and are being replaced, but possibly less so in economies like China where new paths just emerge. At the same time, external agency (like foreign investment) and macro-level factors (like industrial policy), have received less attention although they can be equally central for regional path development (Fuller and Phelps, 2018; Coe and Yeung, 2015; Fu et al., 2012). Thus, many analytical frameworks remain – explicitly or implicitly – derived from challenges relevant for established market economies. While this is not to the detriment of this literature as such, it does limit our understanding of its generalisability across further contexts.

At the same time, a focus on established market economies comes with implicit secondary assumptions that become particularly relevant when studies focus on the technological – rather than directly the industrial portfolio of regions. To sensibly relate variety in the technological space to aspects of economic growth, assumptions regarding the local coherence and integration of regional innovation systems must be taken (Foray, 2014; Asheim, 2012). In established market economies, well-developed regional economies tend to be characterised by a comparatively balanced set-up of actors from science, technology and the business sector as well as a reasonable thematic fit between local technological and economic activities (Asheim and Coenen, 2006). As a result, we tend to implicitly assume that new path creation or renewal through technological efforts can readily translate into actual changes with a view to productivity, value creation or employment. Even in Europe and the U.S., however, such assumptions often conflict with the well-documented fact that well-functioning, localised nexus of science-industry collaboration constitute the exception rather than the rule (Asheim and Coenen, 2006; Bergman and Maier, 2009; Markusen, 1996).

As interactions between economic actors are influenced and driven by various forms of non-spatial proximity (Boschma, 2005), technological capacities relate and become effective at a multi-scalar, trans-regional level (Asheim, 2012; Boschma, 2017). Consequently, the actual intensity of localised interactions between innovators and users remains a factor in local economic development that is as fundamental as context specific (Bathelt et al., 2004). In its absence, most economic effects of local technological activity will materialise outside the region (Foray, 2014), while the region's economy remains dependent on external technology and investment and local path development an exogenously determined outcome decoupled from indigenous dynamism (Isaksen and Trippl, 2017; Blažek, 2016). In practice, the development of regions depends less on regional capacities than on external decisions of locally investing corporations (Asheim and Coenen, 2006; Fuller and Phelps, 2018; Coe et al., 2004; Coe and Yeung, 2015).

Accordingly, the majority of the literature on regional innovation systems has, from the outset, considered a certain degree of thematic fit between technological and economic capacities as an essential, desirable characteristic and precondition for endogenous, innovation-driven regional development (Asheim et al., 2016; Asheim and Gertler, 2005; Cooke, 1998; Cooke et al., 1998). In regions without this fundamental ability to generate local dynamics from integrated local economies, considerations of technological portfolios may well be of an academic nature and not very relevant for local path development in practice. Even in leading economies, the relations between technological variety and local fit of technological and economic capacities remains far from fully understood and the related literature far from unambiguous in its findings (Asheim et al., 2016; Content and Frenken, 2016).

For an emerging economy like China, existing studies suggest that external and macro-level factors have been driving forces for many years and, accompanied by local systemic mismatches, in many cases render intra-regional technological dynamics an outcome rather than a determinant of technological development (Kroll and Schiller, 2010; Liefner and Wei, 2014; Wei, 2014). With decreasing external control of the economy and steeply increasing endogenous dynamics, however, this relation will likely be changing. In this process of change, it seems likely that technology variety begins to emerge in other ways than before, even if processes of regional development in China will continue to differ from those in Western economies in many ways (Liefner, 2014). New momentum in various sectors and provinces may initiate new trajectories, resulting e.g. in a greater prevalence and beneficial effects of within-industry related variety (Wang and Prevezer, 2015; Guo et al., 2015; He et al., 2015; Guo and He, 2017). On many levels, the country's innovation system is experiencing a complex spatial reconfiguration (Kroll, 2016; Guo and He, 2017) the concrete implications of which remain less than fully understood. At the same time, market seeking foreign direct investment and the early steps of China’s technological rise have left an industrial legacy (Kroll and Frietsch, 2014) that will not disappear swiftly but continue to serve as a basis for the further development of technological trajectories (Liu et al., 2018). Moreover, the directionality of emerging trends could well be different. While some regions are striving to find new growth paths, others remain path-bound or are only starting to transform themselves into technology-oriented economies in the first place (He et al., 2018; Guo and He, 2017).

3 Analytical approach and hypotheses

In light of these findings, this paper will proceed in two major steps. First, it will explore to what extent different aspects of variety in regional technological portfolios and local techno-economic fit have had implications for the respective regions' level and dynamics of economic development. Second, it will explore by which specific local characteristics these aspects themselves have been determined in the more recent years since innovative activities in the Chinese industry have sharply taken up.

In operationalising these two main aspects, it is essential to acknowledge that the emergence of technological portfolios and that of economic structures are connected through a circular process of mutual causation. Analytically, and practically, both coexist as different aspects of a complex process of industrial transformation that (co-)determine the future development pathway of the respective other.

Against this background, this paper will address two main hypotheses, differentiating the first one into three different perspectives:

Hypothesis 1: Aspects of regional variety and fit between technological and economic activities can be found associated with the past and present development performance of regions?

Hypothesis 1a: These aspects can be found associated with regions' quantitative level of development (economic size)?

