Integrating Technical Knowledge and Entrepreneurial Skills in Production: A Deconfounding Approach

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Abstract

We propose a model integrating technical, knowledge, and entrepreneurial skills, accounting for potentially unique resources and competitive advantages. This model is operationalized using data from the World Bank (1998–2018). We pay particular attention to deconfounding, which removes potentially spurious correlations and specification bias, thereby allowing for a causal interpretation. Our approach includes global and local production of technical knowledge and entrepreneurial skills, as well as the internal appropriation of globally available knowledge and entrepreneurial expertise within firms. The model is contextualized by modelling its parameters as functions of several underlying fundamental social constructs. Our primary findings reveal that both local and global knowledge enhance productivity and efficiency in production, new knowledge generation, and entrepreneurship. Furthermore, our results underscore the substantial influence of social context on these formative processes.

Key Words: Technical Knowledge; Entrepreneurship; Innovation; World Bank Data; Deconfounding.

1 Introduction

The importance of knowledge in economics, operational research, and business outcomes is widely recognized, with numerous scholars highlighting the crucial role of innovation in knowledge creation (Audretsch and Mahmood, 1994; Cefis and Marsili, 2005; Cefis and Marsili, 2006; Helmers and Rogers, 2010; Baum et al.2019; Murakami, 2024). Two different schools of thought pioneer this type of research: the Schumpeterian perspective, which posits that firms with a substantial internal knowledge reservoir excel in generating novel insights, and the Marshallian viewpoint According to the Schumpeterian notion (Schumpeter, 1952), entrepreneurs revolutionize production by exploiting new inventions or untried technological possibilities to create new commodities, innovate old ones, open new supply sources, or establish new market outlets. This view is shared more commonly by the Austrian school., which suggests that external knowledge spillovers enhance the breadth and coherence of a firm's knowledge base, as formally examined by Antonelli and Colombelli (2015). Knowledge serves as both an input and output in production (Weitzman 1996, 1998), where existing knowledge can be recombined to yield new insights. Antonelli and Colombelli (2015) introduce the concept of the knowledge cost function as a framework that estimates the cost of acquiring and utilizing knowledge, incorporating factors such as R&D expenditure, patent stock, firm age, and regional characteristics.[1] This literature emphasizes that a firm's access to both external and internal knowledge influences the cost of knowledge acquisition and utilization in promoting technological progress. Empirical findings from Kelly and Hageman (1999) and Antonelli and Colombelli (2015) support the Marshallian hypothesis, suggesting that the quantity and composition of external knowledge and a firm's internal knowledge repository significantly impact the reduction of knowledge acquisition costs.

Studies by Cohen and Levinthal (1989, 1990), Saviotti (2007), Quatraro (2010, 2012), and Jones (1995) demonstrate the non-uniform distribution of knowledge externalities and firm-specific knowledge inputs across regions. The process of knowledge generation often arises from pursuing new technologies, emphasizing the importance of experiential learning. Through this iterative process, firms develop effective R&D strategies by analyzing past experiences, which leads to innovation. This dual role of knowledge, serving both as an input and an output, deepens our understanding of its complexity in the production process, as discussed by Doraszelski and Jaumandreu (2013). Following this discussion, it is evident that entrepreneurship parallels the distribution and utilization of knowledge in economic activities. Entrepreneurship involves identifying new opportunities and serves as both an input and an output of the production process. It integrates knowledge of best practices and strategies with effective experimentation to achieve business success. Successful entrepreneurship can reduce the average cost of production by efficiently managing available resources. [2]

Antonelli and Colombelli (2015) and Colombelli et al. (2013) concentrate on firms engaged in R&D investment. However, it's crucial to recognize that knowledge acquisition extends beyond patents and R&D activities, encompassing various other forms of innovation essential for business performance. In addition to entrepreneurial skills and firm-specific resources that create competitive advantages, another type of knowledge is crucial for general business performance. This knowledge involves qualitative practices influenced by market operations, a dynamic process that uncovers new opportunities, recognizes competitive advantages, and identifies supply and demand imbalances. It encompasses experience and the development of entrepreneurial and organizational cultures, fostering responsiveness to market signals [3].

[1] See Crépon, Duguet and Mairesse (1998) for a similar discussion.

[2] Any new entrepreneurial initiative like any new R&D project involves substantial risks and extensive use of resources, which is why the view of Marshallian externalities tends to receive more empirical support (Antonelli and Colombellim 2015).

[3] This type of "knowledge" is compatible with the writings of the Austrian School of Economics (Hayek (1937, 1945). Refer to Kirzner (1997, 1999) for an in-depth discussion of the topic.

Innovation-driven technical knowledge from R&D activities and firm-specific knowledge, including business models and organizational strategies, are integral to business success. Shane (2003) argues that entrepreneurial opportunities are recognized through the value of new information received, contributing to the broader understanding of knowledge and innovation. Firms that succeed in innovation enhance the productivity of other peers in the same cluster and influence those outside of it, with effects extending beyond regional boundaries over time. While the Hayek-Mises-Kirzner type of knowledge influences firms to pursue specific R&D avenues, the Schumpeterian or Marshallian paradigms often garner more empirical support. Understanding the impact of these paradigms on business performance and productivity is crucial, as it reveals which R&D products enhance productivity and how knowledge diffuses throughout the business sector. Despite these complexities, achieving profitability remains the primary goal for all firms, regardless of their focus on innovation.

In market-based economies, the price mechanism plays a central role in driving innovation efforts and entrepreneurial discoveries, thriving on technological advancements from innovating firms. As technical and entrepreneurial knowledge move in tandem, the cost function of non-innovating firms is shaped by 'entrepreneurial capital' and the externalities from the R&D activities of innovating firms. Meanwhile, innovating firms are guided by productivity and the 'entrepreneurial capital' of non-innovating firms, which identify business opportunities that enhance productivity in both sectors. Ultimately, 'success' for the innovating sector is defined by the market value of its products, recognized by other entrepreneurs as opportunities.[4]

The main contribution of this paper is the introduction of a novel production model that incorporates entrepreneurial skills and innovation through a multiple-input, multiple-output approach. Our analysis builds on Barney's (1991) resource-based model, assuming heterogeneous firms in managerial practices, in-house innovation efforts, and risk attitudes. These differences allow firms to develop competitive advantages and compete in various market niches.[5] Our model encapsulates the production of goods and services, innovation, and entrepreneurial skills. In estimating our model for a sample of over 200 countries spanning sixty years, we quantify resource wastage and the impact of productivity shocks. We emphasize the importance of market mechanisms by addressing model specification errors and potential non-causality from confounding factors. We contextualize the model by incorporating social context variables, which remain vital without losing their causal interpretation. Empirically, the estimated deconfounding factors correct for model misspecification bias caused by omitted variables and nonlinearities. Our key findings suggest that firms shape competitive advantages by exploiting unique resources driven by both domestic and global competition. Cross-country effects resulting from changes in global knowledge and entrepreneurial practices also significantly enhance firm-specific resources. The extent to which firms learn from the innovation efforts of others depends on their absorptive capacity, underscoring the importance of firm heterogeneity in accumulating knowledge and entrepreneurial capital. Overall, our findings offer new insights into the Schumpeterian and Marshallian perspectives, underscoring their complementary roles in generating new knowledge.

Methodologically, we address the challenge that deconfounding the effects of unique resources, entrepreneurship, and knowledge skills at the firm level is not feasible. These resources are heavily contextualized within market-based mechanisms, making them difficult to measure at the micro level. However, at the aggregate level, it is possible to proxy these variables. While we cannot measure knowledge appropriation resources and their effects at the micro level, we can assess their contribution at the macro level, which is perhaps more

[4] The rationale for these ideas can be traced back to von Mises (1949), who posited that the market operates primarily due to the speculating entrepreneur's pursuit of increased profits through the production process.

[5] See Fiol(1991, 2001); Talluri et al.(2003); Abbasi and Kaviani(2016) for empirical applications of heterogenous resource-based models.

crucial for growth and welfare implications (Lucas, 2009). At this higher level of aggregation, we can evaluate the role of unique resources in shaping a country's competitive advantage, which is essential for specialization and international trade in a globalized economic environment. Specifically, for a country with low absorptive capacity (e.g., low tertiary education investment), our estimates show that a 10% increase in global innovation boosts productivity by only 0.3%, compared to 1.2% in high-capacity countries. Our study aligns with a broader literature that focuses on holistic paradigms such as the business ecosystem (Moore, 1993), the innovation ecosystem (Adner, 2006), the entrepreneurial ecosystem (Prahalad, 2005), and the knowledge-based ecosystem (van der Borgh et al., 2012).[6]

The structure of the paper is as follows: Section 2 elaborates on all aspects of the conceptual model. Section 3 outlines the data sources, econometric specifications, and presents the findings. Section 4 offers a detailed discussion of the results, including general and group-specific policy implications derived from the model. Section 5 concludes the paper.

2 The model

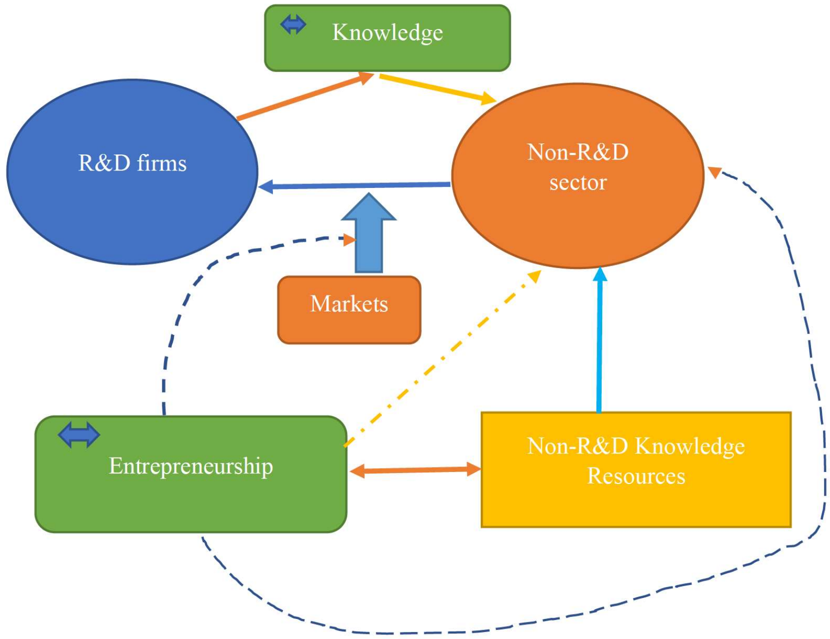
2.1 Conceptual Framework

Markets and market mechanisms moderate the relationship between the R&D and the non-R&D sector. Firms within these sectors are interconnected; R&D firms generate technical knowledge, driven by the needs of the non-R&D sector, which in turn impacts this sector. For non-R&D firms to effectively appropriate this knowledge, significant effort and resources are necessary.

In this feedback mechanism, knowledge is both an input and an output, which is also the case for entrepreneurship and unique resources. Entrepreneurship also helps in moderating the relationship between markets, on the one hand, and firms in the two sectors, on the other.Unique resources contribute to a firm's entrepreneurial capacity, and this capacity, in turn, influences markets and the market mechanism, and also has a direct impact on production in the non-R&D sector. Our conceptual model is summarized in Figure 1.

[6] Ecosystems are understood as socio-economic vortexes rather than as merely district or regional concepts (Becattini, 2003).

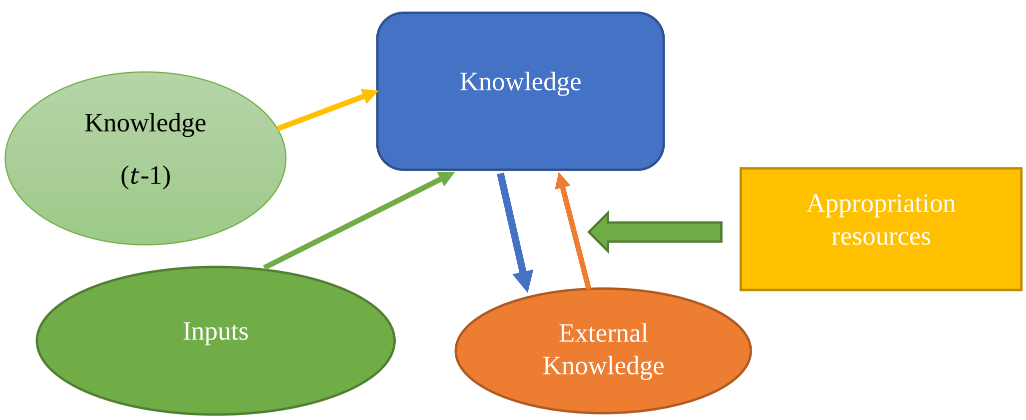
Figure 1: Conceptual Model



Notes: A double arrow indicates both an input and output.

The operative process of knowledge and entrepreneurial capital (K_t) appears in Figure 2. Knowledge serves as both an input and an output, though not simultaneously. The transformation and recombination of existing knowledge into new forms require time. Certain inputs are combined with external knowledge, complemented by contributions from internal knowledge itself. Additionally, resources related to absorptive capacity (appropriation resources) facilitate the appropriation of external knowledge and its transformation into internal knowledge capital.

Figure 2: Knowledge production



To make use of external knowledge, a company needs to have the right technology to absorb and apply that knowledge effectively. This allows the company to turn that knowledge and entrepreneurial skills into real-world business and economic benefits. The company's technological know-how is valuable only when it leads to new products or improvements in processes that other businesses can use. This transformation is made possible by putting in the appropriate effort and resources to assimilate the knowledge. The diagram in Figure 2 also shows that this knowledge can spread and have important effects on the wider economy.

The importance of *productivity* and *efficiency* underscores the transformation of inputs into outputs, as highlighted by Crépon et al. (1993). The estimation of production functions encounters the issue of simultaneity bias, which describes the bias that arises due to the relationship between input selection and unobserved productivity shocks included in the error term (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015; Gandhi et al., 2020). Our empirical methodology addresses these endogeneity problems in estimating production and transformation functions. Next, we present our benchmark estimation framework, including all necessary amendments.

