Regional Entrepreneurship Capital and its Impact on Knowledge Diffusion and Economic Performance

David B. Audretsch, Werner Bönte and Max Keilbach

Abstract

We define a region’s capacity to generate firm start-ups as "entrepreneurship capital", which is an unobservable, hence latent variable. We then investigate the impact of this regional capital on regional economic performance, based on data for German Regions. We use a latent variable approach (LISREL) to do so. We find that entrepreneurship capital has a positive impact on regional economic performance. At the same time we find evidence that knowledge oriented measures drive entrepreneurship. Hence our empirical model provides evidence that entrepreneurship plays an important role in the knowledge spillover process.

JEL-Codes: M13, O32, O47
Keywords: Innovation, Entrepreneurship, Economic Output, Structural Equation Modeling

1 Introduction

The role and perception of entrepreneurship in society has changed strongly over the last half century. During the post-World War II era, the importance of entrepreneurship and small businesses seemed to be fading away. However, this trend has reversed in recent years. While in the US, the relative importance of SMEs, measured through average GDP per firm, decreased between 1947 and 1980, it has reincreased since then (Brock and Evans, 1989; Loveman and Sengenberger, 1991; Acs and Audretsch, 1993). Similar evidence is found when considering only the manufacturing industry (Acs and Audretsch, 1990). This trend reversal was not limited to North America. Audretsch et al. (2002) report that business ownership rate in the Netherlands decreased systematically until the beginning of the 1980’s only to rise again since then. The same trend is
found when measuring the importance of Dutch SMEs though employment
shares (EIM, 2002). Similar evidence has been found for Western Germany,
Portugal and Italy (Acs and Audretsch, 1993; Audretsch and Thurik, 2001).

Together with this increase in the economic importance, the perception
of entrepreneurship in society and public policy is increasing as well. Today,
it is difficult to identify a region or a state that does not offer some form of
entrepreneurship policy (e.g. Storey, 2003) or some form entrepreneurship price.
The rationale behind these policies is the belief that entrepreneurship is able
to create new jobs in new technological fields, therefore generate structural
adjustments in the economy and ultimately create economic growth.

Audretsch and Keilbach (2005) argue that entrepreneurship plays an im-
portant role in the process of knowledge spillovers. Arrow (1962b) states that
knowledge as an input to production is inherently different to the more tradi-
tional inputs such as labor and capital. This is for two reasons. 1) Knowledge
has a public goods characteristic and 2) the economic value of knowledge is
intrinsically uncertain and its potential value is asymmetric across economic
agents.

While the first aspect has been addressed and formalized within the en-
dogenous growth theory (Arrow, 1962a; Lucas, 1988; Romer, 1990, p.S73), the
second one has not. Rather, the endogenous growth theory implicitly assumes
that knowledge, once it has been generated, spills over more or less “automati-
cally” to other firms. However, transforming generally available new economic
knowledge into viable new products or technologies – the essence of knowledge
spillovers – requires investments with uncertain outcomes and therefore bears
risks.

Often, this investment is made by entrepreneurs. By starting up a business,
an entrepreneur literally “bets” on the product he offers (or will be offering)
and thus is willing to shoulder the risk that this process bears. He or she do
so, since they believe that the potential returns are greater than the potential
losses. The economic implication of that process is transformation of generally
available knowledge into a new product. Hence entrepreneurship can be con-
sidered as an important, though in our view neglected mechanism in the trans-
mition of knowledge and the actual spillover process. Acs et al. (2003) refer to
the gap between knowledge and commercialized knowledge as the ‘knowledge
filter’. By commercializing ideas that otherwise would not be pursued and com-
mercialized, entrepreneurship serves as one mechanism facilitating the spillover
of knowledge. Thus, entrepreneurship capital promotes economic performance

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1 This view has been challenged by the literature on absorptive capacity (Cohen and
by serving as a conduit of knowledge spillovers.