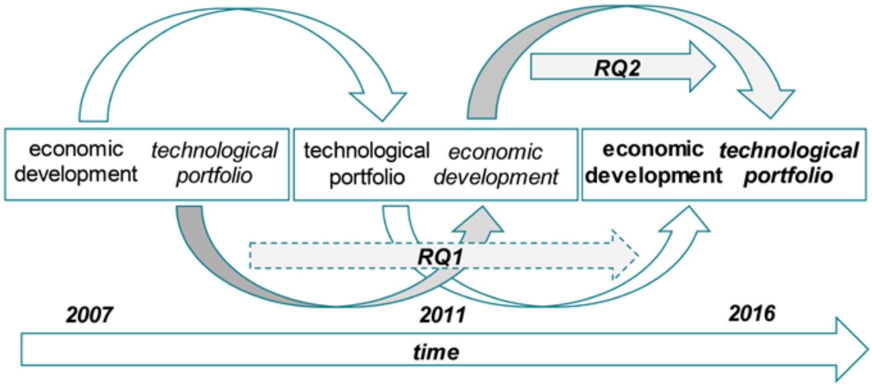
Hypothesis 1b: These aspects can be found associated with regions' qualitative level of development (income per capita)?

Hypothesis 1c: These aspects can be found associated with regions' recent dynamics of development (GDP growth)?

Hypothesis 2: Specific characteristics of regional economies can more recently be found associated with certain aspects of technological variety and the local fit between technological and economic activities?

To disentangle these different aspects of the co-evolutionary process, it is not only permissible but necessary to analyse these reciprocal dependencies during similar, if consciously offset periods: technological portfolio's effects on economic development as well as the effects of newly emerging economic structures on the more recent development of technological portfolios. Figure 1 documents this analytical positioning of the two main hypotheses in the de facto co-evolutionary process, emphasising their respective focus on specific time periods (even if, to check for robustness, both will technically also consider the respective other time period).

Figure 1: Co-evolution of technological portfolios and economic development



Source: Own conceptual figure

The spatial level of analysis chosen for this study is that of China's provinces, municipalities under central administration and autonomous regions (except Hong Kong and Macao). Different from most earlier research (e.g. Content and Frenken, 2016), this paper thus analyses impact factors not at the localised level of agglomerations but at the systemic level of regions. This admittedly rather aggregate level was chosen consciously, as most literature maintains clearly that complex relations between technological and economic dynamics cannot sensibly be captured at a parochial level (e.g. Boschma, 2017; Foray, 2014). With its focus on the technological space, this paper takes a by definition more systemic perspective than existing studies that focus mainly on agglomeration economies. Contrary to those, it does not simply analyse localised industrial trajectories, but examines the role of multi-level variety in the larger context of regional innovation systems. From that angle, China's provinces constitute relevant items of inquiry, as they indeed constitute separate innovation systems with specific institutions and a sufficient amount of localised interactions that are particular and economically relevant (Liu et al., 2018). At the level of counties, most relations are known to be external - so that the most of this paper's premises would be irrelevant to test in the first place. Hence, relations between regional development and the diversity of available knowledge or the systemic goodness of fit between technological and economic activities remain best analysed at a higher – in this case, the provincial level. Furthermore, Chinese county level data is known to be notoriously unreliable (Plekhanov, 2017). Although some earlier studies have taken this path, formal gains in reliability through increased sample sizes would most likely be spurious – in the light of even official acknowledgements of missing data accuracy (Global Times, 2019).

With a view to the period of observation, the time after the financial crisis is of particular interest to operationalise 'more recent' developments as it has witnessed China's genuine shift towards an "innovation-driven" development model. More precisely, this period of technological uptake began around 2011 when patenting figures took off dynamically and an increasing share of the country's technological capacities started to spread beyond its three main metropolitan regions and the coastal rim.

4 Data and methodology

Our analyses are based on a panel dataset from 2007 to 2016, drawing, first, on official Chinese statistics compiled from national and provincial sources and, second, on patent statistics retrieved from the EPO Worldwide Patent Statistical Database (PATSTAT), which provides patent data for more than 80 patent offices worldwide, including the (then) State Intellectual Property Office of China (SIPO). More precisely, the dataset was compiled through a detailed review of various national and provincial level yearbooks, online publications of China's National Bureau of Statistics as well as queries to an in-house PATSTAT database. Additional information to enable the accurate regionalisation of SIPO patents was provided by the National Library of the Chinese Academy of Sciences. For some of the peripheral provinces and certain years, sectoral data underlying the techno-economic fit measures had to be estimated as, for less advanced regions, such figures are not always made publicly available in parallel disaggregation by province and sector. While some missing values in time-series for specific sectors or years were common, most could reliably be estimated using relevant proxy indicators (e.g. local output of sector specific goods), national level sectoral trends, or, in rare cases failing both, trend extrapolation.

With a view to core measures, this study pursues three main avenues. First, it calculates commonly used entropy measures of technological variety for all 31 Chinese provinces and equivalent territories, drawing on the taxonomy of the International Patent Classification (IPC) as an indicator of technological closeness. Second, it establishes a measure of technological coherence directly anchored in known patterns of technological collaboration by adapting the 'LOS-Index' (Los, 2000), to move beyond the 'ex-ante' definition of relatedness (Boschma et al., 2012) in the IPC taxonomy, that the entropy measures rely on. Third, it approaches the issue of regional integration between scientific, technological and economic activities through a cosine similarity measure of fit between technological and economic outputs. These three measures, including selected interaction effects, constitute explanatory variables for development levels and growth under Hypothesis 1. Subsequently, their own, recent emergence will be explored by making them dependent variables in Hypothesis 2. Finally, control variables will be introduced to account for further central aspects of regional economies - becoming explanatory variables in analysis related to Hypothesis 2.