2.2 A simplified technology

There is a vector $k_{it} \in \mathbb{R}^{d_k}$ of quasi-fixed inputs and a vector $x_{it} \in \mathbb{R}^{d_x}$ of variable inputs that can be changed in the short-run. Decision making units are denoted by $i \in \{1, \ldots, n\}$ and time periods by $t \in \{1, \ldots, T\}$. Outputs are in vector $y_{it} \in \mathbb{R}^{d_y}$. Production possibilities are described by a transformation function of the form

$$g(y_{it}; \beta_{(g)}) = f(k_{it}, x_{it}; \beta_{(f)}) + v_{it} + \omega_{it} - u_{it}, \tag{1}$$

where $\beta_{(g)}$ and $\beta_{(f)}$ are parameter vectors, $g(y_{it}; \beta_{(g)})$ can be considered as "generalized output" under joint production, $f(k_{it}, x_{it}; \beta_{(f)})$ is a usual production function which depends on both quasi-fixed and variable inputs[7], v_{it} represents statistical noise, ω_{it} is productivity and $u_{it} \geq 0$ represents technical inefficiency in production (efficiency is defined as $r_{it} = e^{-u_{it}}$ following Kumbhakar and Lovell(2000)). Most behavioral assumptions lead to first-order conditions of the form

$$x_{it} = \Phi(k_{it}, \omega_{it}, u_{it}; \beta_{(\Phi)}) + \xi^x_{it}, \tag{2}$$

where Φ is a vector function that relates the K inputs to quasi-fixed inputs, productivity, and inefficiency. Moreover, $\beta_{(\Phi)}$ is a vector of unknown parameters, and ξ^x_{it} is an error term supported in $\mathbb{R}^{d_x}$. Relative to previous solutions to the endogeneity problem, [8] our approach allows for deviations from the first-order conditions in the form of error terms $\xi^{(x)}_{it}$. We do not make particular behavioral assumptions opting instead for Φ to be a flexible vector function, which allows us to accommodate a wide range of behavioral assumptions.[9]

2.3 Entrepreneurship

Entrepreneurship is associated with several variable inputs $x_{E,it} \in \mathbb{R}^{d_{x_E}}$ and quasi-fixed inputs denoted $k_{E,it} \in \mathbb{R}^{d_{k_E}}$ and, as it is a multi-dimensional concept, there are several outputs, say $y_{E,it} \in \mathbb{R}^{d_{y_E}}$. Our general transformation function is

$$g_E(y_{E,it}; \beta_{(g_E)}) = f_E(k_{E,it}, x_{E,it}, y_{E,i,t-1}, z_{E,it}; \beta_{(f_E)}) + \xi^E_{it} + \omega^E_{it} - u^E_{it}, \tag{3}$$

where $\beta_{(g_E)}$ and $\beta_{(f_E)}$ are vectors of unknown parameters, ξ^E_{it} is an error term, $k_{E,it}$ denotes

[7]Within our joint production framework, assuming a separate production function is not appropriate. The current general transformation function is known as the "distance function" (Kumbhakar and Lovell, 2000, pp. 28–32) of the general form $\mathcal{D}(x_{it}, y_{it}) = 1$. Output-oriented distance functions are linearly homogeneous in outputs and input-oriented distance functions are linearly homogeneous in inputs. Under the separability assumption, (1) is consistent both with an output-oriented and an input-oriented distance function. In the present study, we adopt an output-oriented distance function of the production technology which is defined generically by the following production possibilities set $\mathcal{T} = \{(x, y)|x \text{can produce} y\}$.

[8]Previous studies usually assume control input function, either investment or materials in (2) that can be inverted in terms of ω_{it}, and can be used to approximate for unobserved productivity shocks.

[9]A method of sieves (Olley and Pakes, 1996; Levinsohn and Petrin, 2003) is used to approximate this unknown function. This involves the assumption: $\Phi(k, \omega, u; \beta_{(\Phi)}) = \sum_{i=1}^{P} \sum_{j=1}^{P} \sum_{h=1}^{P} \beta_{(\Phi),i,j,h} k^i \omega^j u^h$, where similar terms are omitted.

quasi-fixed inputs used in the entrepreneurial process, and $z_{E,it}$ is a vector of variables that mediate the formation of entrepreneurial capital. Entrepreneurial outputs at period $t-1$ become entrepreneurial inputs in period t. Parameters $\omega_{it}^{E}, u_{it}^{E}$ denote productivity and inefficiency in the entrepreneurial process.

2.4 Innovation

Innovation depends on inputs $x_{I,it}$ and outputs $y_{I,it}$ that are produced according to the transformation function

$$g_I(y_{I,it};\beta_{(g_I)}) = f_I(k_{I,it}, x_{I,it}, y_{I,i,t-1}, z_{I,it}, \beta_{(f_I)}) + \xi_{it}^{I} + \omega_{it}^{I} - u_{it}^{I}, \tag{4}$$

where $\beta_{(g_I)}$ and $\beta_{(f_I)}$ are vectors of unknown parameters, ξ_{it}^{I} is an error term, $k_{I,it}$ denotes quasi-fixed inputs used in the entrepreneurial process and $z_{I,it}$ is a vector of variables that mediate the formation of innovation capital. Innovation outputs at period $t-1$ become innovation inputs in period t. Parameters $\omega_{it}^{I}, u_{it}^{I}$ denote productivity and inefficiency in the innovation process.

Similar to (2) we express with analogous notation the endogenous vector function that relates K inputs to quasi-fixed inputs and the other latent parameters as:

$$x_{E,it} = \Phi_{(E)}(k_{E,it}, \omega_{it}^{E}, u_{it}^{E}, z_{E,it}; \beta_{\Phi_{(E)}}) + \xi_{it}^{E}, \tag{5.1}$$

$$x_{I,it} = \Phi_{(I)}(k_{I,it}, \omega_{it}^{I}, u_{it}^{I}, z_{I,it}; \beta_{\Phi_{(I)}}) + \xi_{it}^{I}, \tag{5.2}$$

Innovation inputs encompass R&D-related activities and variables that describe the dynamic transformation from R&D into knowledge and innovations that can be utilized for practical applications or related business purposes.

2.5 A more focused technology

In the presence of innovation and entrepreneurship, the transformation function is modified as follows.

$$g(y_{it};\beta_{(g)}) = f(k_{it}, x_{it}, y_{I,i,t-1}, y_{E,i,t-1}, y_{I,i,t-1} \times y_{E,i,t-1}; \beta_{(g)}) + v_{it} + \omega_{it} - u_{it}, \tag{6}$$

where the main change relative to (1) is that innovation and entrepreneurship outputs $(y_{I,i,t-1}, y_{E,i,t-1})$ are now used as inputs, potentially influencing both productivity and inefficiency. Here, $y_{I,i,t-1}$ and $y_{E,i,t-1}$ represent *local* and *global* knowledge inputs, respectively, and their interaction, y$_{I,i,t-1} \times y_{E,i,t-1}, capturespotentialcomplementaritiesbetweenabsorptivecapacityandinternati$
$\alpha_i + \rho_\omega \omega_{i,t-1} + y'_{I,i,t-1}\gamma_1 + y'_{E,i,t-1}\gamma_E + \xi_{it}^{\omega}$, (7) where α_i represents individual effects, ρ_ω is an autoregressive coefficient, and γ_L, γ_G are coefficient vectors for local and global innovation, respectively. The interaction term $(y_{I,i,t-1} \times y_{E,i,t-1})$ reflects the synergy between local innovation capacity and global spillovers. Finally, ξ_{it}^{ω} is an error term.

2.6 Knowledge and innovation

Given innovation outputs $y_{I,it}$,, external knowledge K_{it} is unobservable. Following our previous discussion, there is a feedback relationship between external and internal innovation which can be captured via the following model:

$$K_{it} = \eta_i^K + \rho_K K_{i,t-1} + y'_{I,it}\gamma_K + \xi_{it}^K, \tag{9.1}$$

$$y_{I,it} = \lambda_I K_{it} + \xi_{it}^{y^I}, \tag{9.2}$$

where ξ_{it}^K and $\xi_{it}^{y^I}$ are error terms, λ_I is a vector of loadings, which represent how lagged external innovation loads on the various innovation output indicators, η_i^K represents individual effects, and ρ_K is an autoregressive parameter that represents persistence in the state of aggregate knowledge. A similar process is adopted for entrepreneurial capital:

$$E_{it} = \eta_i^E + \rho_E E_{i,t-1} + y'_{E,it}\gamma_E + \xi_{it}^E, \tag{10.1}$$

$$y_{E,it} = \lambda_E E_{it} + \xi_{it}^{y^E}. \tag{10.2}$$

Systems (9.1)-(9.2) and (10.1)- (10.2) allow for feedback effects between external and internal innovation and entrepreneurial capacity, respectively.

2.7 The role of markets

As illustrated in Figure 1, our central thesis posits that markets facilitate knowledge conversion into innovation, which is subsequently utilized by the business sector. Therefore, this intermediation plays a crucial role in (6), where market mechanisms inform businesses about the value of any given innovative or entrepreneurial practice, thereby influencing its adoption. Therefore, in principle, $y_{I,i,t-1}, y_{E,i,t-1}$ have a role in (6) after they have been "filtered out" by the experience of several entrepreneurs and the market mechanism as a whole. [10] This proposition suggests that entrepreneurs implement innovation influenced by their market perceptions, resulting in significant diversity in initial business practices. Despite the elusive nature of the Austrian concept of "entrepreneurial opportunity" it is influenced by both local and global innovation, domestic and foreign markets, and the dynamic interaction between knowledge and innovation.

Therefore, we theorize the main testable hypothesis as:

$$\begin{bmatrix} y_{it}^I \\ y_{it}^E \end{bmatrix} = \sum_{l=1}^{L} \Lambda_l \tilde{M}_{i,t-l} + \xi_{it}^{I,E}, \tag{11}$$

where Λ_l is a matrix of unknown coefficients, $\xi_{it}^{I,E}$ is a vector error term, and $\tilde{M}_{i,t-l}$ denotes lagged values of the "market" $(1 \le l \le L)$. We allow for several lags (L) because the process of determining the actual value of an innovation or entrepreneurial practice in specific organizational contexts naturally requires time. As the market is unobserved, its definition relies on several relevant indicators which we denote $x_{M,it}$:

$$\tilde{M}_{it} = \eta_i^{\tilde{M}} + \rho_{\tilde{M}} \tilde{M}_{i,t-1} + x'_{M,it}\gamma_{\tilde{M}} + \xi_{it}^{\tilde{M}}, \tag{12}$$

where η_i^M denotes individual effects, γ_M is a vector of unknown parameters, $\xi_{it}^{\tilde{M}}$ is an error term, and $\rho_{\tilde{M}}$ reflects persistence in market perceptions. In the aggregate, this formulation reflects Shane's (2000) importance of prior knowledge of the market as it is transformed into the (posterior) realization of an "entrepreneurial opportunity".

2.8 Inefficiency

Finally, we consider inefficiency in the production of final goods in (6), innovation in (4), and entrepreneurship in (3). Inefficiency represents unrealized capabilities given the

[10] For example, prior knowledge of customer problems will influence the discovery of products and services to exploit new technology in mitigating them (Shane, 2000, p. 452).

levels of inputs or the amount of waste in real resources that could have been saved by engaging in efficient production. [11] Our econometric specification for inefficiency bears resemblance to (7), namely

$$\psi_{it} = \alpha_i + \rho_{\psi^I}\psi_{i,t-1} + z_{it}'\gamma_\psi + \xi_{it}^{\psi}, \tag{15.1}$$

$$\psi_{it}^I = \alpha_i^I + \rho_{\psi^I}\psi_{i,t-1}^I + y_{I,i,t-1}'\gamma_{\psi^I,1} + y_{E,i,t-1}'\gamma_{\psi^I,2} + \xi_{it}^{\psi^I}, \tag{15.2}$$

$$\psi_{it}^E = \alpha_i^E + \rho_{\psi^E}\psi_{i,t-1}^E + y_{I,i,t-1}'\gamma_{\psi^E,1} + y_{E,i,t-1}'\gamma_{\psi^E,2} + \xi_{it}^{\psi^E}, \tag{15.3}$$

where z_{it} is a vector of variables that affect inefficiency in economy-wide production, generically $\psi_{it} = \ln \frac{r_{it}}{1-r_{it}}$, $r_{it} = e^{-u_{it}}$ represents technical efficiency defined in $(0,1]$ and γs represent vectors of unknown parameters. This formulation allows changing variables from a non-negative error component ($u_{it} \geq 0$) to a quantity like $\psi_{it} = \ln \frac{r_{it}}{1-r_{it}}$, which can be defined along the real line, and has a natural interpretation as a log odds ratio (also known as Fisher's transformation).

2.9 Appropriating mechanisms

Even innovations or entrepreneurial practices that have passed through the "filter" of market mechanisms ((11)) and feedback mechanisms ((9.1), (9.2), (10.1), (10.2)) become integrated into production through specific appropriation technologies. Therefore, the presence of $y_{I,i,t-1}$ and $y_{E,i,t-1}$ in (6) overlooks the fact that such resources require appropriation. Appropriation technology entails time, real resources, and costs, and is contingent upon current organizational hierarchies and cultures at the firm level. Essentially, external resources must be "re-produced" to become suitable for the firm's operative process, or they may need to be adapted to fit the organizational and operational context. To model the appropriation process, we further modify (6) as follows:

$$\begin{aligned} g(y_{it};\beta_{(g)}) = f(k_{it}, x_{it}, \varphi_{it}^I \odot y_{I,t-1}^*, \varphi_{it}^E \odot y_{E,t-1}^*, y_{I,i,t-1}, y_{E,i,t-1}; \beta_{(f)}) + v_{it} \\ + \omega_{it} - u_{it}), \end{aligned} \tag{16}$$

where $y_{I,t-1}^*$ and $y_{I,t-1}^*$ are counterparts of $y_{I,i,t-1}$and $y_{E,i,t-1}$ and denote *global innovation* and *entrepreneurial outputs.* The operator $\odot$ denotes Hadamard (element-wise product) and φ_{it}^I, φ_{it}^E represent access to external innovation and entrepreneurship, respectively. By definition, $\varphi_{it}^I, \varphi_{it}^E \in (0,1]$ as they represent rates of external knowledge adoption and best practices. As the values of these parameters are bounded between zero and one we assume the following models.

$$\varphi_{it}^I = \mathcal{F}(\tau_{it}, z_{I,it}; \beta_{(\varphi^I)}), \tag{17.1}$$

$$\varphi_{it}^E = \mathcal{F}(\tau_{it}, z_{E,it}; \beta_{(\varphi^E)}), \tag{17.2}$$

where $\mathcal{F}$ is any distribution function (for example, the standard normal), $\beta_{(\varphi^I)}$ and $\beta_{(\varphi^E)}$ are vector of unknown parameters and τ_{it} represents a time trend (i.e. $\tau_{it} = t$ for all i and t).[12]

[11] It should be noted that resource wastage is not unrelated to specific mechanisms for appropriating external knowledge, innovation, and best entrepreneurial practices.

[12] A simple example of an appropriation function is $\varphi_{it}^I = \frac{1}{1+e^{-b_i t}}$ ($b_i > 0$) which indicates a logistic-like "rate of adoption" of new technological innovations. The rate at which this adoption or appropriation takes place (b_i) is a function of the organizational structure and the "portability" of new technology (expressed in relative terms).