Baumol and Oates (1988) distinguishes this entrepreneurial function explicitly from the role of larger incumbent corporations who are rather engaged into routinized processes of large scale innovation. While these processes are quantitatively more important in that R&D expenditure and the number of patents generated are larger, a number of systematic studies have provided evidence that breakthroughs and new products are rather introduced by small and young firms, i.e. by entrepreneurs.\(^2\) In that sense Baumol and Oates (1988) refers to innovation as an integrated process based on a division of labor between small firms, who launch new products and introduce new technologies, and large firms, who take on these ideas and develop them. Hence entrepreneurial firms and large firms coexist in what Baumol (2002) calls a “David-Goliath Symbiosis”. In that respect, entrepreneurship plays an important role for the economic dynamics and for the growth process of an economy.

By taking on the risk of developing this uncertain knowledge, entrepreneurs increase the amount of utilized knowledge spillovers. Hence this function of risk taking is an important one in the innovation process. In that spirit, the OECD (1998) states that

> Entrepreneurs are agents of change and growth in a market economy and they can act to accelerate the generation, dissemination and application of innovative ideas. Entrepreneurs not only seek out and identify potentially profitable economic opportunities but are also willing to take risks to see if their hunches are right

However the idea that entrepreneurs play an important economic function by taking on risks is certainly not new. In the 4th book of his *Principles*, Marshall (1920) considered four “agents of production”: land, labor, capital and organization. He understood “organization” in a structural sense (i.e. in the sense that the notion “industrial organization” reflects) but also in the sense of an activity. Referring to entrepreneurs as “business men” or “undertakers” he states that:

> They [i.e. the entrepreneurs] “adventure” or “undertake” its risks [i.e. the risks of production]; they bring together the capital and the labour required for the work; they arrange or “engineer” its general plan, and superintend its minor details. Marshall (1920, p. 244)

In this respect, the Marshallian “something in the air” (Marshall, 1920, p. 225) that is usually cited in connection with spatial knowledge spillovers\(^3\) does

\(^2\)e.g. Scherer (1980) or CHI Research Inc. (2002). The U.S. Small Business Administration (1995, p.114) enumerates some 70 important innovations by small firms in the 20th century, ranging from low-tech innovations such as the Zipper or Bakelite to high-tech ones such as the Nuclear Magnetic Resonance Scanner or the Microprocessor.

\(^3\)See Keilbach (2000, Chapter 3) for a review.
also apply to a regional culture of risk preference and entrepreneurial behavior. In that respect, entrepreneurial behavior can be considered as a capacity of the region to generate entrepreneurship. We define this capacity as the regions’ entrepreneurship capital. It is the regional milieu of agents and institutions of an economy, a region or a society that is conducive to the creation of new firms. This involves a number of aspects such as social acceptance of entrepreneurial behavior but of course also individuals who are willing to deal with the risk of creating new firms and the activity of bankers and venture capital agents that are willing to share risks and benefits involved. Hence entrepreneurship capital reflects a number of different legal, institutional and social factors and forces. Regions with a high degree of entrepreneurship capital facilitate the startup of new firms based on uncertain and asymmetric ideas. On the other hand, regions with a low degree of entrepreneurship capital impede the ability of individuals to start new firms. Entrepreneurship capital promotes the spillover of knowledge by facilitating the startup of new firms.

As such, entrepreneurship capital is unobservable and can be considered as a latent variable (e.g. Bartholomew and Knott, 1999). The model to be presented in the next section 2 can explicitly deal with this kind of variables. Furthermore, it allows us to investigate the role of entrepreneurship in increasing the permeability of the knowledge filter. As we argued above, entrepreneurial activity increases the utilization of new knowledge which has been created by incumbent firms. If this argument holds, it is important to distinguish the direct effect of knowledge on economic performance from the more indirect effect of knowledge that is taken on by newly started firms which in turn increase the economic performance. The econometric model which is described in more detail in the following section takes this distinction into account.

The aim of this paper is to investigate empirically the relationship between regional innovative activities, entrepreneurship and economic performance for West-German counties. In particular, we examine whether creation of new technological opportunities through past innovative activities of incumbent firms does lead to an increase in the productivity of a region’s manufacturing sector. In doing so, we distinguish between direct and indirect effects. The latter will occur if technological opportunities positively influence the regions’ entrepreneurship capital and in turn productivity. In contrast to previous empirical studies in this field of research we do not employ ‘classical regression analysis’ but make use of the LISREL method. This is a statistical structural

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4In that respect the notion of entrepreneurship capital is close to the one of social capital (e.g. Putnam, 1993), though not identical. See Audretsch and Keilbach (2004a) for an in-depth discussion of this issue.
modeling method that allows us to estimate causal relationships among latent variables, like knowledge, entrepreneurship capital and productivity.