Core variables

Indices for unrelated as well as related variety were calculated based on patent filings at the SIPO. As this paper seeks to reconsider fundamental assumptions of the related variety literature under different circumstances, we decided to use some of the most established measures of technological relatedness. While these may be basic, they have the advantage of clarity and conciseness. Using the entropy formula proposed by Frenken et al. (2007), 'unrelated variety' (UV) refers to variety at the level of the eight main IPC sections A-H (1-digit categories). 'Related variety' (RV) is calculated at the level of IPC 3-level sub-classes (e.g. A01, B05).

$$\mathrm{UV} = \sum_{g=1}^{G} P_g \log_2\left(\frac{1}{P_g}\right) \qquad (1)$$

$$\mathrm{RV} = \sum_{g=1}^{G} P_g H_g$$

where (2)

$$H_g = \sum_{i \in S_g} \frac{p_i}{P_g} \log_2\left(\frac{1}{p_i/P_g}\right) \qquad (3)$$

In an alternative approach, the LOS-index (Los, 2000) documents technological coherence based on observable patterns of collaboration rather than hypothetical assumptions of closeness derived from the predefined taxonomy. While the original LOS-index draws on the degree to which sectors use similar inputs, our adapted, technological LOS-index is based on co-patenting. As a reference framework, we establish a matrix of co-patenting between all IPC 3-level classes for worldwide transnational patent filings[1], thus documenting a globally valid 'standard degree' or 'average' of co-occurrence of technological 'inputs' in specific classes of patent documents. As the number of applications differs strongly by class, co-patenting figures are normalised by

1 Transnational patent filings have been proposed as an internationally comparable measure of patent filings by Frietsch and Schmoch (2010). Transnational patents are patents filed via the PCT-procedure at the World Intellectual Property Organization (WIPO) or at the European Patent Office, excluding double counts. They can also be described as patent families with at least an EPO- or a PCT-member.

the product of patent volume in either of the concerned classes, i.e. the theoretical maximum number of co-patents between all patents in either field. For the purpose of designing the final index, the respective values are then divided by the highest overall value to attain values between 0 and 1, as in the original LOS-index (Los, 2000). As, unlike the original LOS-index, our derivative is not based on input-output matrices in which the sum for all s_i is 1 for each j, the index can become smaller than 1/n. Also, there can be missing cells in the 123 patent classes, requiring that cases in which $s_{ik} * s_{jk}$ would be zero are omitted. Unlike the variety indices, high LOS-index values indicate coherence whereas low values indicate a lack thereof, i.e. diversity:

$$\mathrm{Los}_k = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(s_{ik}\cdot s_{jk}\cdot a_{ij})}{\sum_{i=1}^{n}\sum_{j=1}^{n}(s_{ik}\cdot s_{jk})} \qquad (4)$$

To reflect this paper's argument of context specificity, moreover, a ‘similarity index' between regional technological and economic capacities was calculated. It reflects the cosine similarity between the vectors of regional patent applications by IPC classes and of regional industrial output by China's standard industrial classification. As these two types of data come in different classification systems, they have to be aligned in order to transfer the respective profiles into mathematically comparable vectors. To that end, regions' patent output was translated from IPC to industrial classifications based on a matching of PATSTAT and the company database ORBIS from Bureau van Dijk at the micro-level, i.e. the level of patent applicants and firms, respectively. In the ORBIS database, information is available for firms' industrial classification (NACE Rev. 2). With the help of a string matching algorithm on company names, both databases could be matched and the patent applicants in PATSTAT thus assigned to industrial sectors. On aggregate, this allows us to create a matrix of patent shares by IPC classes and NACE sectors, i.e. to document how patent filings at the level of certain IPC classes distribute across NACE sectors. With the help of these shares, NACE-based vectors could be translated into directly comparable IPC-based vectors. Subsequently, the cosine similarity between both vectors can be established as below.

$$\cos(\theta) = \frac{\mathbf{A}\cdot\mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \qquad (5)$$

Due to the high level of correlation between them, the different variety measures will in the following analyses be considered as alternative rather than complementary analytical approaches. In line with the analytical ambition of this paper, in contrast, the measure of local techno-economic fit will be considered in parallel. Table 1 illustrates the correlations between the core explanatory variables and Table Annex 1 where each province's individual positioning is displayed with a view to all four core measures.

Table 1: Correlations between main variety measures

	unrelated variety		related variety		LOS-Index (adj.)	
related variety	0.809	***				
LOS-Index (adj.)	-0.681	***	-0.376	***		
cos-sim tech-ind	0.421	***	0.201	***	-0.551	***

Source: Own calculations, based on data from SIPO and NBS China

Control variables

Beyond the core measures, control variables are introduced to capture central, known determinants of technological and economic development, insofar as they are available from official Chinese statistics. They constitute control variables for Hypothesis 1 and explanatory variables for Hypothesis 2.

First, *population density* is included to set apart urban from rural areas and at the same time capture part of the differences between China's advanced, densely populated coast and its less developed, sparsely populated west. Second, regions' *export quota* reflects the extent to which external investments or domestic investments with a foreign market perspective may have influenced local growth paths in the manner outlined above. Third, the *number of SIPO invention patent applications* was included to capture the technological, separate from the economic, size of a region. Fourth, the *share of industry in GDP* is not only another proxy for urbanisation but should at the same time capture specific characteristics pertinent to some regions' economic history. Fifth, the *share of university graduates in the population* reflects the degree of public investment in human capital, as does, sixth, the *regional R&D intensity* with respect to broader investments in science and technology. Both are key factors influencing the shift towards an innovation-based development model. Finally, the *ratio between new product sales and GDP* documents the degree of knowledge orientation that a specific regions' industry has already achieved. The models for Hypothesis 2, moreover, include the *total wage bill of employees in the region* to control for economic level effects which may be particularly important in a diverse and dynamic development process that different regions have entered subsequently. The descriptives of both core and control variables are reported in Table 2 below.