The processes of productivity are written as:

$$\omega_{it}^{I} = \alpha_i^I + \rho_{\omega,I}\omega_{i,t-1}^{I} + y'_{I,i,t-1}\gamma_{I,1} + y'_{I,i,t-1}\gamma_{I,2} + \xi_{it}^{\omega^I}, \tag{18.1}$$

$$\omega_{it}^{E} = \alpha_i^E + \rho_{\omega,E}\omega_{i,t-1}^{E} + y'_{E,i,t-1}\gamma_{E,1} + y'_{E,i,t-1}\gamma_{E,2} + \xi_{it}^{\omega^E}. \tag{18.2}$$

The inefficiency equations are written as:

$$\psi_{it} = \alpha_i + \rho_{\psi,i}\psi_{i,t-1} + y'_{I,i,t-1}\gamma_{I,1} + y'_{E,i,t-1}\gamma_{I,2} + \xi_{it}^{\psi^I}, \tag{19.1}$$

$$\psi_{it}^{I} = \alpha_i^I + \rho_{\psi^I,i}\psi_{i,t-1}^{I} + y'_{I,i,t-1}\gamma_{I,1} + y'_{E,i,t-1}\gamma_{I,2} + \xi_{it}^{\psi^I}, \tag{19.2}$$

$$\psi_{it}^{E} = \alpha_i^E + \rho_{\psi^E,i}\psi_{i,t-1}^{E} + y'_{I,i,t-1}\gamma_{E,1} + y'_{E,i,t-1}\gamma_{E,2} + \xi_{it}^{\psi^E}. \tag{19.3}$$

2.10 Global knowledge and global entrepreneurial practices

To define global measures of knowledge/innovation (K^*) and entrepreneurship (E_t^*), we have to rely on country-specific indicators of K_{it} and E_{it}. Global knowledge and entrepreneurship are persistent processes, so we assume:

$$K_t^* = \rho_{K^*}K_{t-1}^* + \sum_{i=1}^{n}\delta_{K^*,i}K_{it} + \xi_t^{K^*}, \tag{20.1}$$

$$E_t^* = \rho_{E^*}E_{t-1}^* + \sum_{i=1}^{n}\delta_{E^*,i}E_{it} + \xi_t^{E^*}, \tag{20.2}$$

where ρ_{K^*} and ρ_{E^*} are autoregressive coefficients, $\delta_{K^*,i}$ and $\delta_{E^*,i}$ are weights attached to country-specific knowledge and entrepreneurial stock, and $\xi_t^{K^*}$, $\xi_t^{E^*}$ are error terms. For the weights we assume

$$\begin{array}{l} \delta_{K^*,i} \geq 0 \ (i = 1, \ldots, n), \ \sum_{i=1}^{n}\delta_{K^*,i} = 1, \\ \delta_{E^*,i} \geq 0 \ (i = 1, \ldots, n), \ \sum_{i=1}^{n}\delta_{E^*,i} = 1. \end{array} \tag{21}$$

Finally, the last part of the model set-up refers to the incorporation of socio-economic variables in the specification of appropriating mechanisms (17.1) and (17.2). Moreover, firms may not be able to appropriate all or part of the variables in vectors $y_{I,it}$ and $y_{E,it}$ and may, instead, appropriate K_{it}^* and E_{it}^*,viz. the generalized constructs that are predicated on innovation and entrepreneurship. This is a testable hypothesis to the alternative (16)

$$\begin{array}{c} g(y_{it};\beta_{(g)}) = f(k_{it}, x_{it}, \varphi_{it}^{I}K_{t-1}^*, \varphi_{it}^{E}E_{t-1}^*, K_{it}, E_{it}; \beta_{(f)}) + v_{it} \\ +\omega_{it} - u_{it}. \end{array} \tag{22}$$

Although both (22) and (16) are confronted with the same data, the former is more parsimonious. We determine which specification better describes the data using formal statistical procedures. Additionally, specification (**??**) allows for both domestic and globally available knowledge, innovation, and entrepreneurial practices denoted by K_{it} and E_{it}, respectively. Our model provides a formal and coherent framework for examining "entrepreneurial opportunity" and its transformation into market realizations, while also facilitating the interplay between global and local knowledge.[13]

[13] Our framework provides a deeper understanding of the Austrian "black box", where previous knowledge translates into the recognition of an "opportunity". This is accomplished through the use of appropriation technology, which aligns with the Austrian narrative, even in the absence of formal testing beforehand.

3 Data and empirical analysis

3.1 Data Sources

The measurement of knowledge, entrepreneurial activities, and innovation outcomes are determined by the available data. As previously emphasised, firm-level data may provide more insights into innovative firms and their R&D activities (or potential spillovers), while aggregate data typically allow for identifying the operational processes involved in the formation of innovative, entrepreneurial, and knowledge constructs. The use of microdata makes it possible to account for firm and unit heterogeneity, which is important in the decision-making process of R&D. The absence of firm-level data may be a drawback in the empirical implementation of our framework; however, from a global perspective, a holistic view is more appropriate than focusing solely on specific firms or regions. Future researchers could replicate our framework with a smaller number of countries but with greater within-country disaggregation, in order to test whether the pattern of current results changes substantially.

In the current context, it is increasingly important to contextualise our results in environments that transcend the boundaries of individual firms, sectors, and countries, especially given the significant increase in access to technological opportunities and best entrepreneurial (or managerial) practices brought about by globalisation. Spillover effects, central to the modern theory of technological knowledge and R&D, can still be measured at the aggregate level, reflecting their importance in creating and sustaining competitive advantages, which should be evident in global trade. Additionally, growth and welfare implications can be studied more thoroughly at this level (Lucas, 2009). This highlights the crucial need to measure managerial, innovation, and knowledge practices across countries, as demonstrated by Bloom et al. (2015, 2019).

We use data from the World Bank's TCdata360 which is an initiative of the World Bank Group's Macroeconomics, Trade & Investment Global Practice (`http://prosperitydata360.worldbank.org/en/home`). The TCdata360 is an unbalanced panel of more than 200 countries over the period 1955-2016 covering the following five broad categories: innovation, investment, industrial sectors, trade and macroeconomic activity. We refer to the World Bank (2024) for further details regarding data availability across countries and years.[14] We summarize the model's structure and operationalization in Table 1.

Table 1: Definition of variables

Inputs	Outputs
1. Gross capital formation*	1. GDP (agriculture)
2. Infrastructure*	2. GDP (manufacturing)
3. Imports, Creative goods	3. GDP (services)
4. Imports, Creative services	4. Exports, creative goods
5. Hours, low-skilled	5. Exports, creative services
6. Hours, medium-skilled	6. Other exports
7. Hours, high-skilled	7. Investments
8. Innovation*	8. Innovation
9. Entrepreneurship*	9. Entrepreneurship

Notes: * denotes a quasi-fixed input.

[14]The creation of this comprehensive dataset signifies an initiative designed to support countries in achieving the twin goals of the World Bank Group: eliminating extreme poverty, fostering prosperity, and sustaining broad-based economic growth, with a primary focus on private sector-driven initiatives.

Innovation and entrepreneurship are inputs and outputs, albeit not at the same time as it takes time to diffuse and absorb good practices. Various inputs produce innovation and have multiple dimensions summarized in Table 2.

Table 2: Definition of innovation inputs and outputs

Inputs	Outputs
1. ICT use in business overview*	1. Annual growth rates of creative goods exports
2. Research and development expenditure (% of GDP)*	2. Scientific and technical journal articles
3. % of workforce in the ICT sector	3. Trademark applications, total
4. Hiring and firing practices, 1-7 (best)*	4. Value added in the ICT sector (%)
5. Firm-level technology absorption, 1-7 (best)*	5. 12th pillar Innovation
6. Researchers in R&D (per million people)*	6. Patent applications, nonresidents
7. Imports of creative services	7. ICT goods exports
8. Intellectual property protection*	8. Patent applications, residents
9. Company spending on Research & Development*	9. ICT Value added (%)
10. 5th pillar Higher education and training*	10. Trademark applications, direct nonresident
11. University-industry collaboration in Research & Development*	11. Trademark applications, direct resident
12. Availability of scientists and engineers*	12. Values and shares of creative goods, exports
13. GCI 4.0: Pillar 6: Skills*	13. Triadic patent families
14. Extent of staff training*	14. Values and shares of creative industries related goods exports
15. 9th pillar Technological readiness*	15. Exports of creative services
16. Charges for the use of intellectual property, payments (BoP, current US$)	
17. Charges for the use of intellectual property, receipts (BoP, current US$)	

Notes: * denotes a quasi-fixed input.

The variables used to represent entrepreneurship and outcomes of market and social context are presented in Table 5. Descriptive statistics for all variables are reported in the Appendix.

Table 3: Categorization of Variables

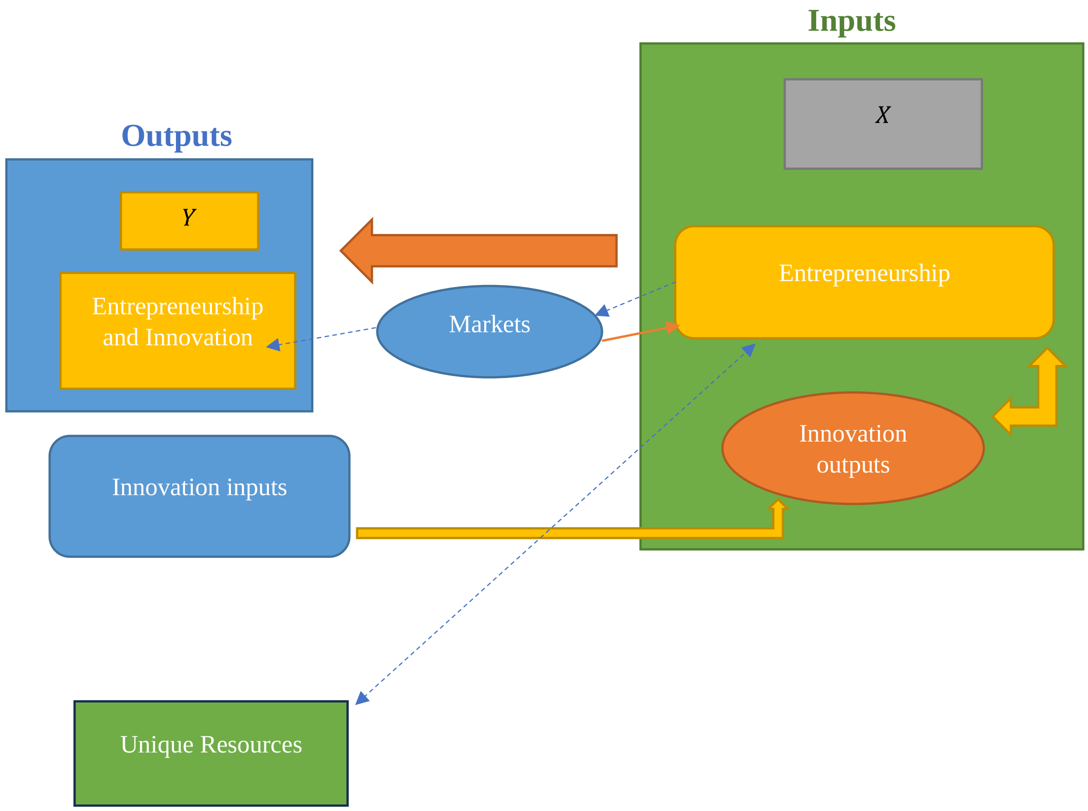
Entrepreneurship	Markets	Social Context
1. Entrepreneurial Culture*	1. GCI 4.0: Innovation ecosystem component	1. Unemployment, total (% of total labor force) (modeled ILO estimate) (WDI)
2. Access to Finance	2. Extent of market dominance	2. Life expectancy at birth, female (years)
3. Self-employed*	3. Intensity of local competition	3. GINI index (World Bank estimate)
4. Manufacturing by Business Size*	4. GCI 4.0: Efficiency of the clearance process	4. Alternative and nuclear energy (% of total energy use)
5. Entrepreneurial Markets*	5. GCI 4.0: Competition in services	5. Poverty gap at $1.90 a day (2011 PPP) (%)
6. Entrepreneurial Policy*	6. GCI 4.0: 7.B Foreign competition	6. Poverty gap at $3.10 a day (2011 PPP) (%)
7. Gender Entrepreneurship*	7. GCI 4.0: 7.A Domestic competition	7. Poverty headcount ratio at $1.90 a day (2011 PPP) (% of pop.)
8. Entrepreneurial Activity	8. GCI 4.0: Distortive effect of taxes and subsidies on competition	8. Poverty headcount ratio at $3.10 a day (2011 PPP) (% of pop.)
	9. GCI 4.0: Trade tariffs	9. GCI 4.0: Pillar 5: Health
	10. GCI 4.0: Complexity of tariffs	10. Gender / Percent of firms with majority female ownership
		11. Gender / Proportion of permanent fulltime workers that are female %
		12. Gender / Percent of firms with a female top manager
		13. Do female and male surviving spouses have equal rights to inherit assets?
		14. Does the government support or provide childcare services?
		15. Does a woman's testimony carry the same evidentiary weight in court as a man's?
		16. Are childcare payments tax deductible?
		17. Does the law mandate equal remuneration for work of equal value?
		8. Does the law mandate non-discrimination based on gender in hiring?
		19. Is there legislation on sexual harassment in employment?
		20. Registering property: Equal access to property rights index
		21. Starting a business: Cost - Women / Men
		22. Starting a business: Time - Women / Men
		23. Does the law prohibit discrimination in employment based on gender?
		24. Starting a business: Procedures - Women
		25. Do married couples jointly share legal responsibility for financially maintaining the family's expenses?

Notes: * denotes a quasi-fixed input.

3.2 Model Specification

In the usual transformation of inputs "X" into outputs "Y" (1), our model includes entrepreneurship and innovation both as inputs and outputs. Their implementation occurs through the mediating role of the market. Innovation inputs are used to produce innovation outputs which, in turn, affect innovation in the next period. A summary of our structural model is presented in Figure 3.

Figure 3: Structure of the model



Innovation outputs and entrepreneurship are interrelated, with unique resources of the firm's resource-based view associated with entrepreneurship. We acknowledge entrepreneurship as both an input and output, influenced by market dynamics. Entrepreneurship may also play a role in transforming innovation inputs to outputs indirectly through the market system.