The paper is arranged as follows: In the following section 2 we describe the empirical model used in this study and present the data. Section 3 discusses the empirical findings and section 4 concludes the paper.

2 Model and Data

We aim at investigating the relationship between technical knowledge, entrepreneurship capital and the level of productivity at the regional level. Based on the theoretical considerations discussed in the introductory section we developed a path model where the arrow (1) indicates the assumed direct effect from ‘technical knowledge’ on ‘productivity’ (see figure (einfügen)). However, this direct impact has been examined in a number of empirical studies (see, for, instance ???). We contribute to the literature by explicitly analyzing the indirect effect of ‘technical knowledge’ which is illustrated by arrows (2) and (3). Arrow (2) indicates the (assumed) positive impact of ‘technical knowledge’ on entrepreneurship capital which in turn may positively affect productivity, arrow (3).

Since technical knowledge, entrepreneurship capital and economic performance are hypothetical constructs we treat them as latent variables which cannot be perfectly measured by one indicator but can merely be measured imperfectly by multiple indicators. Hence, we take measurement errors into account. In order to analyze linear causal relationships among the variables we make use of structural equation modelling (SEM) with latent variables. We use the statistical package LISREL which allows us to estimate parameters of the equation system and to present statistical tests for the direct and indirect effects of technical knowledge. For a detailed description of LISREL refer to Appendix A.

Sample: To estimate this model we make use a data from 310 West-German counties or Kreise. The counties are the smallest geographical units for which data of interest can be obtained. One might have doubts, however, whether counties are the appropriate geographical units for our purpose. It could be argued, for instance, that the institutional background, like propriety rights or administrative barriers, which is important for the ability of individuals to start new firms is country- or state-specific rather than county-specific. Then, one would expect a high variation of entrepreneurship capital between countries or states but not between counties. Our data, however, show a lot of variation at the county level suggesting that the endowment with entrepreneurship capital
is at least to some extent county-specific.

**Entrepreneurship Capital:** Observed indicators for this latent variable are cumulated numbers of startups in high-tech or ICT industries within a county in the years 1998 to 2000, relative to the county’s population. Thus, we assume that the entrepreneurship intensity is the higher the the higher the level of the latent variable ‘entrepreneurship capital’ is. A high-tech industry is defined as one whose share of R&D employment in total employment is above 2.5%, ICT industries comprise products and services that are related to information and communication technologies. For a further discussion of this measure see Audretsch and Keilbach (2004b).

**Productivity:** The observed indicators for the latent variable productivity are the level of average labor productivity (output/labor input) and the level of average capital productivity (output/capital input) in a region’s manufacturing sector. This latent variable is related to well-known measures of total factor productivity (TFP) because the productivity of both, labor as well as capital inputs, is taken into account (see Solow, 1957). However, while one has to make restrictive assumptions about the payment of inputs and the degree of competition when computing traditional TFP measures, this is not the case for our approach. We have restricted our attention the productivity of the manufacturing sector because the bulk of private innovation efforts is is performed within this sector and we therefore expect the direct as well as indirect effects of technical knowledge on productivity to be stronger in the manufacturing sector than in other sectors.

**Output** is measured as Gross Value Added in year 2000 of the manufacturing industries corrected for purchases of goods and services, VAT and shipping costs. The stock of **Physical Capital** used in the manufacturing sector of the Kreise has been estimated using a perpetual inventory method, which computes the stock of capital as a weighted sum of investments done in the producing sector in the period 1980 to 2000. For a more detailed description of this procedure see e.g. Audretsch and Keilbach (2004b). Statistics including Output and investment are published every two years on the level of Kreise by the Working Group of the Statistical Offices of the German Länder, under “Volkswirtschaftliche Gesamtrechnungen der Länder”. **Labor** is expressed as the number of employees in the manufacturing industries in 2000. This data is published by the Federal Labor Office, Nürnberg that reports number of employees liable to social insurance on the Level of German counties.