Table 2: Summary statistics of core and control variables

	Mean	Std. Dev.	Min	Max	Obs.	years
Core variables						
unrelated variety	2.586	0.25	0.993	2.841	310	10
related variety	2.625	0.25	1.650	2.968	310	10
adjusted LOS-Index	0.005	0.00	0.003	0.015	310	10
cos-sim tech-ind	0.518	0.19	0.170	1.000	310	10
Control variables						
GDP	17165.7	14962.6	342.2	80854.9	310	10
R&D intensity	1.42	1.07	0.19	6.01	310	10
wage bill	2285.0	2248.3	80.6	14156.8	310	10
population density	43.29	64.86	0.20	382.50	310	10
export quota	226.77	266.50	10.73	1234.80	310	10
share industry in GDP	0.47	0.08	0.19	0.61	310	10
invention patents	17363.6	27751.7	23.0	184632.0	310	10
graduates per population	46.56	15.57	17.39	95.71	310	10
new product sales per GDP	1429.0	1088.6	0.0	4911.2	310	10

Source: Own calculations, based on data from SIPO and NBS China

Model setup and estimation method

To test the assumptions made in Hypothesis 1 and Hypothesis 2, we employ a series of fixed-effects panel models, whose within estimators eliminate fixed effects by centering each variable on its individual-specific mean. Thus, we take into account any potential endogenous individual effects. A simple pooled OLS estimator would be biased in case models are subject to unobserved heterogeneity, which is correlated with the explanatory variables. Hence, we apply linear panel-data models that take into account our data structure and eliminate unobserved heterogeneity. The Hausman-Test showed that the random-effects assumption (explanatory variables are uncorrelated with province-specific effects) is violated and a random-effects model would lead to biased coefficients and standard errors. Hence, we opted for fixed-effects estimation. This stands to reason as time-variance is directly controlled for while the relevant remainder of uncontrolled for influences can be assumed to be province specific and time-invariant. On the contrary, correlations between effects that are not controlled must be considered the rule in regional analyses so that alternative random-effects estimators would be more biased and less efficient. Furthermore, we employ cluster robust standard errors by province to control for non-constancy in the residual variance of the variables in our regression model (White, 1980).

Fundamentally, we use the following linear panel-data model in all analyses:

$$y_{it} = x_{it}\beta + p_i + u_{it} \qquad i = 1,...,n \qquad t = 1,...T \quad (6)$$

where y_{it} is the explained variable of unit i in period t, x_{it} is a vector of explanatory variables, β is a coefficient vector, p_i is a province-specific effect and u_{it} idiosyncratic errors. On the basis of this fixed-effects estimator, we run a series of models to test the assumption made in Hypothesis 1 and 2.

In a first set of models addressing Hypothesis 1, we analyse the effect of the suggested variety measures (unrelated variety, related variety, LOS-index) on GDP levels, GDP per capita levels and GDP growth:

$$\begin{aligned} GDP_{it} &= \alpha_{1it}VM_{it} + \alpha_{2it}CosSimTechInd_{it} + x'_{it}\beta_{it} + p_i + u_{it} \\ GDPperCap_{it} &= \alpha_{1it}VM_{it} + \alpha_{2it}CosSimTechInd_{it} + x'_{it}\beta_{it} + p_i + u_{it} \\ GDPgrowth_{it} &= \alpha_{1it}VM_{it} + \alpha_{2it}CosSimTechInd_{it} + x'_{it}\beta_{it} + p_i + u_{it} \end{aligned} \quad (7)$$

with $i = 1,...,n \qquad t = 1,...T$

where GDP_{it} denotes a province's GDP, $GDPperCap_{it}$ its GDP per capita and $GDPgrowth_{it}$ denotes the growth of GDP between two years, in logarithmic expression ln(y_t / y_{t-1}). VM_{it} denotes the respective variety measure of unit i in period t and $CosSimTechInd_{it}$ the described measure of techno-economic fit. x_{it} is a vector of control variables (including period-specific controls as well as all the explanatory variables described above and in model specification (7)), p_i is a province-specific effect and u_{it} idiosyncratic errors.

In a second set of models addressing Hypothesis 2, the above variety measures (VM) as well as the measure of techno-economic fit are used as dependent variables to determine which factors have more recently become relevant for their emergence.

$$\begin{aligned} VM_{it} = {} & \alpha_{1it}Popdens_{it} + \alpha_{2it}GDP_{it} + \alpha_{3it}Expquot_{it} + \alpha_{4it}IndshareGDP_{it} \\ & + \alpha_{5it}Pat_{it} + \alpha_{6it}Gradperpop_{it} + \alpha_{7it}RD\mathrm{int}_{it} + \alpha_{8it}NewprodsalesGDP_{it} + x'_{it}\beta_{it} + p_i + u_{it} \end{aligned} \quad (7)$$

with $i = 1,...,n \qquad t = 1,...T$

where VM_{it} denotes the respective variety measure (the core variables) of unit i in period t, $Popdens_{it}$ and GDP_{it} are the population density of the province and its GDP, respectively. $Expquot_{it}$ denominates the export quota per province, $IndshareGDP_{it}$ is the share of industry in GDP as described above, while Pat_{it} and $Gradperpop_{it}$ are the total number of SIPO invention patent filings and the share of graduates per population. $RD\mathrm{int}_{it}$ and $NewprodsalesGDP_{it}$ denominate the regional R&D intensity and the ratio between new product sales and GDP. Furthermore, x_{it} is a vector of further control variables (in this model only period-specific controls), p_i is a province-specific effect and u_{it} idiosyncratic errors.