For the interest of clarity, we present the model indexing unknown parameters by "i" to account for firm heterogeneity which is prevalent in production economics (Tsekouras et al.2017). When we consider aggregate or global knowledge innovation (K^*_{t-1}) and global entrepreneurship (E^*_{t-1}) along with their domestic counterparts, K_{it} and E_{it}, the aggregate transformation function is[15]

$$\begin{aligned} g(y_{it};\beta_{(g,i)}) &= f(k_{it}, x_{it}, \varphi^I_{it}K^*_{t-1}, \varphi^E_{it}E^*_{t-1}K_{it}, E_{it}; \beta_{(f,i)}) + v_{it} \\ &+\omega_{it}(\varphi^I_{it}K^*_{t-1}, \varphi^E_{it}E^*_{t-1}; \beta_{(\omega,i)}) - u_{it}(\varphi^I_{it}K^*_{t-1}, \varphi^E_{it}E^*_{t-1}; \beta_{(u,i)}), \end{aligned} \tag{23}$$

Innovation depends on inputs $x_{I,it}$ and outputs $y_{I,it}$ are produced according to the transformation function

$$g_I(y_{I,it};\beta_{(g_I,i)}) = f_I(k_{I,it}, x_{I,it}, y_{I,i,t-1}, z_{I,it}, \beta_{(f_I,i)}) + \xi^I_{it} + \omega^I_{it} - u^I_{it}, \tag{24}$$

For entrepreneurship, we have:

$$g_E(y_{E,it};\beta_{(g_E,i)}) = f_E(k_{E,it}, x_{E,it}, y_{E,i,t-1}, z_{E,it}; \beta_{(f_E,i)}) + \xi^E_{it} + \omega^E_{it} - u^E_{it}, \tag{25}$$

Input endogeneity is accounted for as in (2), (5.1), and (5.2):

$$x_{it} = \Phi(k_{it}, \omega_{it}, u_{it}; \beta_{(\Phi,i)}) + \xi^x_{it}, \tag{26.1}$$

$$x_{E,it} = \Phi_{(E)}(k_{E,it}, \omega^E_{it}, u^E_{it}, z_{E,it}; \beta_{\Phi_{(E,i)}}) + \xi^E_{it}, \tag{26.2}$$

$$x_{I,it} = \Phi_{(I)}(k_{I,it}, \omega^I_{it}, u^I_{it}, z_{I,it}; \beta_{\Phi_{(I,i)}}) + \xi^I_{it}, \tag{26.3}$$

For knowledge, we have:

$$K_{it} = \eta^K_i + \rho_{K,i}K_{i,t-1} + y'_{I,it}\gamma_{K,i} + \xi^K_{it}, \tag{27.1}$$

$$y_{I,it} = \lambda_{I,i}K_{it} + \xi^{y^I}_{it}., \tag{27.2}$$

For entrepreneurial capital, we have:

$$E_{it} = \eta^E_i + \rho_{E,i}E_{i,t-1} + y'_{E,it}\gamma_{E,i} + \xi^E_{it}, \tag{28.1}$$

$$y_{E,it} = \lambda_{E,i}E_{it} + \xi^{y^E}_{it}. \tag{28.2}$$

For the market mechanism, we have:

$$\begin{bmatrix} y^I_{it} \\ y^E_{it} \end{bmatrix} = \sum_{l=1}^{L} \Lambda_{l,i}\tilde{M}_{i,t-l} + \xi^{I,E}_{it}, \tag{29}$$

where Λ_l is a matrix of unknown coefficients, $\xi^{I,E}_{it}$ is a vector error term, and $\tilde{M}_{i,t-l}$ denotes lagged values of (indicators related to) the "market" ($1 \leq l \leq L$). The optimal number of lags (L) allowed is $L = 2$. [16] Since the market is unobserved its definition relies on several relevant indicators denoted by $x_{\tilde{M},it}$:

$$\tilde{M}_{it} = \eta^{\tilde{M}}_i + \rho_{\tilde{M},i}\tilde{M}_{i,t-1} + x'_{\tilde{M},it}\gamma_{\tilde{M},i} + \xi^{\tilde{M}}_{it}. \tag{30}$$

The operationalization of (30) is shaped by the entrepreneur's perspective. For the Austrian school, the emphasis is on leveraging prior knowledge for discovery and market outcomes. Essentially, the market reflects the aggregation of these individual knowledge bases and the transformation of opportunities into tangible outcomes, as captured in $x_{\tilde{M},it}$.

The appropriation mechanisms are given as

[15] All transformational functional forms are assumed to be Cobb-Douglas for ease of interpretation. The posterior means and posterior standard deviations are reported in Panel B of Table 2.

[16] The value of lags, L, is determined by using the marginal likelihood criterion from Sequential Monte Carlo.

$$\varphi_{it}^{I} = \mathcal{F}(\tau_{it}, z_{I,it}; \beta_{(\varphi^{I},i)}), \tag{31.1}$$

$$\varphi_{it}^{E} = \mathcal{F}(\tau_{it}, z_{E,it}; \beta_{(\varphi^{E},i)}), \tag{31.2}$$

where $\mathcal{F}(\cdot)$ stands for the standard normal distribution function.

Productivity equations are as follows:

$$\omega_{it} = \alpha_i + \rho_{\omega,i}\omega_{i,t-1} + K_{i,t-1}\gamma_{\omega,1,i} + E_{i,t-1}\gamma_{\omega,2,i} + \xi_{it}^{\omega}, \tag{32.1}$$

$$\omega_{it}^{I} = \alpha_i^{I} + \rho_{\omega^{I},i}\omega_{i,t-1}^{I} + K_{i,t-1}\gamma_{\omega^{I},1,i} + E_{i,t-1}\gamma_{\omega^{I},2,i} + \xi_{it}^{\omega^{I}}, \tag{32.2}$$

$$\omega_{it}^{E} = \alpha_i^{E} + \rho_{\omega^{E},i}\omega_{i,t-1}^{E} + K_{i,t-1}\gamma_{\omega^{E},1,i} + E_{i,t-1}\gamma_{\omega^{E},2,i} + \xi_{it}^{\omega^{E}}. \tag{32.3}$$

The main changes relative to previous formulations are that (i) innovation and entrepreneurial outputs are replaced with their lagged constructs (i.e. $K_{i,t-1}$ and $E_{i,t-1}$) in (32.2) and (32.3), and (ii) $K_{i,t-1}$ and $E_{i,t-1}$ affect aggregate productivity in (32.1). Therefore, process inefficiency depends on both innovation and entrepreneurial skills. We define the inefficiency equations as:[17]

$$\psi_{it} = \alpha_i + \rho_{\psi,i}\psi_{i,t-1} + K_{i,t-1}\gamma_{\omega,1,i} + E_{i,t-1}\gamma_{\omega,2,i} + \xi_{it}^{\psi^{I}}, \tag{33.1}$$

$$\psi_{it}^{I} = \alpha_i^{I} + \rho_{\psi^{I},i}\psi_{i,t-1}^{I} + K_{i,t-1}\gamma_{\psi^{I},1,i} + E_{i,t-1}\gamma_{\psi^{I},2,i} + \xi_{it}^{\psi^{I}}, \tag{33.2}$$

$$\psi_{it}^{E} = \alpha_i^{E} + \rho_{\psi^{E},i}\psi_{i,t-1}^{E} + K_{i,t-1}\gamma_{\psi^{E},1,i} + E_{i,t-1}\gamma_{\psi^{E},2,i} + \xi_{it}^{\psi^{E}}. \tag{33.3}$$

Finally, the formation of external knowledge and entrepreneurship is given as follows.

$$K_t^{*} = \rho_{K^{*},i}K_{t-1}^{*} + \sum_{i=1}^{n}\delta_{K^{*},i}K_{it} + \xi_t^{K^{*}}, \tag{34.1}$$

$$E_t^{*} = \rho_{E^{*},i}E_{t-1}^{*} + \sum_{i=1}^{n}\delta_{E^{*},i}E_{it} + \xi_t^{E^{*}}, \tag{34.2}$$

where $\rho_{K^{*}}$ and $\rho_{E^{*}}$ are autoregressive coefficients, $\delta_{K^{*},i}$ and $\delta_{E^{*},i}$ are weights attached to reach country-specific knowledge and entrepreneurial stock, and $\xi_t^{K^{*}}$, $\xi_t^{E^{*}}$ are error terms. For the weights, we assume

$$\begin{aligned} \delta_{K^{*},i} \geq 0\ (i = 1, \ldots, n),\ \textstyle\sum_{i=1}^{n}\delta_{K^{*},i} = 1, \\ \delta_{E^{*},i} \geq 0\ (i = 1, \ldots, n),\ \textstyle\sum_{i=1}^{n}\delta_{E^{*},i} = 1. \end{aligned} \tag{35}$$

The formulation of initial conditions in (34.1) and (34.2) is potentially significant. Here, we adopt a Mundlak device to parameterize the initial conditions for date $t = 0$:

$$\begin{aligned} K_0^{*} = \textstyle\sum_{i=1}^{n}\varpi_{K,i}K_{i0} + \xi_0^{K^{*}};\ \varpi_{K,i} \geq 0\ (i = 1, \ldots, n),\ \textstyle\sum_{i=1}^{n}\varpi_{K,i} = 1, \\ E_0^{*} = \textstyle\sum_{i=1}^{n}\varpi_{E,i}E_{i0} + \xi_0^{E^{*}};\ \varpi_{E,i} \geq 0\ (i = 1, \ldots, n),\ \textstyle\sum_{i=1}^{n}\varpi_{E,i} = 1, \end{aligned} \tag{36}$$

where $\varpi_{K,i}$ and $\varpi_{K,i}$ are country-specific weights, and $\xi_0^{K^{*}}$, $\xi_0^{E^{*}}$ are error terms.[18] For $\tilde{M}_{i0}$ in (30) we assume that they are unknown parameters.

[17] Equations 32.1 and 33.1 do not include determinants of inefficiency, z_{it}.

[18] The Mundlak device formulates a generalization of both fixed and random effects. When $\xi_0^{K^{*}} = 0$ we obtain fixed effects, whereas $\varpi_{K,i} = 0$ $(1 \leq i \leq n)$ we have pure random effects. In between, there is a spectrum of special cases which generalize both fixed and random effects.

3.3 Contextualization

So far, we've overlooked social context variables, yet they crucially shape technology, innovation, and entrepreneurial outcomes, influencing productivity and inefficiency.[19] Table 5 considers social context variables, $z_{it} \in \mathbb{R}^{d_z}$., which allow to specify a dynamic factor model

$$\begin{aligned} z_{it} &= \Pi_i \zeta_{it} + \xi_{it}^z, \\ \zeta_{it} &= \Lambda_i \zeta_{i,t-1} + \xi_{it}^\zeta, \end{aligned} \tag{37}$$

where Π_i is a $d_z \times m$ matrix of unknown parameters (factor loadings), ζ_{it} is an $m \times 1$ vector of factors, ξ_{it}^z is an error term supported in $\mathbb{R}^{d_z}$, Λ_i is an $m \times m$ matrix of unknown parameters (dynamic factor loadings), and ξ_{it}^ζ is an error term supported in $\mathbb{R}^m$. The dynamic factor model decomposes the d_z contextual variables into $m < d_z$ country-specific common factors that capture the main variation in social context. We estimate (37) in advance (see footnote 21). Using marginal likelihoods and Bayes factors (Kass and Raftery, 1995; DiCiccio et al., 1997; O'Hagan, 1995) we find that the optimal number of factors is $m = 3$. In our contextualization, $\theta_i \in \mathbb{R}^d$ denotes the entire vector of unknown parameters as follows:

$$\theta_i = \sum_{t=1}^{T} \Phi_t \zeta_{it} + \xi_{it}^\theta, \tag{38}$$

where Φ_t is $d \times m$ $(t = 1, \ldots, T)$, contains unknown parameters, and ξ_{it}^θ is an error term supported in $\mathbb{R}^d$. In (38), the parameters become functions of the underlying contextual variables. Given ζ_{it}s, the remaining equations (23)–(36) of the model are estimated under the assumption that contextualization of the various operative processes works through (38). To estimate the model, [20] we use the Gibbs sampler of Markov Chain Monte Carlo (MCMC) (Tierney, 1994) along with sequential Monte Carlo as in Creal and Tsay (2015) as the model involves dynamic, nonlinear and latent variables (Andrieu et al., 2014).[21]

3.4 Causal interpretation

Before presenting results, we aim to minimize specification errors and ensure the model has a causal interpretation. Numerous factors and assumptions in the model could contribute to non-causality, ranging from missing variables to inappropriate functional forms. For causal interpretation, it's essential that (i) parameters of interest remain stable when adding or removing concomitant variables (Pratt and Schlaifer, 1988); and (ii) the model's predictive ability doesn't deteriorate with changes in concomitant variables. We adopt Wang and Blei's (2019) approach to deconfound the model. This method acknowledges that apparent non-causality may arise from unobserved variables affecting correlations, rather than direct causal relationships. Deconfounding involves proxying for such variables, with Wang and Blei (2019) suggesting linear or quadratic factor models.

$$\underset{(N\times 1)}{D_{it}} = \underset{(N\times M)}{A} \underset{(M\times 1)}{\psi_{it}} + \xi_{it}^D, \tag{39}$$

[19] For recent work on the social context of entrepreneurship, see Farny et al. (2019); Muñoz et al. (2019); Muñoz& Kimmitt, (2019); Muñoz& Kibler (2016)).

[20] We model all error terms as independent, identically distributed normals with zero means and distinct scale parameters $\boldsymbol{\sigma}$, reparameterizing $\boldsymbol{\sigma} = e^{\mathbf{s}}$ for unrestricted $\mathbf{s}$. For model parameters, we adopt independent Laplace priors $p(\theta_j) \propto e^{-\bar{h}|\theta_j - \bar{a}|}$, with θ_j from the parameter vector, and set $\bar{a} = 0$, $\bar{h} = 10$ for diffuse priors akin to LASSO for parameter proliferation (Zellner, 1971). Cobb-Douglas function parameters are constrained non-negative, using rejection sampling for compliance (Terrell, 1996).

[21] We perform 150,000 MCMC iterations omitting the first 50,000 during the burn-in phase to mitigate the possible impact of starting values. We employ 1,000 particles per MCMC iteration, a stable and adequate choice validated by Creal and Tsay (2015). Geweke's (1992) diagnostics assess MCMC convergence and numerical behavior.

where D_{it} consists, in our case, of lagged values of all observed variables, N is the number of these variables, A is a matrix of unknown coefficients, M is the unknown number of common factors, ξ_{it}^D is an error term supported in $\mathbb{R}^N$, and the factors are ψ_{it}. The quadratic factor model alternative to (39) is

$$\underset{(N\times 1)}{D_{it}} = \underset{(N\times M)}{A}\underset{(M\times 1)}{\psi_{it}} + \underset{(N\times M)}{A_o}\psi_{it}^2 + \xi_{it}^D, \tag{40}$$

where A_o is a matrix of unknown parameters and ψ_{it}^2 denotes the squares of all elements of ψ_{it}. Including interactions among factors, yield as another possible model the following.

$$\underset{(N\times 1)}{D_{it}} = \underset{(N\times M)}{A}\underset{(M\times 1)}{\psi_{it}} + \underset{(N\times M')}{A_o}\underset{(M'\times 1)}{vech(\psi_{it}\psi_{it}')} + \xi_{it}^D, \tag{41}$$

where $vech(\psi_{it}\psi_{it}')$ denotes terms of the form $\psi_{it,j}\psi_{it,k}$ $(1 \le k \le j \le M)$ excluding similar terms (notice that $M' = \frac{M(M+1)}{2}$), assuming $\psi_{it} = [\psi_{it,j}, 1 \le j \le M]$. Deconfounders ψ_{it} are included in all model equations to act as "nuisance variables" whose purpose is to ensure that the model is causal according to the (statistical) criteria we have adopted. The predictive ability of a causal model is not compromised in different sub-samples of the data. To mitigate specification errors or outliers, we follow Bühlmann (2014) using bootstrapped samples $D^*_{(b)}$ of size $n' < nT$ from the original data set $(1 \le b \le B)$, where B is the total number of bootstrapped samples, and use the corrected posterior

$$p^*(\vartheta|D) = B^{-1}\sum_{b=1}^{B} p^*(\vartheta|D^*_{(b)}). \tag{42}$$

The bagged posterior, as defined in (42), helps mitigate specification errors and outliers by addressing potential variations in model behavior across different sub-samples, indicated by changes in the parameter (ϑ). While a causal model should not exhibit such behavior, if it does, it suggests non-causality even after attempts at confounding using ψ_{it} (as in equations (39), (40), or (41)). Despite this, if ψ_{it} constructions offer causal interpretations, the bagged posterior approach can still be useful. If substantial differences persist, causality may be questioned or accepted as a "working hypothesis," and statistical inferences can be made using the bagged posteriors. However, researchers should remain open to the possibility of alternative deconfounding methods being necessary in such cases.