**New Knowledge:** In empirical practice it is common to use R&D efforts or patents to proxy for a region’s innovative activity. While R&D may be regarded as an input, patents tend to measure the innovative output. However, not all
the innovative output is patented by firms (Griliches, 1990). We make use of both indicators. The observed indicator for latent variable ‘innovation input’ (R&D) is a region’s \textit{R&D Intensity}, which is measured as the number of non-public R&D-employees in all industries relative to our measure of labor for the years 1987, 1991 and 1995. This data has been provided by the Stifterverband für die Deutsche Wissenschaft. The observed indicators for the latent variable ‘innovation output’ (\textit{technical knowledge}) is a region’s number of patents relative to our measure of labor. We use German patent data for the years 1995 and 1996. This data is taken from Greif and Schmiedl (2002). These proxy measures for knowledge are taken for periods earlier than 1998 since it is unlikely that R&D takes an immediate effect on entrepreneurship capital and output.

3 Empirical Findings

In this section we present the results of a maximum likelihood estimations of variants of the model described in section 2. Since by its very nature the structure of the model is more complex than that of the general linear model, it is convenient to display the results in graphical form. For a more detailed estimation results refer to the tables in Appendix B.

Figure 1 shows the impact of latent variable ‘technical knowledge’ where the observed indicators of this variable are the patent intensities in 1995 and 1996 (model A).\(^5\) Figure 2 is based on the same structure as the previous model (Figure 1), however this time, we use an \textit{input}-measure of innovation, namely the regional R&D-intensity (model B). Figure 3 combines the two previous models, thus mapping the innovation process from R&D input to innovation output (patents) and then to productivity. \textit{Entrepreneurship capital} is now modelled as to benefit from innovation inputs as well as from innovation outputs (model C). To maintain readability in Figure 3, we skipped the measurement variables, depicted as circles in Figures 1 and 2.

The estimations results for models A, B and C suggest that a region’s technical knowledge has a direct, positive and significant impact on productivity of the manufacturing sector. Moreover it is also positively linked to the a region’s entrepreneurship capital, which in turn seems to increase the level of productivity of the manufacturing sector. All these relations are measured positive and statistically significant.

Global fit indicators suggest that the models fit the data very good (see tables 1, 2 and 3 in Appendix B). The \(\chi^2\)-statistic of model A is 8.31 (\(P=0.21\)) at 6 degrees of freedom, that of model B is 13.28 (\(P=0.210\)) at 10 degrees of

\(^5\) All values of the indicators are transformed to logarithms.
freedom and that of model C is 34.95 (P=0.029) at 21 degrees of freedom. RMSEA (Root Mean Squared Error of Approximation) is below 0.05 for all three models which means a very good fit. Moreover, the Adjusted Goodness of Fit Index (AGFI) is 0.95 or higher for all models where values above 0.9 indicate a very good fit.

Figure 1: Technical Knowledge, Entrepreneurship Capital and Productivity in the Manufacturing Sector: Model A

Figure 2: Technical Knowledge, Entrepreneurship Capital and Productivity in the Manufacturing Sector: Model B

We turn now to the discussion of the direct effects, the indirect effects as well as the total effects of exogenous and endogenous latent variables.  

6P denotes the p-value or exact significance level. See Appendix A for the details of global fit indicators.

7Computation of total and indirect effects is described in Appendix A.
Figure 3: Technical Knowledge, Entrepreneurship Capital and Productivity in the Manufacturing Sector: Model C

In model A the estimated direct effect of the latent variable ‘innovation output’ on the latent variable ‘productivity’ is 0.10 (with a t-value of 6.48) and the indirect effect on productivity via entrepreneurship capital is 0.02 (with a t-value of 2.36). Consequently, the total effect of an increase in technical knowledge on productivity is 0.12 with a t-value of 8.07, i.e. significant at \( \alpha = 0.01 \). Thus an increase in technical knowledge (‘innovation output’) by one percent leads to an increase in productivity by 0.12 percent.  