Robustness

To test for robustness, we re-ran all models in a specification with a one year time-lag on all regressors to control for potential endogeneity issues within the models. In addition, we re-estimated all Hypothesis 1 models for three different periods: 2007- 2016 (main models) 2007-2010, and 2011-2016 (cf. Table Annex 2). Typically, the introduction of lags did not affect the models substantially. Where analyses across different time periods resulted in different findings of analytical substance, these are highlighted in the results section and subsequently discussed. Furthermore, we tested instrumentation scenarios with available indicators that might fulfil basic criteria of instrument variables e.g. the Gini Coefficient across IPC classes (for GDP levels) or the level of R&D expenditure in the industry (for GDP per capita and GDP growth). These, too, were found to in part affect significance, but not usually the sign and direction of main effects. Ex-post Davidson-MacKinnon tests of exogeneity on these instrumented equations did, with rare exceptions, not suggest endogeneity issues.

5 Results

Hypothesis 1a

The analysis finds that the current level of **gross regional product** (referring, to an extent, to successful past growth trajectories), is significantly predicted by technological size effects (number of inventions), differences between centres and peripheries (population density) and the regional role of research and development (R&D intensity). In most cases, these control variables remain significant independent of the main measure of variety considered the period of measurement. With a view to the core variables, no measure of variety displays any explanatory power over the entire period, while the local fit between technological and economic structures is found relevant throughout (Table 3). Remarkably, however, low unrelated variety (that is, generic specialisation) did predict high GDP levels in the 2007-10 period while related variety comes close to displaying a significantly positive effect on GDP levels in the 2011-16 period ($p = 0.144$).

Hypothesis 1b

In contrast, **gross regional product per capita** depends positively on related variety across the entire period, supported in particular by significantly positive effects during the 2011-16 period, while, for the 2007-2010 period no such effect can be identified. Instead, a positive effect of generic specialisation (low unrelated variety) can be documented for that earlier period. Different from the findings for the level of GDP, however, the match between technological and economic capacities does not help to predict regional GDP per capita levels. Overall, technological size effects (number of inventions) are by far the most significant predictor. All else equal, there is also a negative relation between the regional export quota and regional GDP per capita.

Hypothesis 1c

Finally, **the log growth of the gross regional product** depends positively on regions' export quota as well as, once more, on technological size effects (number of inventions). Technological variety measures, in contrast, do not display any significant predictive power. Possibly, however, the local fit between technological and economic structures may have a certain (positive) influence as, in all models, it comes systematically close to significance at the 10% level. Overall, the key takeaway of these analyses is that, when controlling for many other factors, including trends over time, the structure of technological portfolios does not significantly relate to economic growth in a long-term perspective. Against this background, it appears relevant to at least document the quite different findings that emerge when the strict control for trends over time is released. While controls for yearly effects are generally advisable, one may question if they might - in this particular case - cancel out too much of the subject proper of the analysis. Thus it appears at least worth noting that both related variety and the adjusted LOS-index become robust, positive predictors of growth for the 2011-2016 period once year dummies are taken out of the equations - while no such effects could yet be identified for the 2007-2010 period (cf. Table Annex 3).

Table 3: Influence of variety measures and local techno-economic fit on aspects of regional economic development, 2007-2016

Models for Hypothesis 1	*dV: GDP*	*dV: GDP*	*dV: GDP*	*dV: GDP p Pop*	*dV: GDP p Pop*	*dV: GDP p Pop*	*dV: GDP Growth*	*dV: GDP Growth*	*dV: GDP Growth*
	M1.1a	**M1.1b**	**M1.1c**	**M1.2a**	**M1.2b**	**M1.2c**	**M1.3a**	**M1.3b**	**M1.3c**
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
unrelated variety	-1103.910			0.102			-0.030		
related variety		5313.581			2.599 **			-0.085	
LOS-Index (adj.)			-561129						0.062
cos-sim tech-ind	6718.199 **	5910.148 *	5882.552 *	-0.630	-0.818	-0.557	0.077 (0.127)	0.074 (0.110)	0.070 (0.130)
R&D Intensity	7151.221 **	6802.310 **	7574.657 ***	0.667	0.430	0.630	-0.021	-0.010	-0.020
invention patents	0.189 ***	0.191 ***	0.194 ***	0.000 ***	0.000 ***	0.000 ***	0.000 *	0.000 *	0.000 *
population density	-110.300 **	-104.872 **	-106.264 **	-0.003	-0.001	-0.003	0.000	0.000	0.000
share industry in GDP	-6501.409	-6699.627	-5161.869	1.873	1.883	1.764	0.424	0.417	0.421
graduates per population	32.424	31.333	41.061	-0.003	-0.005	-0.003	-0.001	-0.001	-0.001
export quota	-0.485	-0.048	1.050	-0.002 **	-0.002 **	-0.002 **	0.000 **	0.000 *	0.000 **
new product sales per GDP	0.286	0.233	0.223	0.000	0.000	0.000	0.000	0.000	0.000
Constant	5027.08	-10919.70	3631.47	1.731	-4.407	1.874	1.14 ***	1.27 ***	1.06 ***
Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
sigma_u	11554.68	11108.05	11236.91	2.146	2.388	2.246	0.054	0.040	0.051
sigma_e	-0.05	2266.18	2249.57	0.374	0.356	0.373	0.047	0.047	0.048
rho	-0.092	0.960	0.961	0.970	0.978	0.973	0.562	0.411	0.530
Number of regions covered	31	31	31	31	31	31	31	31	31
Observations	310	310	310	310	310	310	279	279	279
R^2 within	0.9032	0.904	0.9054	0.9244	0.9313	0.9248	0.6427	0.6438	0.6418
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Significance level: *P < 0.1, **P < 0.05, ***P < 0.01.