We apply deconfounding techniques using (39), (40), and (41), finding that only the full quadratic factor model (41) supports causal inferences. This conclusion is based on the stability of marginal posterior densities of parameters and functions of interest when (i) adjusting concomitants, (ii) across data sub-samples, and (iii) without compromising the model's predictive capability under conditions (i) and (ii). [22]

We determine the optimal number of factors in (41) and (37) using marginal likelihood from the sequential Monte Carlo procedure (Andrieu et al., 2014), with results detailed in Table 4. Both models require $m = 3, M = 4$ factors. We focus solely on (41) due to failed causal interpretation tests. [23]

Table 4: Bayes factors for ARMA model selection

[22] For estimating of these models, see footnote 21. Using (41) the optimal number of deconfounding factors, ψ_{it}, was $M = 3$. In D_{it} we have included squares and interaction terms of all continuous and Likert-scaled variables in the data set. This practice is related to nonlinear principal components (Song and Li, 2021).

[23] Bayes factors indicate 7 factors for the linear factor model in (39) and 5 for the quadratic specification in (40).

panel data model	$\psi_{it,1}$	$\psi_{it,2}$	$\psi_{it,3}$	$\psi_{it,4}$
AR(1)	1.000	1.000	1.000	1.000
AR(2)	7.44	0.025	0.001	**44.43**
ARMA(1,1)	32.55	0.001	0.001	2.55
ARMA(2,2)	**71.82**	0.001	0.001	0.517

Notes: Reported are Bayes factors in favor of a panel AR(1) model and against the other models listed. Therefore, the Bayes factor of a panel AR(1) is normalized to one. Bayes factors less than 0.001 are set equal to 0.001.

3.5 Identifying unique resources?

As deconfounding factors equip the model with a causal interpretation without remaining differences in bagged posteriors to reflect other specification errors, unique resources must be measured differently. Our approach to identifying unique resources is based on the assumption that they follow a path dependence (Tsekouras et al., 2017) that can be described by an autoregressive process (Wibbens, 2019). If deconfounding factors ψ_{it} can be related to a panel ARMA(1,1) model, this part could be attributed to the contribution of unique resources. To show formally this relationship, we first assume the following profit equation

$$y_t = x_t + \xi_{t,(1)}, \tag{43}$$

where y_t is profit, x_t is an operating resource for which we have

$$x_t = \lambda_1 x_{t-1} + \xi_{t,(2)}. \tag{44}$$

The model gives rise to an ARMA(1,1) model for y_t. If we have higher-order resources

$$z_t = \lambda_2 z_{t-1} + \xi_{t,(3)}, \tag{45}$$

and (44) is replaced with

$$x_t = \lambda_1 x_{t-1} + z_t + \xi_{t,(4)}, \tag{46}$$

which implies, in turn, an ARMA(2,2) model.

Our test results are summarized in Table 5. Based on this analysis, the first deconfounding factor appears to support a panel ARMA(2,2) model, while the fourth factor is consistent with a panel AR(2) model. The other deconfounding factors do not exhibit autocorrelation. This suggests that second-order resources are captured by the first factor, and first-order resources by the fourth factor. The coefficients of determination (R^2, computed as the squared correlation between actual and fitted values) for these two factors are 0.314 and 0.225, respectively. Therefore, any unique resources identified explain a relatively low proportion of the variation in the deconfounding factors. This indicates that these factors are primarily associated with correcting for specification errors (Shah and Bühlmann, 2018).

Table 5: Additional robustness checks

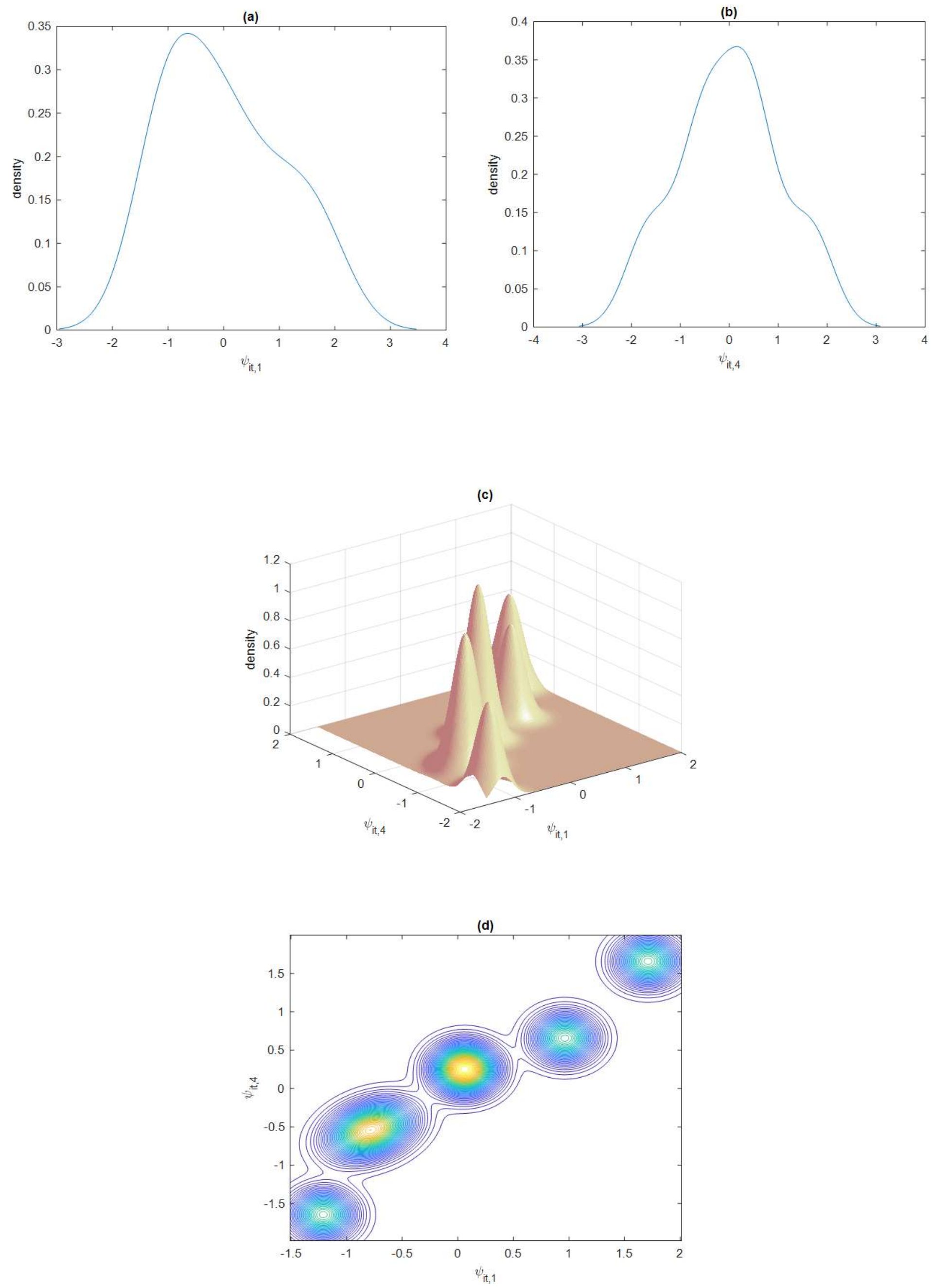
Check	DM (1995)	Parameter stability	Concomitants
Drop contextualization in (38)	0.000–0.013	0.000–0.015	0.000–0.000
Drop market filter in (29) and (30)	0.000–0.004	0.000–0.000	0.000–0.003
Set adoption rates in (31.1) and (31.2) to unity	0.000–0.000	0.000–0.000	0.000–0.006
Omit formulation in (32.1)	0.000–0.007	0.000–0.000	0.000–0.003
Omit formulation in (32.2)	0.000–0.002	0.000–0.004	0.000–0.005
Omit formulation in (32.3)	0.000–0.013	0.000–0.003	0.000–0.000
Assume all ρ parameters are zero	0.000–0.003	0.000–0.005	0.000–0.000

Notes: Reported are ranges of p-values (minimum to maximum). DM (1995) denotes the Diebold and Mariano (1995) equal predictive ability test between the new model and the benchmark model in 1,000 alternative sub-samples whose size is randomly selected between 10 and 100. "Parameter stability" examines parameter stability across the different 1,000 alternative sub-samples. "Concomitants" adds a random number (selected between 1 and 5) of concomitant variables from the fiscal-monetary and policy uncertainty variables in each one of the different 1,000 alternative sub-samples. p-values less than 10^{-6} are set to zero.

Taking these coefficients of determination at face value, we extract a summary of unique resources from $\psi_{it,1}$ and $\psi_{it,4}$ using their fitted values from the respective panel ARMA(2,2) and AR(2) models. The distributions of the two factors, for all countries, are shown in Figure 4.[24] Panels (a) and (b) show the marginal posterior densities of $\psi_{it,1}$ and $\psi_{it,4}$ for all countries, with their bivariate density and contour plot in panels (c) and (d). While panels (a) and (b) suggest data clustering, panels (c) and (d) identify at least five distinct clusters, indicating a positive and nonlinear relationship between the two deconfounding factors. Despite their a priori independence, deconfounding factors become interdependent when conditioned on the data.

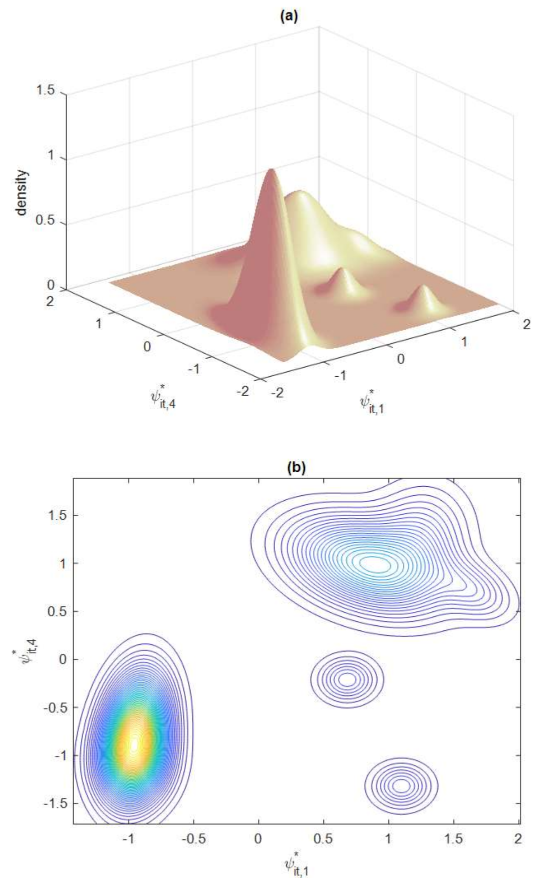
[24] Figures for specific countries are available from the authors upon request.

Figure 4: Marginal posterior densities of confounding factors



Considering the fitted values from panel ARMA processes for the two deconfounding factors (denoted $\psi^*_{it,1}$ and $\psi^*_{it,4}$), the results are reported in Figure 5. Although it is hard to make a case out of Figure 5, there is a main group where the two unique resources are positively correlated and another minor group where the correlation is negative but the spread of the distribution is higher.

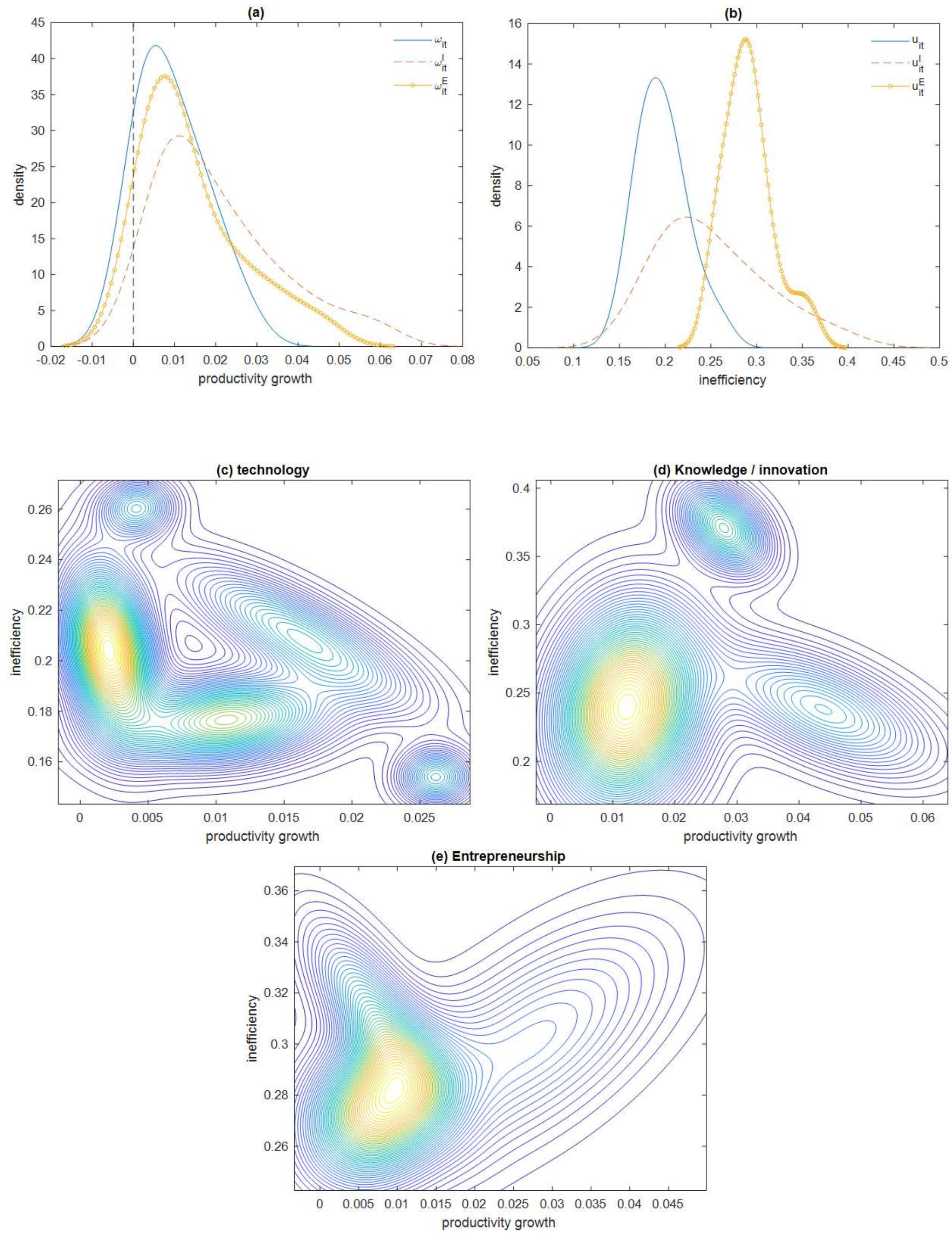
Figure 5: Bivariate posterior densities of unique resources