In model B the estimated direct effect of the latent variable ‘innovation input (R&D)’ is 0.05 (with a t-value of 2.42) and the indirect effect on productivity is 0.03 with a t-value of 2.84. The total effect of an increase in the latent variable ‘innovation input (R&D)’ is estimated as 0.08 (with a t-statistic of 5.37). As this model makes evident, the direct impact of ‘innovation input (R&D)’ on productivity of the manufacturing sector is weakly significant whereas there is a strong positive and significant impact on the regions’ entrepreneurship capital. Hence a region’s entrepreneurship capital seems to increase the impact of industrial R&D on productivity substantially.

In model C the total effect of the exogenous latent variable ‘innovation input (R&D)’ on productivity – passing through the creation of knowledge and the creation of new firms – is estimated at 0.05 (with a t-statistic of 5.35, hence significant at \( \alpha = 0.01 \)). Its direct effect on entrepreneurship capital is estimated at 0.28 (with a significant t-statistic of 8.32) and its direct impact on innovation output is 0.31 (with a significant t-statistic of 5.91). We have also postulated a direct link between the latent variable ‘innovation input’ and the latent variable ‘productivity’ but this is not statistically significant.

The total effect of the endogenous variable ‘innovation output’ on endogenous latent variable ‘productivity’ – direct as well as indirect through its impact

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8Note, that all values of the observed indicators are transformed to logarithms.
9This corresponds with OLS and 3SLS estimates that we report elsewhere (Audretsch and Keilbach, 2004b, 2005).
on entrepreneurship capital – is estimated at 0.11 (with a significant t-statistic of 7.47). This corresponds with the finding of model A (Figure 1) in that entrepreneurship capital increases the impact innovation output.

It is interesting to note that the latent variables ‘innovation input’ and ‘innovation output’ seem to have a separate and identifiable impact on entrepreneurship. We have also tested a model where patents and R&D are assumed to be indicators of the same latent variable ‘technical knowledge’ but the global fit indicators suggest that they are indicators of two distinct latent variables. Thus, both innovation input and innovation output may capture different aspects (channels) of knowledge diffusion and may thus be conducive to entrepreneurial activity in the high-tech and ICT industries. Hence if an analysis considers only the impact of innovation input on regional innovation output, it would strongly underestimate the impact of R&D.

Hence we identify two channels how knowledge has an impact on productivity of a region’s manufacturing sector. On the one hand, parts of the technical knowledge in a region is taken on by incumbent firms, increasing productivity of a region’s manufacturing sector directly. On the other hand, parts of that technical knowledge is taken on by newly created firms who in turn increase the level of productivity as well. Note however that both trajectories describe distinct processes. While new knowledge within incumbent firms increases the level of productivity within the existing production process, entrepreneurial activity increases it through the creation of new firms.

4 Summary and Conclusion

In this paper, we ask “What is the contribution of entrepreneurship to the dissemination and utilization of new technical knowledge?” and then “What is the impact of this process on regional economic performance?” While the endogenous growth theory assumes knowledge to spill over automatically to all existing firms, we argue that this is actually not the case since new economic knowledge is intrinsically uncertain. Therefore, developing new knowledge is risky and new knowledge is not fully transformed into new products by incumbent firms. This creates opportunities for newly created firms to develop new products on the basis of this “unused” new knowledge. Entrepreneurs are agents who shoulder this risk and by this process increase the yield of new knowledge; hence entrepreneurship is one mechanism in the process of knowledge spillovers.

Seen through the lens of endogenous growth theory, this arguments define

10 Scatter plots of the observed indicators R&D and patents show that these are not very strongly correlated.
several mechanisms. First, while new knowledge will increase the economic performance of an economy or a region, it will not do so at full extent. Parts of the new knowledge will be taken on by entrepreneurs, hence new knowledge will increase the level of entrepreneurship in an economy or a region. Second, by this very process, entrepreneurship will increase the exploitation of new knowledge and as such have a positive impact on regional economic performance. Thus, we suppose that new knowledge has a direct positive effect on regional economic performance and an indirect positive effect via entrepreneurial behavior. Since both mechanisms are closely intertwined, we aim to model them simultaneously. A straightforward way to do so is by referring to structural equation modeling, an approach that allows for reciprocal causation, simultaneity and interdependence.