Source: own calculations, based on data from SIPO and NBS China

Hypothesis 2

In recent years following 2010, the level of regional **unrelated variety** is found to depend negatively on the level of overall patenting as well as on the export orientation of the regional economy and positively on the level of industrial new product sales per value added (GDP). In short, high levels of inventive activity and export orientation remain associated with specialisation in one a few broader IPC fields - while the presence of innovative industries seems to broaden the industrial basis in the generic terms of unrelated variety - relations that are equally found in the analysis across the entire time period. Remarkably, neither economic size nor regional R&D intensity display any significant effects as such.

Regional **related variety**, in contrast, has in recent years become strongly associated with a set of factors including high population densities, high wage bills and high shares of graduates per population. At the same time, it displays a negative association with the local share of industry in overall value added. As a tendency, therefore, related variety seems to be increasing emerging in urban, high wage, science-driven environments but less so in industrially dominated ones. Most importantly, however, these findings hold only for the 2011-16. Literally none of the listed effects can be identified in analysis for the 2007-10 or the complete time period.

Findings for the **adapted LOS-index** remained more or less stable over time. Overall, these seem to mirror the findings for unrelated variety in that the LOS-Index depends positively on high levels of inventive activity while the prevalence of industrial new product development has a de-concentrating effect. Beyond these similar findings, however, the adapted LOS-index also depends negatively on regions' overall wage bill and positively on regional R&D intensity - thus associating techno-economic development with higher diversity. In recent years, it has also become to depend positively on the number of graduates in the local population. In a sense, it thus assumes a position between unrelated and related variety.

The **regional cosine similarity** between technological and economic capacity, finally, depends positively on the technological size of a region (invention patents) as well as the local R&D intensity but negatively on the overall regional wagebill as well as on the level of industrial new product sales per value added. Additionally, it depends positively on the share of graduates in the population in recent years (2011-16).

Table 4: Association of regions' economic characteristics with variety measures and local techno-economic fit, 2007-2016 vs. 2011-16

Models for Hypothesis 2 coeffients multiplied by 10,000	*dV: Unrelated variety*		*dV: Related variety*		*dV: LOS-Index (adj.)*		*dV: cos-sim tech-ind*	
	M2.1a (total)	**M2.1a** (2011-16)	**M2.1b** (total)	**M2.1b** (2011-16)	**M2.1c** (total)	**M2.1c** (2011-16)	**M2.1d** (total)	**M2.1d** (2011-16)
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
wage bill	0.222	0.150	0.128	0.143 ***	-0.001 *	-0.001 *	0.066	-0.066
R&D Intensity	-1,091.6	-1,142.8	729.1 *	514.7	7.2 **	13.7 *	900.8 *	1,186.4 **
invention patents	-0.025 ***	-0.025 ***	-0.006	-0.002	0.000 *	0.000 ***	-0.002	0.007
population density	-11.521	-35.718	-6.747	48.331 **	0.039	0.260	7.991	-61.872 *
share industry in GDP	1,640	4,018	169	-2,773 *	25 *	-36	-1,342	-3,687
graduates per population	-7.021	-31.094	11.416	80.249 ***	0.061	0.857 ***	38.108	67.734 **
export quota	-2.136 ***	-3.533 **	-0.072	-0.824	0.020	0.017	1.774 (0.102)	0.326
new product sales per GDP	0.330	0.562 **	0.089	0.119	-0.001	-0.004 *	0.349 *	0.346 (0.141)
Constant	2.636 ***	2.871 ***	2.474 ***	2.087 ***	0.003 **	0.000	0.165	0.430 *
Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES
sigma_u	0.35	0.51	0.25	0.51	0.00	0.01	0.15	0.42
sigma_e	0.09	0.06	0.04	0.03	0.00	0.00	0.07	0.06
rho	0.936	0.986	0.971	0.997	0.934	0.989	0.835	0.981
Number of regions covered	31	31	31	31	31	31	31	31
Observations	310	186	310	186	310	186	310	186
R^2 within	0.191	0.193	0.1896	0.4449	0.1117	0.2735	0.2258	0.2344
Prob > F	0.005	0.088	0.000	0.000	0.000	0.000	0.001	0.004

Significance level: *P < 0.1, **P < 0.05, ***P < 0.01.

Source: own calculations, based on data from SIPO and NBS China

6 Discussion

Combining different sources of Chinese data in a novel manner, this paper provided a first comprehensive overview of central characteristics of China's provinces' technological portfolios as well as these portfolios' fit with industrial activities in their surrounding regional economies. For the first time, it has mapped established variety measures across all Chinese provinces, thus establishing a first foundation for analyses beyond of well-covered Western contexts.

In line with much of the literature on China, its analytical findings confirm a continued legacy of the country's initial, focused development trajectory around specialised technological poles (Kroll and Schiller, 2010; Liefner and Wei, 2014) evidenced in the prevalent association of generic specialisation and development in earlier years. Furthermore, it suggests that standard assumptions on technological portfolios' role in economic development do not hold in China, at least not beyond its key urban centres. Tellingly, related variety is found associated more with the quality (GDP per capita), much less the quantity (GDP level) of development. Futhermore, it confirms that the impact of technological portfolios' internal structure remains in many perspectives eclipsed by that their regional economic embedding. Across the entire time period, the fit between regions' economic and technological portfolios remains a more reliable predictor of economic development than any variety measure as such – while the LOS-index, as the most sophisticated measure, remains weakest among all.