Sample distributions of posterior mean estimates of productivity growth (defined as $\omega_{it} - \omega_{i,t-1}$) and inefficiency are reported in panels (a) and (b) of Figure 6. Although technological knowledge (or innovation), and entrepreneurial productivity are, in general, positive, there are substantial inefficiencies, particularly in the entrepreneurial formative processes. Panels (c), (d), and (e) of Figure 6 depict contours of the sample distributions of posterior mean estimated efficiencies and productivity in our key areas. Analysis reveals contrasting associations: a negative link between inefficiency and productivity in technology, but a positive relationship in both knowledge and entrepreneurship. In the latter sectors, productivity and inefficiency co-vary, suggesting efficiency improvements coincide with productivity gains. Conversely, heightened productivity reduces inefficiency in technology, indicating a decrease in technological slack with productivity growth. Higher productivity might elevate inefficiency in monopolistic or oligopolistic markets, as resources become less constrained and management prioritizes expansion over resource efficiency. [25]

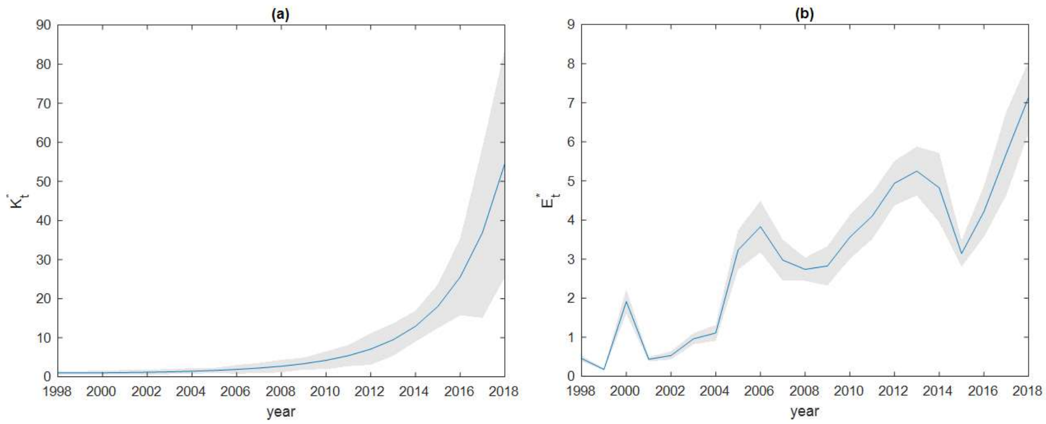
[25] This is known as Hick's "quiet life hypothesis" (Hicks, 1935; Hart, 1983; Scharfstein, 1988; Schmidt, 1997; Bertrand and Mullainathan, 2003) but it is not confirmed when we examine the aggregate level. So, management is concerned with the optimal use of resources even when productivity growth is positive.

Figure 6: Sample distributions of posterior mean estimates of productivity and inefficiency



Our posterior mean estimates of aggregate knowledge and entrepreneurial skills, filtered through Sequential Monte Carlo, are presented in Figure 7 with 95% Bayes probability intervals. The stock of technological knowledge shows significant growth over time, while aggregate entrepreneurial skills exhibit a generally positive trend, despite fluctuations and a notable downturn during the subprime crisis (2008-2009).

Figure 7: Aggregate knowledge and entrepreneurial skills



Notes: The shaded areas correspond to 95% Bayes probability intervals.

Country- specific knowledge production (K_{it}) and entrepreneurial practices (E_{it}) are depicted in Figure 8 for selected countries and regions of the world. The evidence indicates positive trends in the production of new knowledge across all selected countries and regions, albeit at varying rates. Regarding country-specific entrepreneurial skills, panel (c) countries demonstrate significant production, whereas production is notably lower in panel (d) countries. How effective are appropriation technologies (of K^*_t and E^*_t) is, of course, an important issue, which can be addressed using (31.1) and (31.2). Posterior mean estimates of adoption rates in 2018 are reported in Figure 9.

Figure 8: Country- specific knowledge production (K_{it}) and entrepreneurial practices (E_{it})

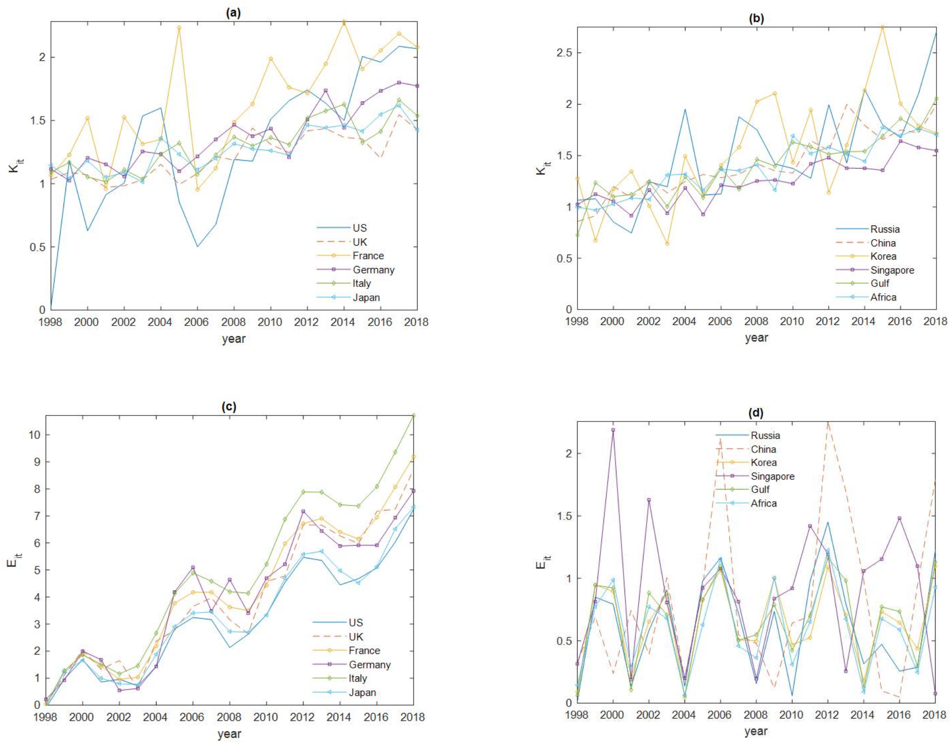
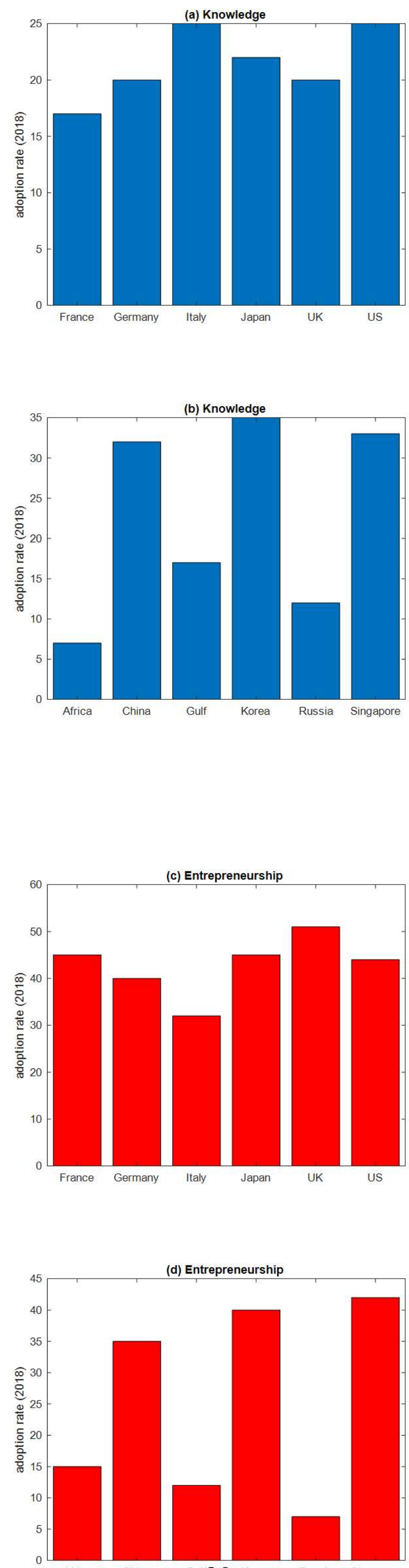
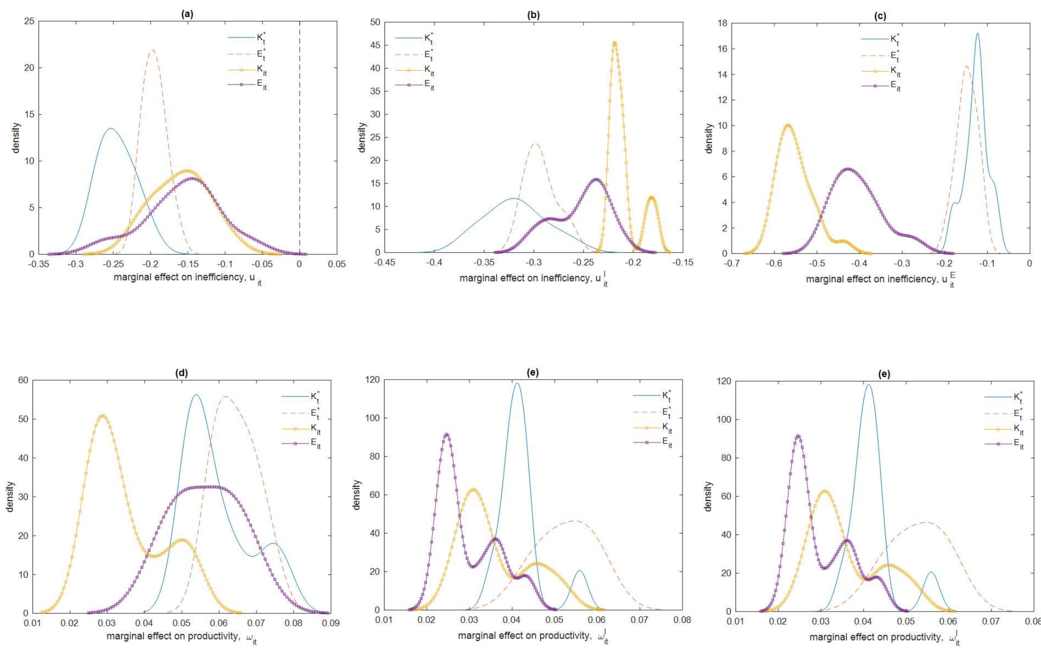


Figure 9: Posterior mean appropriation rates (2018)



Finally, we examine the influence of both firm-specific and aggregate forms of knowledge and entrepreneurship on three types of inefficiency and productivity. Figure 10 presents the marginal effects across all countries and years. Panels (a), (b), and (c) display the sample distributions of posterior mean estimates for the marginal effects of firm-specific (K_{it}, E_{it}) and aggregate (K_t, E_t) knowledge and entrepreneurship on the three types of productivity. Conversely, panels (d), (e), and (f) detail the marginal effects of these factors on the three types of inefficiency.

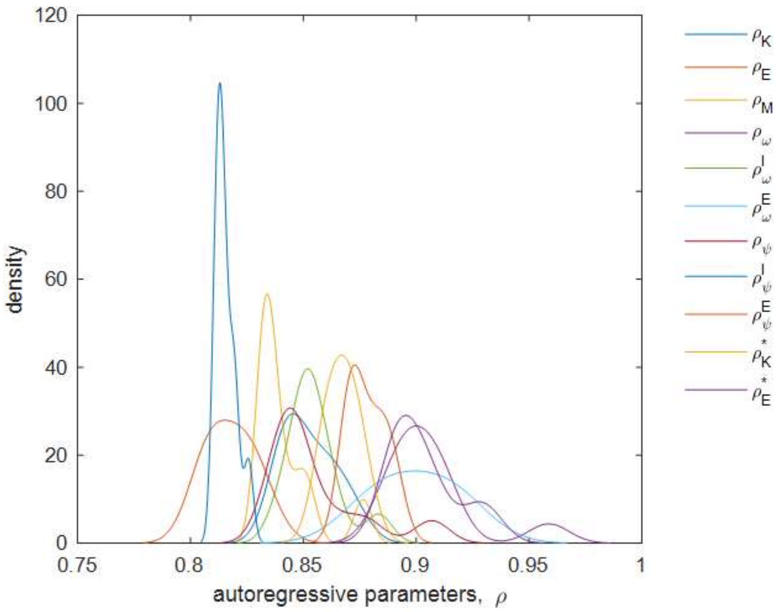
Figure 10: Marginal effects



We examine various persistence parameters (ρ) and certain other factor loadings in Figure 11, where marginal posterior densities of persistence parameters are illustrated. We first average persistence parameters for all MCMC draws and provide the sample distributions of posterior mean estimates for each persistence parameter so that sample distributions in Figure 11 reflect cross-country variation. The persistence parameters range approximately between 0.80 and slightly less than unity, indicating that all formative processes are highly persistent or path-dependent (Tsekouras et al., 2017). [26]

[26] Without imposing stationarity conditions (viz. $|\rho| < 1$) it turns out that these formative processes are stationary.

Figure 11: Sample distributions of posterior mean estimates of persistence parameters



4 Further Discussion and Policy Insights

4.1 General Remarks

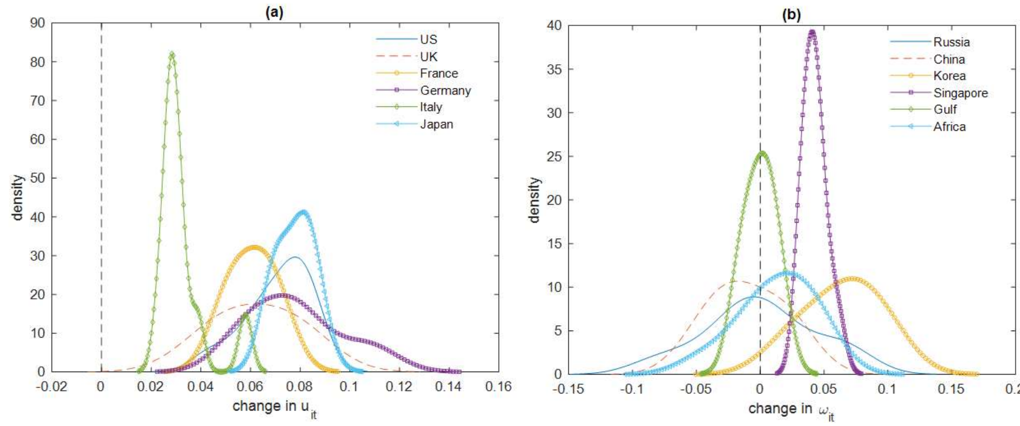
We utilize the causal properties of the model to address the following pivotal policy questions: (i) what are the cross-country effects of changes in global knowledge and entrepreneurial practices? (ii) which countries are more important in driving global knowledge and entrepreneurial practices? (iii) what is the role of the social context? (iv) is it possible that the configuration of unique resources changes when the social context changes?