A second reason to use this approach is as follows. We denote the capacity of an economy or a region to generate firm start-ups as *entrepreneurship capital*. This concept covers political as well as institutional, economic and personal characteristics. As such, entrepreneurship capital is an unobservable hence latent variable. Structural equation modeling based on the *LISREL* estimation approach which allows to explicitly deal with this type of variable.

Using data for 310 West-German counties, we test the above hypotheses using different proxies for new technical knowledge, one being input oriented (R&D) one rather output oriented (patents). Using the LISREL method, we obtain the following results. First, new knowledge has a positive and significant impact on economic performance. Moreover, new knowledge has a significant positive impact on the regions’ entrepreneurship capital which in turn has a significant positive impact on economic performance. Hence we can indeed identify knowledge to increase the regions’ entrepreneurship capital and moreover that entrepreneurship capital to increase the regions’ economic performance. Thus we find evidence for the above hypotheses.

A straightforward policy implication would be that in a knowledge based economy it is not sufficient to focus policies to generate stronger economic growth on the generation of new knowledge. Equally important is the exploration and use of new knowledge. Entrepreneurship is one mechanism that goes in that direction. Thus entrepreneurship policies can be one mechanism to solve the “European Paradox” that has been mentioned by the EU Commission in their December 1995 Green Paper On Innovation and which states that while Europe is strong in its innovation process, it is comparatively weak in exploring that new knowledge and transforming it into economic growth.
A Appendix: LISREL Approach

LISREL (Jöreskog and Sörbom, 2001) is a statistical package developed for analyzing linear structural relationships among latent or unobserved variables (concepts). Like multiple regression analysis, it can be used to estimate the parameters in linear equations. In contrast to the former, however, structural equation modeling (SEM) allows for analyzing relationships among latent variables taking into account, for instance, the existence of multiple indicators for each latent variable, measurement errors, reciprocal causation and correlated error terms. Hence, multiple regression can be seen as a special case of SEM. The more flexible assumptions of SEM compared to multiple regression are an important advantage for the analysis of the relationship between such variables.

LISREL requires to classify all latent variables as either endogenous or exogenous. A variable is exogenous if it only causes other variables of the model but is itself never affected by other variables. A variable is endogenous if it is directly caused or influenced by at least one of the other variables (Hayduk, 1987). LISREL consists of a structural equation model and measurement model which we will briefly explain.

**Measurement model:** The LISREL approach differentiates between latent variables and observed indicators. The values of the observed indicator variables are assumed to be determined by the underlying latent variable and the measurement model links the endogenous (exogenous) latent variables to observable endogenous (exogenous) indicators $y(x)$

\[
y = \Lambda_y \eta + \varepsilon
\]

\[
x = \Lambda_x \xi + \delta
\]

where $\Lambda_y$ and $\Lambda_x$ are the matrices of unknown parameters, or loadings, $(\lambda_{yi}^y)$ and $(\lambda_{xi}^x)$ that represent the structural coefficients and $\varepsilon$ and $\delta$ are the vectors of errors. Thus, the measurement model takes measurement errors explicitly into account. Controlling for measurement errors allows us to obtain unbiased estimates of the structural coefficients.

Note, in order to assign each latent variable to a metric the value of the respective structural coefficient $(\lambda_{yi}^y, \lambda_{xi}^x)$ is set to one. In other words, the selected indicator is the reference item and the respective latent variable is measured in units of this reference item.  

However, this does not affect the sign and the significance of the estimated coefficients. 

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Structural equation model: The following equation comprises all direct effects between the endogenous and exogenous variables:

\[ \eta = B\eta + \Gamma \xi + \zeta \]  

where \( \eta \) is the vector of endogenous latent variables (in our case economic performance and entrepreneurship capital), \( \xi \) is the vector of exogenous latent variables (endowment with knowledge), \( B \) is the matrix of unknown parameters \( (\beta_{ii}) \) that reflect the effect of endogenous concepts on each other, \( \Gamma \) is the matrix of unknown parameters \( (\gamma_{ii}) \) which reflect the influence of the exogenous variables on the endogenous variables and \( \zeta \) is an error variable. It is also possible to compute the total and the indirect effects of latent variables. The total effect of a change in the exogenous latent variables \( \xi \) is given by: \((I - B)^{-1}\Gamma\) and their indirect effect is: \((I - B)^{-1}\Gamma - \Gamma\).