Contrary to what the literature on Western countries might be taken to imply (Content and Frenken, 2016), GDP levels do not display any visible association with either related variety or technological coherence. Instead, the identified influences of unrelated variety and local fit during early phases resonate with existing literature on the initial build-up of selected technological sectors (Kroll and Schiller, 2010; Segal, 2003) or, reactively, capacities around the specific requirements of an export oriented industrial basis (Fu et al., 2012; Liefner and Wei, 2014; Wang et al., 2015).

Findings with a view to GDP per capita, in contrast, resonate with more recent studies' suggestions that China's trajectory of economic development may be transitioning to a different, more innovation driven mode (He et al., 2018; Guo and He, 2017; Peyman, 2018) – in particular where more efficient regional economies already support higher wages and thus higher GDP per capita levels.

At the same time, the dynamics of development remain solidly dependent on technological capacity per se (Kroll and Frietsch, 2014; Kroll, 2016), export orientation (Coe and Yeung, 2015) and are, if anything, weakly favoured by good matches of technological and economic capacity that help leverage potentials of an improved integration of regional innovation systems (Liu et al., 2018).

With a view to the most recent origins of technological variety, this impression of newly emerging, parallel dynamics finds additional confirmation. One notable finding in this respect is that the local fit between technological and industrial activities has become best in regions where capacities are high both on the academic (graduates per population) and the industrial side (R&D intensity) (cf. Liefner and Wei, 2014; Liu et al., 2018). Moreover, wealthy, urban environments with high levels of academic activity show an increasing propensity to develop and profit related variety as Zhang (2013) has suggested - a relation not yet detectable in pre-crisis times. In parallel, the fact that generic specialisation continues to depend on provinces' export quota and the overall level of inventive activities, suggests a continued role of existing structural legacies (Kroll, 2016; Guo and He, 2018). Even here, however, innovative dynamism and new product development in industry seem to work towards their gradual transformation - in line with what recent papers suggested (He et al., 2018).

From a meta-perspective, our study unveils that the dynamics of regional development within a globally important national innovation system relate to technological variety quite differently than those typically studied by the regional science literature (Content and Frenken, 2016). Zhang's (2013) finding that other factors remain crucially important besides related variety, even in innovative hotspots, still seems to hold six years onwards. Possibly, our finding that - in certain specifications - related variety and technological coherence begin to assume a role for growth provides first evidence that things are about to change. By and large, however, related variety seems to remain a function rather than a cause of techno-economic development, in its association with high GDP per capita levels as much as its more recent manifestation in leading environments. At an aggregate level, it must remain doubtful if it has so far played any substantial role for regional path development at all.

7 Conclusion

This paper sought to spur additional reflections on the foundations of existing studies on related and other forms of technological variety by applying known concepts and methodologies to the specific case of China's regional economies. Its main ambition was less to advance new methodologies of measurement in the technological space than to apply existing ones to a decidedly different economic context.

Its comparatively clear finding is that, under the framework conditions of a catching-up economy, regional development has less noticeably depended on variety in technological portfolios than often found for established economics, which, however, may be about to change in the future. Thus, this paper's findings are relevant for future research from a twofold perspective. First, they underline that while prior research has revealed important general principles of regional path development, their relevance remains strongly context specific. At earlier stages of economic development, different development logics may apply and in countries positioned differently in global value chains and in terms of institutions. In those, factors like external corporate decisions and macro-level political agency may superimpose local trajectories and inhibit the emergence of new dynamics at the micro-level. Second, however, they underlines that irrespective of this, all technological activities' relevance remains dependent on the local economic context into which they are placed. Even this paper's sketchy consideration of "goodness of fit" variables illustrates this point very clearly.

Accordingly, future studies should invest additional effort into acknowledging the presence of multiple and in part counteracting economic development logics in cross-national studies. In line with the findings of Boschma and Capone (2015) this may be relevant also for those studies that span different Western institutional systems. Pan-European datasets, for example, cover countries at very different development levels and with very different institutional settings. In those cases, a conscious inclusion of complementary explanatory or control variables may be advisable. In other words, renewed efforts to account for context and contingencies may improve and sharpen our understanding of the genuine effects of technological variety proper. Against that background, further studies should follow Content and Frenken's (2016) call for additional analysis of the effects of variety *in the technological space*.

In the context of China, in contrast, future research may want to invest further efforts into exploring the role and effects of emerging related variety in a reduced sample of well-developed regions and specific, leading urban environments for which this study found traces of swiftly advancing innovation-driven development. In those, more elaborate measures could be considered both as dependent variables and to capture technological variety. It would be interesting to see if, in the course of leading regions' transition to innovation driven economies, technological variety will eventually assume a similar role as in Western economies. On the one hand, technological advances suggest that the impact of micro-agency at the firm level might become strengthened - prompting an eventual of convergence of empirical findings. On the other hand, China's very different institutional system and continued political intervention into the economic process may well prevent that from happening.