In the event of a shift in global knowledge or entrepreneurial practices, we anticipate corresponding changes in the productivity and efficiency of technology, as well as in the transformation functions of knowledge and entrepreneurship. Specifically, Figure 12 shows the marginal effects of a 10% (0.10) increase in global knowledge and entrepreneurial practices in 2018. Figure 13 presents posterior means of factor loadings in equations (34.1) and (34.2). The findings align with expectations, highlighting that the leading economies of the U.S., U.K., France, Germany, Japan, and Korea are driving the diffusion of global knowledge. [27]

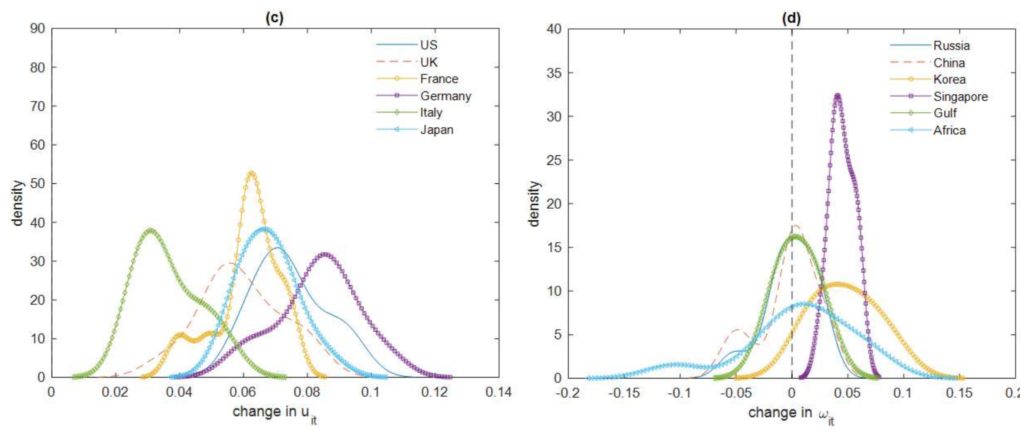
[27] Results for additional countries are available from the authors upon request.

Figure 12: Marginal effects of a 10% (0.10) increase in global knowledge or entrepreneurial skills

I. Marginal effects of a 10% (0.10) increase in global knowledge



II. Marginal effects of a 10% (0.10) increase in global entrepreneurship

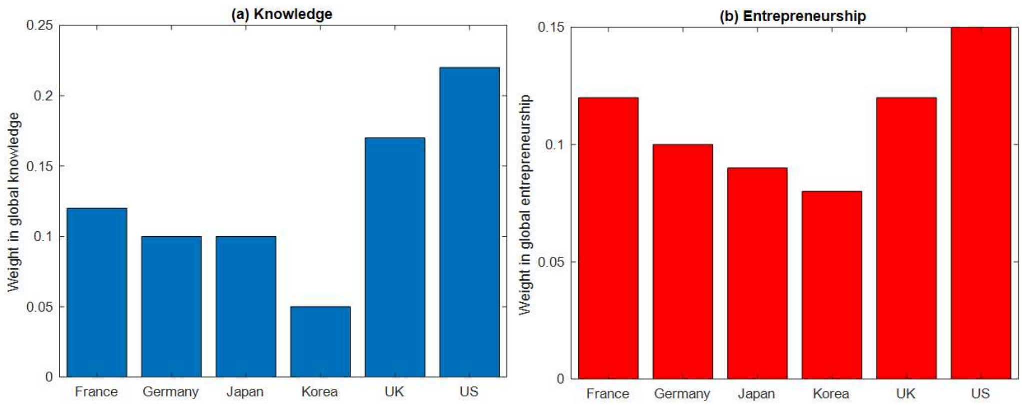


To complement Figures 12 and 13, Table 4 provides a compact summary of the estimated marginal effects of global and local knowledge on productivity growth and inefficiency reduction. This tabular format highlights the relative importance of global spillovers compared to country-specific factors and facilitates cross-country comparisons.

Table 4: Summary of marginal effects of global vs. local knowledge on productivity and inefficiency

	Global Knowledge	Local Knowledge	Notes
Productivity Growth	0.12 (0.05)	0.04 (0.03)	Global dominates, sig. at 5%
Inefficiency Reduction	0.08 (0.04)	0.03 (0.02)	Global stronger, robust

Figure 13: Country scores in terms of contributions to global knowledge and entrepreneurship



As an illustration of the policy relevance of these marginal effects, consider the experience of Korea and the United States. In Korea, targeted R&D tax incentives and sustained government support for absorptive capacity in manufacturing sectors amplified the productivity gains from external technological spillovers. Similarly, in the United States, programs such as the R&D Tax Credit have demonstrated how adoption incentives can translate estimated marginal effects into measurable innovation and growth outcomes. These examples highlight that our framework can directly inform the design of national-level policies aimed at fostering adoption and strengthening absorptive capacity, beyond a focus on specific firms or regions.

Social context encapsulates the determinants of coefficients ζ_{it} in (38), necessitating a complete re-evaluation and re-estimation of the entire system if these factors change by a half standard deviation. In our experiment, we manipulated these factors 1,000 times, each time utilizing varying values for ζ_{it} equivalent to half standard deviations. Then, we recalculated the posterior means for both parameters and the functions of interest. Figure 14 shows the results of this experiment. Figure 15 shows the impact on unique resources and the market index $\tilde{M}_{it}$ (30) following exogenous changes in our simulation experiment. While unique resources appear to show minimal change with shifts in the social context, the market, on the other hand, exhibits a positive response to these changes. The model's causal interpretability remains robust, as shown in Table 5, which confirms that every aspect is essential even after excluding specific modules and reassessing our results. While our aggregate-level identification strategy allows us to address causality via deconfounding in high-dimensional settings, it inevitably limits analysis of firm-level behavioral heterogeneity. Future research could extend this framework to microdata or firm-level panel structures to better capture within-country differences in knowledge absorption, entrepreneurial function, and organizational diversity.

Figure 14: Changes in efficiency and productivity when social context changes

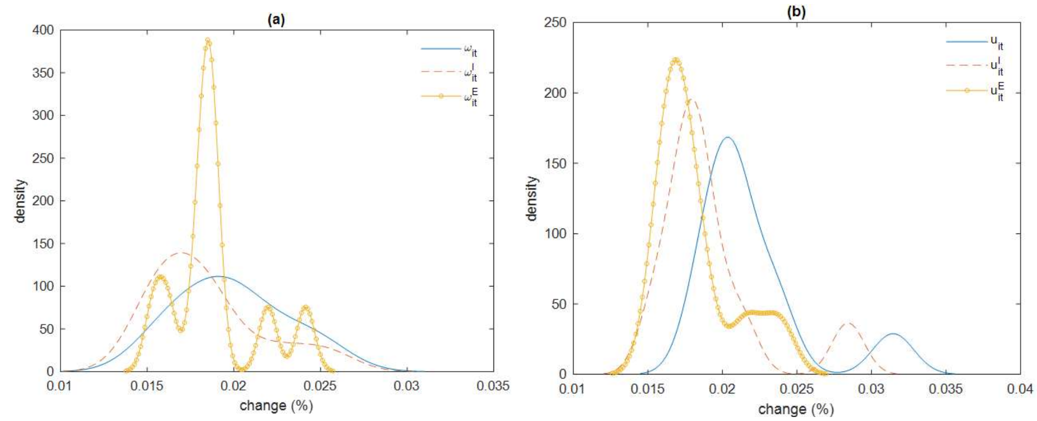
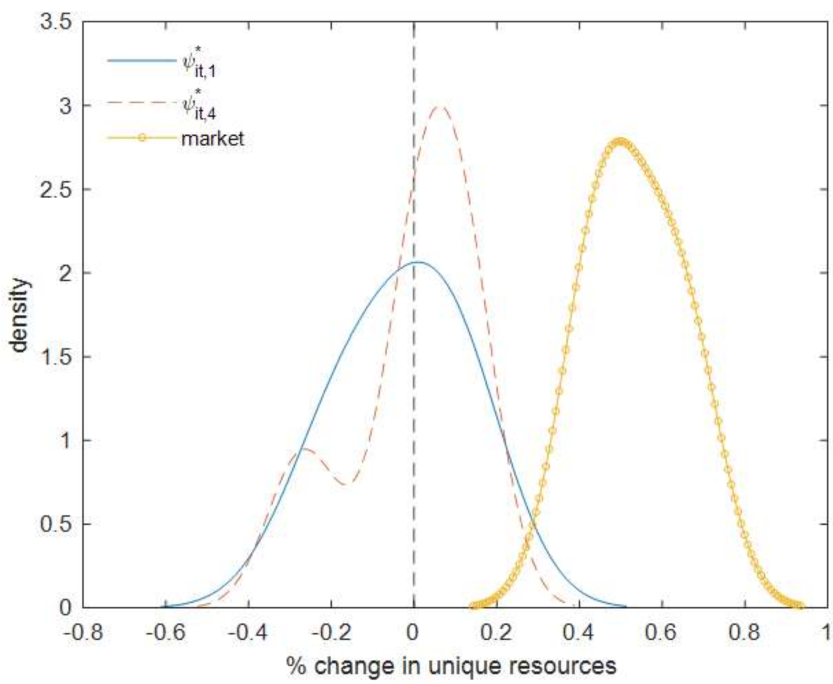


Figure 15: Effect of changes in social context on unique resources

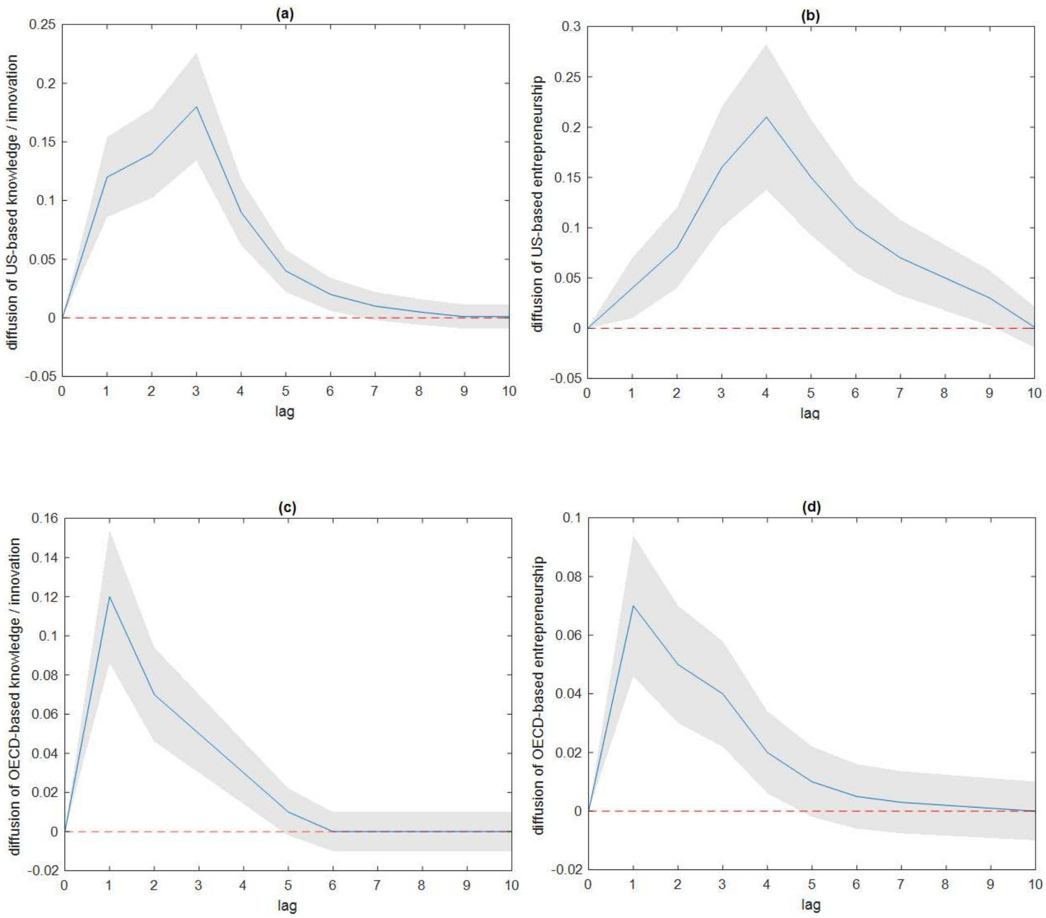


4.2 US and OECD Shocks through Generalized Impulse Response Functions

In Figure 16, Panels (a) and (b) depict the generalized impulse response functions (GIRFs, Koop et al., 1996; Pesaran and Shin, 1998) illustrating the global diffusion of knowledge and entrepreneurial skills originating from the US. The graphs show the average cross-country GIRFs in K_{it} and E_{it} after a standard deviation shock in the US-based metrics. Panels (c) and (d) calculate the GIRFs for a similar shock originating from the OECD-20, excluding the US. The diffusion dynamics differ significantly based on their origin. Shocks originating from the US show a slightly longer persistence, with effects peaking near three years, whereas shocks from OECD countries have a shorter duration, peaking within a year. This stark contrast highlights the unique impacts of US versus OECD-based knowledge and entrepreneurial skill shocks. Figure 17 reports how a standard deviation increase in US-based entrepreneurship impacts different types of productivity (panels (a)-(c)) and inefficiency (panels (d)-(f)) through the GIRFs. Analogously, Figure 18 shows the impact through GIRFs after a unit standard deviation in US-based innovation. Figures 17 and 18 demonstrate that changes in US-based entrepreneurship and innovation have long-lasting effects on both productivity and inefficiency, which can be accurately estimated as evidenced by the relatively narrow 95% Bayesian probability intervals.