Model implied covariance and estimation of parameters: It is assumed that random components in the model satisfy the following assumptions

- \( \epsilon \) is uncorrelated with \( \eta \)
- \( \delta \) is uncorrelated with \( \xi \)
- \( \zeta \) is uncorrelated with \( \xi \)
- \( \zeta, \epsilon \) and \( \delta \) are mutually uncorrelated

and the model-implied covariance matrix written in terms of model parameters is given by

\[
\sum = \begin{pmatrix}
\sum_{yy} & \sum_{yx} \\
\sum_{xy} & \sum_{xx}
\end{pmatrix}
= \begin{pmatrix}
\Lambda_y(I - B)^{-1}(\Gamma\Phi\Gamma' + \Psi)(I - B')^{-1}\Lambda_y' + \Theta_\epsilon & \Lambda_y(I - B')^{-1}\Gamma\Lambda_x' \\
\Lambda_x\Phi\Gamma'(I - B')^{-1}\Lambda_y' & \Lambda_x\Phi\Lambda_x' + \Theta_\delta
\end{pmatrix}
\]

where \( \Phi \) is the matrix of covariances among the exogenous latent variables, \( \Psi \) is the matrix of covariances among the residuals in equation (3) and the matrices \( \Theta_\delta \) and \( \Theta_\epsilon \) contain the covariances among the errors of the equation (2) and (1).

It is the purpose to estimate the parameters of the model from the sample covariance matrix \( S \). The maximum likelihood estimates of the model parameters are obtained by minimizing the following fit function.
where p (q) are the numbers of the observed indicators of latent endogenous (exogenous) variables. In other words, maximum likelihood estimation provides parameter values which have the greatest chance of reproducing the observed sample covariance matrix.

**Model fit and model development:** The fit of a model reflects the extent to which the covariance matrix predicted by the model corresponds to the sample covariance matrix. The overall fit of a model is often judged by the chi-square ($\chi^2$) measure. Its computation is based on the differences between observed covariance matrix and the one estimated on the assumption that the model being tested is the true model. In principle, the $\chi^2$-measure can be used as a test-statistic where p-values below 0.05 imply a rejection of the model. However, Jöreskog and Sörbom (2001) state that the chi-square test should be regarded as a goodness-of-fit measure in the sense that large chi-square values correspond to a bad fit and small values to a good fit. Alternatively, the RMSEA (Root Mean Squared Error of Approximation) or the Adjusted Goodness of Fit Index (AGFI) may be used as supplementing global measures. If the fit of the model is very good, the value of the former is lower than 0.05 and the value of the latter exceeds the value 0.9.

In order to improve the model fit ‘modification indexes’ can be used which are a univariate form of the Lagrange Multiplier test. The modification index of each fixed parameter measures the predicted decrease in $\chi^2$ if this parameter restriction is relaxed. The usual procedure is to relax only one parameter at a time and as a rule of thumb those parameters should be relaxed which have modification indices above 7 indicate. Moreover, such a modification should be in line with the underlying theory.
<table>
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<tr>
<th>latent variables</th>
<th>observed variables</th>
<th>Parameter</th>
<th>Estimate</th>
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<td>$\theta_{44}^c$</td>
<td>0.10</td>
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</tr>
<tr>
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<td></td>
<td>$\theta_{11}^d$</td>
<td>0.03</td>
<td>(0.01)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\theta_{22}^d$</td>
<td>0.03</td>
<td>(0.01)</td>
</tr>
</tbody>
</table>

$\chi^2$ 8.31 P=0.21  
d.f. 6  
AGFI* 0.97  
RMSEA** 0.035

Notes: *Adjusted Goodness of fit index,**Root Mean Squared Error of Approximation.