Annex

Table Annex 1: Distribution of core variables across provinces (mean 2007-16)

Region	unrelated variety	related variety	adjusted LOS-index	cosinus similarity
Anhui	0.12	0.43	0.45	0.59
Beijing	-0.54	-1.44	-1.41	0.22
Chongqing	0.24	1.22	-0.24	0.91
Fujian	0.66	0.33	-0.67	0.43
Gansu	-0.61	0.00	0.47	-1.11
Guangdong	0.28	-0.63	-1.44	2.56
Guangxi	-0.80	0.26	0.67	-0.42
Guizhou	-0.49	0.26	0.74	-0.90
Hainan	-1.13	-2.01	0.79	-0.26
Hebei	0.57	0.65	0.03	0.01
Heilongjiang	0.37	0.00	-0.70	-1.11
Henan	0.42	0.47	-0.46	-0.04
Hubei	0.61	0.77	-0.76	0.11
Hunan	0.62	0.46	-0.36	1.18
Inner Mongolia	-0.06	-0.28	1.27	-1.21
Jiangsu	0.82	0.98	-0.20	2.03
Jiangxi	0.41	0.40	-0.39	0.01
Jilin	0.26	-0.84	-0.70	-0.10
Liaoning	0.44	0.80	-0.09	0.75
Ningxia	-0.14	0.52	1.20	-0.84
Qinghai	-0.55	-1.37	0.12	-0.95
Shaanxi	0.42	0.43	-0.90	-0.79
Shandong	0.37	-0.03	-0.73	1.23
Shanghai	0.47	-0.37	-1.19	2.03
Shanxi	0.50	0.48	-0.03	-1.48
Sichuan	0.57	0.32	-0.94	0.11
Tianjin	0.62	0.65	-0.65	0.91
Tibet	-1.39	-3.80	0.97	-1.37
Xinjiang	0.06	-0.73	0.29	-0.26
Yunnan	-0.53	-0.37	0.58	-0.58
Zhejiang	0.96	0.72	-0.55	0.86

Source: Own calculations, based on data from SIPO and NBS China

Table Annex 2: Alternative specification for Model 1.3 (2011-16; without year dummies)

Models for Hypothesis 1	*dV: GDP Growth*		*dV: GDP Growth*		*dV: GDP Growth*	
	M1.3a		**M1.3b**		**M1.3c**	
	Coef.		Coef.		Coef.	
unrelated variety	-0.108					
related variety			0.221	**		
LOS-Index (adj.)					14.579	**
cos-sim tech-ind	0.090		0.077		0.088	
R&D Intensity	-0.214	***	-0.217	***	-0.218	***
invention patents	0.000		0.000		0.000	
population density	0.001		0.001		0.001	
share industry in GDP	0.915	***	0.838	***	0.857	***
graduates per population	-0.003		-0.003		-0.003	
export quota	0.000	*	0.000		0.000	*
new product sales per GDP	0.000		0.000		0.000	
Constant	1.34		0.57		1.03	
Time Dummies	NO		NO		NO	
sigma_u	0.25		0.28		0.26	
sigma_e	0.06		0.06		0.06	
rho	0.945		0.954		0.950	
Number of regions covered	31		31		31	
Observations	186		186		186	
R^2 within	0.3764		0.3787		0.3811	
Prob > F	0.000		0.000		0.000	

Significance level: *P < 0.1, **P < 0.05, ***P < 0.01.

Source: Own calculations, based on data from SIPO and NBS China

Table Annex 3: Robustness checks of main models for Hypothesis 1

	iV: unrelated variety		iV: related variety		iV: LOS-Index (adj.)	
	Coef.		Coef.		Coef.	
Robustness checks M1.1						
dV: GDP, all iVs lagged by 1 year	-1265.641		5118.825		-584,851	
cos-sim tech-ind	6359.513	**	5633.180	*	5,803	*
dV: GDP, only years before 2010	-2868.078	***	-356.262		-124,929	
cos-sim tech-ind	7391.468	**	5383.859	(0.118)	5,273	(0.116)
dV: GDP, only years after 2010	1358.663		12938.170	(0.144)	-77,302	
cos-sim tech-ind	1122.146		1436.982		1,214	
dV: GDP , instrumented fe panel (instrument: IPC gini-coefficient)	-2067.238		-7430.308		4,589,694	
cos-sim tech-ind	5655.890	**	5777.024	**	8,687	
Robustness checks M1.2						
dV: GDP p Pop, all iVs lagged by 1 year	0.256		1.981	*	34.769	
cos-sim tech-ind	-0.630		-0.818	(0.141)	-0.557	
dV: GDP p Pop, only years before 2010	-0.314	*	-0.186		-19.943	
cos-sim tech-ind	0.188		-0.014		-0.122	
dV: GDP p Pop, only years after 2010	-0.072		2.214	**	41.761	
cos-sim tech-ind	-0.150		-0.132		-0.047	
dV: GDP p Pop , instrumented fe panel (instrument: R&D exp industry)	1.218		2.260		-274.12	
cos-sim tech-ind	-1.524	**	-1.395	**	-1.40	**
Robustness checks M1.3						
dV: GDP growth, all iVs lagged by 1 year	0.012		-0.058		3.125	
cos-sim tech-ind	0.039		0.047		0.044	
dV: GDP growth, only years before 2010	-0.046		-0.104		10.508	
cos-sim tech-ind	0.030		0.050		0.057	
dV: GDP growth, only years after 2010	-0.024		-0.023		2.068	
cos-sim tech-ind	0.083		0.027		0.029	
dV: GDP growth, instrumented fe panel (instrument: R&D exp industry)	0.187		0.497		-43.301	
cos-sim tech-ind	0.022		0.040		0.031	

Significance level: *P < 0.1, **P < 0.05, ***P < 0.01.

Source: Own calculations, based on data from SIPO and NBS China

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