B Appendix: Estimation Results
Table 2: Estimation Results: Model B

<table>
<thead>
<tr>
<th>Latent Variables</th>
<th>Observed Variables</th>
<th>Parameter</th>
<th>Estimate (S.E.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge ($\xi$)</td>
<td>R&amp;D 87</td>
<td>$\lambda_{11}$</td>
<td>0.95 (0.05)</td>
</tr>
<tr>
<td></td>
<td>R&amp;D 91</td>
<td>$\lambda_{21}$</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>R&amp;D 95</td>
<td>$\lambda_{31}$</td>
<td>1.11 (0.10)</td>
</tr>
<tr>
<td>Productivity ($\eta_1$)</td>
<td>labor productivity</td>
<td>$\lambda_{31}$</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>capital productivity</td>
<td>$\lambda_{41}$</td>
<td>0.48 (0.27)</td>
</tr>
<tr>
<td>Entrepreneurship capital ($\eta_2$)</td>
<td>high-tech start ups</td>
<td>$\lambda_{12}$</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>ict start ups</td>
<td>$\lambda_{22}$</td>
<td>0.77 (0.05)</td>
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<tr>
<td></td>
<td></td>
<td>$\beta_{12}$</td>
<td>0.09 (0.03)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\gamma_{11}$</td>
<td>0.04 (0.02)</td>
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<tr>
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<td></td>
<td>$\gamma_{21}$</td>
<td>0.34 (0.04)</td>
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<td>$\text{var}(\zeta_1)$</td>
<td>0.03 (0.02)</td>
</tr>
<tr>
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<td>$\text{var}(\zeta_2)$</td>
<td>0.13 (0.02)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\theta_{11}$</td>
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<td>$\theta_{33}$</td>
<td>0.00 (0.02)</td>
</tr>
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<td>$\theta_{44}$</td>
<td>0.11 (0.01)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\theta_{11}$</td>
<td>0.28 (0.05)</td>
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<tr>
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<td>$\theta_{22}$</td>
<td>0.56 (0.07)</td>
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<td>$\theta_{33}$</td>
<td>0.32 (0.06)</td>
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<td>$\theta_{21}$</td>
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<table>
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<tr>
<th>$\chi^2$</th>
<th>13.28</th>
<th>$P=(0.21)$</th>
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<td>d.f.</td>
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<tr>
<td>AGFI$^*$</td>
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<tr>
<td>RMSEA$^{**}$</td>
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Notes: After initial estimation we relaxed the zero restriction on $\theta_{21}$ since modification indices suggested that this improves the fit of the model.

$^*$Adjusted Goodness of fit index,$^{**}$Root Mean Squared Error of Approximation.
<table>
<thead>
<tr>
<th>latent variables</th>
<th>observed variables</th>
<th>Parameter</th>
<th>Estimate</th>
<th>(S.E.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge ($\xi$)</td>
<td>R&amp;D 87</td>
<td>$\lambda_{11}$</td>
<td>0.95</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Input</td>
<td>R&amp;D 91</td>
<td>$\lambda_{21}$</td>
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</tr>
<tr>
<td></td>
<td>R&amp;D 95</td>
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<tr>
<td>Knowledge ($\eta_1$)</td>
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<td>Output</td>
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<td>$\lambda_{54}$</td>
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<tr>
<td>Productivity ($\eta_2$)</td>
<td>labor productivity</td>
<td>$\lambda_{61}$</td>
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<tr>
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<td>capital productivity</td>
<td>$\lambda_{61}$</td>
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<td>(0.24)</td>
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<tr>
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<tr>
<td></td>
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<td>$\beta_{13}$</td>
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<td>(0.02)</td>
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<td>$\gamma_{21}$</td>
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<td>(0.03)</td>
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<td>$\gamma_{31}$</td>
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<td>(0.05)</td>
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<td></td>
<td>$\text{var}(\zeta_1)$</td>
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<td>$\text{var}(\zeta_2)$</td>
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<td>$\text{var}(\zeta_3)$</td>
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</tr>
</tbody>
</table>

$\chi^2$ 34.95  $P=(0.029)$
d.f. 21
AGFI* 0.95
RMSEA** 0.045

Notes: *Adjusted Goodness of fit index, **Root Mean Squared Error of Approximation.
References