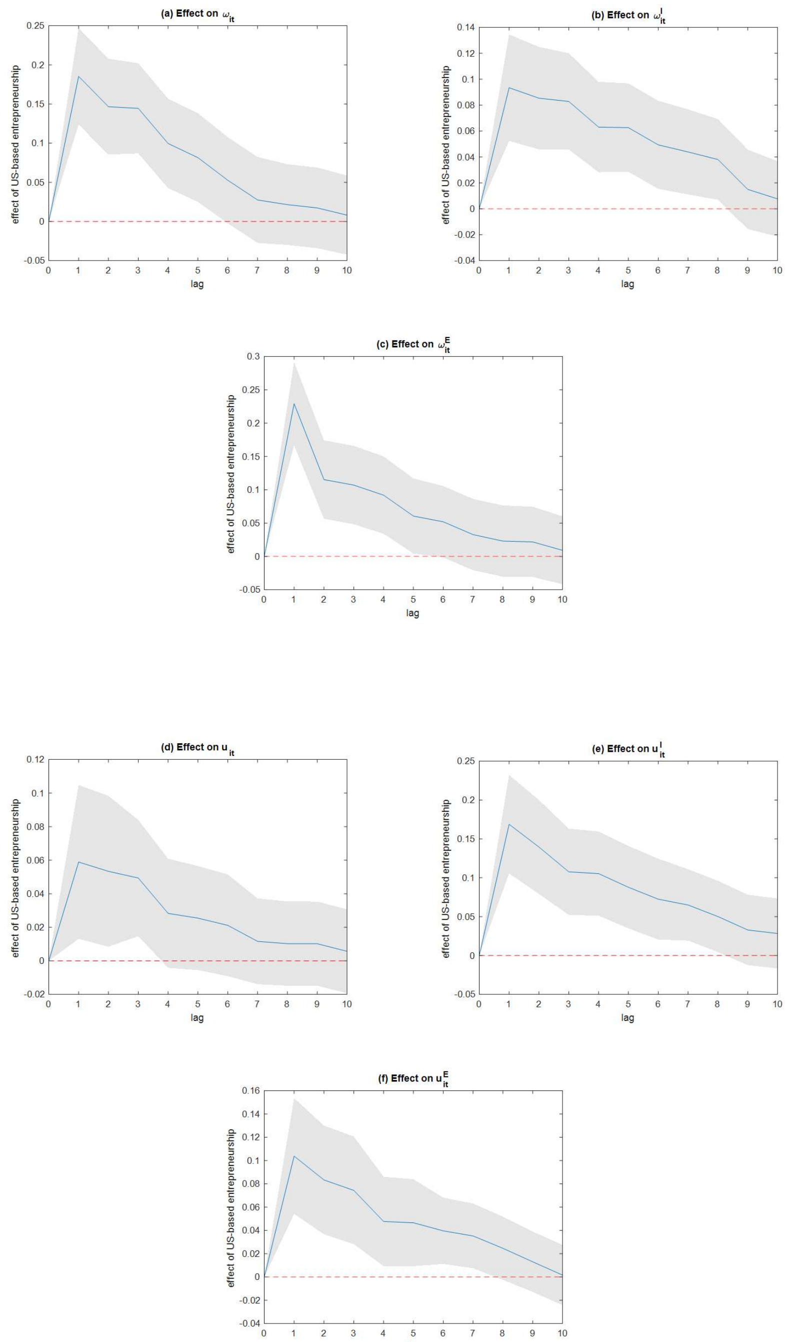
Table 4 summarizes the marginal effects of local and global knowledge variables on productivity and inefficiency outcomes, based on our empirical estimates.

Figure 16: GIRFs of US and OECD



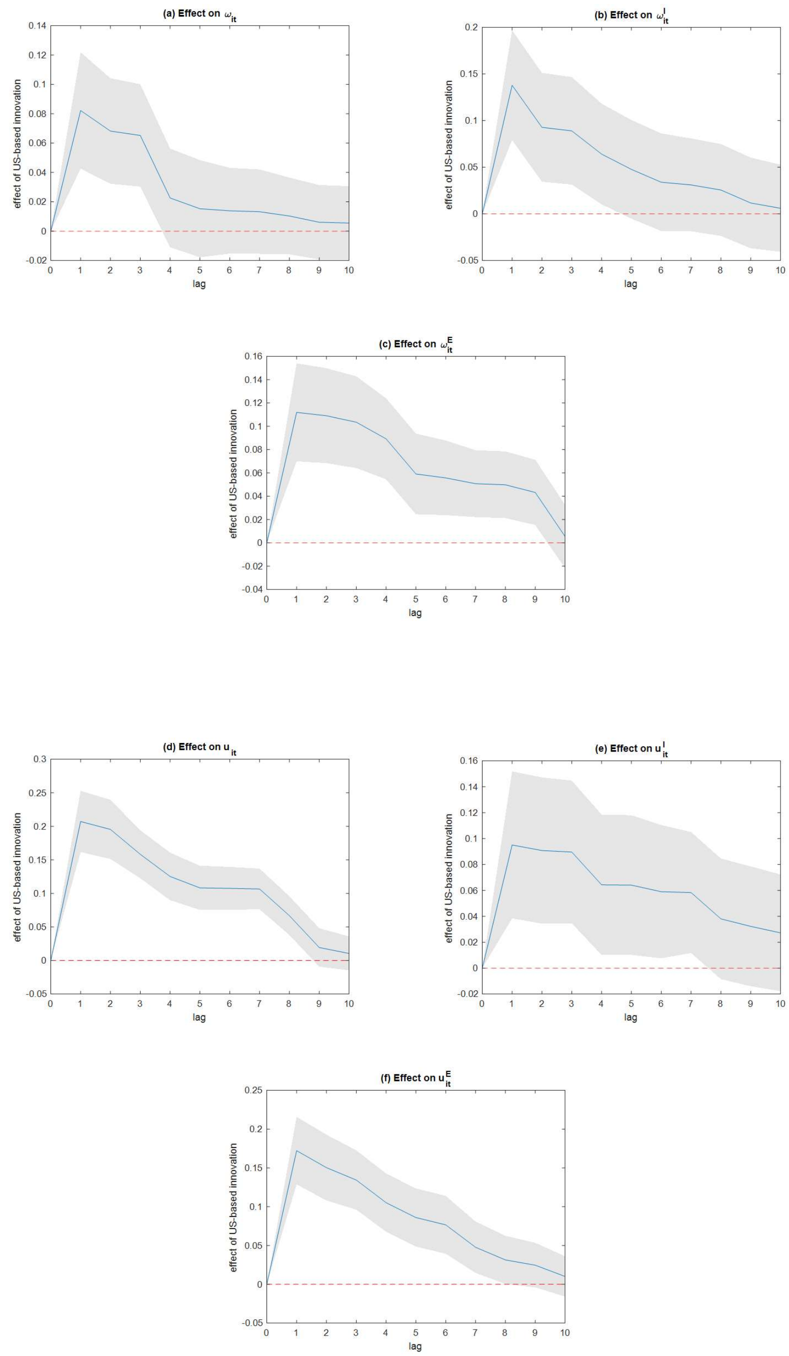
Notes: Shaded areas correspond to 95% Bayes probability intervals.

Figure 17: GIRFs of US-based entrepreneurship on the different types of productivity and inefficiency



Notes: Shaded areas correspond to 95% Bayes probability intervals.

Figure 18: GIRFs of US-based innovation on the different types of productivity and inefficiency



Notes: Shaded areas correspond to 95% Bayes probability intervals.

5 Concluding remarks

We introduce an empirical production model that incorporates technical knowledge and entrepreneurial skills at both local and global levels, utilizing a multiple-input, multiple-output approach to encapsulate the production of goods and services, innovation, and entrepreneurial capital. We explore efficiency and productivity within these processes, aiming to quantify resource wastage and the impact of productivity shocks. The model emphasises the role of market mechanisms, drawing on contemporary production function literature that accounts for endogeneity in variable inputs due to inefficiency and productivity shocks. We rigorously address model specification errors and potential non-causality from confounding factors by employing statistical proxies for omitted variables. This approach ensures the model's predictive accuracy and the robustness of key parameters across various data subsets and against the inclusion of additional variables. The analysis reveals that estimated deconfounding factors relate to unique resources linked to domestic and global competitive advantages. However, they primarily correct for model misspecifications caused by omitted variables and nonlinearities. Although these unique resources remain unaffected by social context changes, market dynamics exhibit sensitivity to such changes.

Efficiency and productivity in technical knowledge, innovation, and entrepreneurship exhibit persistence and path dependence, driven by both domestic and global innovation and entrepreneurship through appropriation mechanisms that vary substantially across the world. The model connects the technology for producing goods and services with the technology for fostering innovation and entrepreneurship, accounting for the country-specific absorptive capacity of global knowledge and best entrepreneurial practices. Despite path dependence on generating new technical knowledge and entrepreneurial skills, the model remains sensitive to changes in best practices at both local and global levels and is influenced by the structure of the socioeconomic environment. The contextualization of the model remains robust, maintaining its causal interpretation regardless of the inclusion or exclusion of socioeconomic variables. Identifying unique resources related to the resource-based view of the firm is challenging due to extensive deconfounding, but some deconfounding factors weakly relate to this view, loading differently on domestic and global markets. This indicates that unique resources are linked to both domestic and global competition, providing competitive advantages. The model also reveals cross-country effects of changes in global knowledge and entrepreneurial practices, as well as country-specific contributions to the evolution of global knowledge and entrepreneurship.

Our study is novel in integrating appropriation technologies within a comprehensive production framework that encompasses not only goods and services but also innovation and entrepreneurial skills. The contextualization adopted in this study is of wider significance, as the social context is incorporated into the analysis in a way that can allow for causal interpretation. More precisely, our approach offers a robust approximation of how the development of technical knowledge and entrepreneurship, on both local and global levels, impacts the economic system.

Our findings offer fresh insights into the empirical importance of the Schumpeterian and Marshallian perspectives on knowledge creation. Our study suggests that the Schumpeterian view, where firms with a substantial stock of internal knowledge excel in generating new knowledge, and the Marshallian perspective, which posits that knowledge externalities are the main source of knowledge promotion within a firm, are both relevant and equally important processes in enhancing a firm's knowledge stock. Additionally, converting innovation and knowledge inputs into outputs through market facilitation supports the Hayek-Mises-Kirzner notion of knowledge creation, which suggests that adopting successful best practices influences innovative firms to engage in specific types of R&D that support new business opportunities. Overall, our analysis demonstrates that global and local knowledge flows, together with entrepreneurship and inefficiency, are central drivers of productivity dynamics. The policy implications are clear: fostering absorptive capacity and reducing inefficiency can significantly amplify the benefits of global knowledge spillovers. More broadly, our integration of inefficiency and knowledge flows into the production and entrepreneurship framework also connects to management and accounting practices. By distinguishing between productive capacity and realized output, the model offers insights for benchmarking, cost control, and innovation-related investment. Moreover, conceptualizing global and local knowledge as productive resources raises relevant questions for transfer pricing and the valuation of intangible assets in multinational corporations, particularly in the context of digital trade (Rodrik, 2019).

Declarations

The authors declare that they have no conflicts of interest. The authors received no external funding for this research. All three authors contributed equally to conceptualization, data collection, empirical analysis, and manuscript preparation. The datasets and code used in this study are available from the corresponding author upon reasonable request.

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A Appendix A

A.1 Summary Statistics

Variable	Mean	S.D.	Min	Max
Entrepreneurship				
Entrepreneurial Culture PCA	-3.18E-09	5.202103	-9.59715	13.05509
Access to Finance PCA	5.86E-09	2.195229	-5.02726	5.587615
Self-employed PCA	-8.99E-10	1.154384	-2.75131	3.510163
Manufacturing by Business Size PCA	2.75E-09	2.959229	-2.08221	12.7713
Entrepreneurial Markets PCA	2.57E-09	2.286578	-2.66886	5.960937
Entrepreneurial Policy PCA	-5.01E-09	5.663176	-15.7091	18.2018
Gender Entrepreneurship PCA	-7.49E-09	1.828578	-5.597451	5.678212
R&D expenditure (% of GDP)	0.9316269	0.941206	0.00544	4.95278
Company spending on R&D	3.340535	0.890364	1.628526	6.120293
University-industry collaboration in R&D	3.611065	0.900293	1.506101	5.968146
Availability of scientists and engineers	4.075251	0.763908	2.190862	6.297107
Extent of staff training	3.989529	0.714161	2.203271	5.945371
GCI 4.0: Innovation ecosystem component	69.16543	39.71289	1	141
Scientific and technical journal articles	9059.988	38298.06	0	528263.3
Researchers in R&D (per million people)	1996.61	1936.761	5.91183	8255.404
Markets				
Gross Capital Formation	3.48E+11	1.39E+12	-2.47E+09	2.30E+13
Infrastructure	2.700193	0.696334	1.1	4.44
Imports, Creative goods	2.48E+09	8.41E+09	3444	1.06E+11
Imports, Creative services	4.47E+08	1.25E+09	-324000	2.24E+10
Exports, creative goods	2.42E+01	2.71E+01	0	1.00E+02
Exports, creative services	4.68E+08	1.44E+09	-156000	2.34E+10
Charges for the use of intellectual property(BoP, current US$)	9.61E+08	4.53E+09	-1.39E+07	9.43E+10
Annual growth rates of creative goods exports	12.10941	92.53526	-66.6977	1510.12
Trademark applications, total	16344.87	60886.61	1	2104414
Value added in the ICT sector (%)	8.053331	2.822208	0.91	16.75
Patent applications, nonresidents	4751.398	18454.01	1	336340
ICT goods exports	2.44E+10	5.65E+10	2000000	5.50E+11
Patent applications, residents	9011.695	55799.64	1	1393815
ICT Value added (%)	5.969929	1.864372	3.784	11.932
Trademark applications, direct nonresident	4626.648	7554.485	1	140906
Trademark applications, direct resident	12692.71	57973.63	1	1997058
Values and shares of creative goods, exports	6.83E+08	4.74E+09	1	1.91E+11
Triadic patent families	773.1554	2643.777	0	36256
Social Context				
GDP per capita (constant 2015 US$)	18493.18	19076.57	347.5331	124343.2
GDP per capita growth (annual %)	2.568795	2.937308	-11.018	22.96213
LF participation rate, total (% of total pop. 15+)	63.75873	11.18565	34.502	88.805
LF with intermediate education (% of total pop.)	63.70957	18.50278	5.179204	97.46704
Share of youth not in education or training (% of youth pop.)	18.57457	10.72294	4.003843	56.9404
Share of youth not in education or training, female (% of female youth pop.)	23.43336	15.48912	5.207835	75.62576
Share of youth not in education or training, male (% of male youth pop.)	13.88271	7.836932	2.69933	38.67615
Adolescent fertility rate (births per 1,000 women ages 15-19)	39.34372	48.22773	0.635	204.5023
Unemployment, total (% of total labor force) (modeled ILO estimate)	7.973996	6.475833	0.245	31.073
Unemployment, female (% of female labor force) (modeled ILO estimate)	8.949844	7.51324	0.268	34.019
Unemployment, male (% of male labor force) (modeled ILO estimate)	7.207482	5.726073	0.203	29.022
Ease of getting electricity (0 = lowest performance to 100 = best performance)	85.97803	18.68256	1.4	100
Government expenditure on education (% of GDP)	4.947364	1.48676	0.913003	10.07196
Government expenditure on education (% of government expenditure)	14.17132	4.402727	5.194	24.73
Government expenditure per student, primary (% of GDP per capita)	13.87482	7.164995	2.525722	49.2697
Government expenditure per student, secondary (% of GDP per capita)	22.17272	9.436065	3.361467	60.06448
Government expenditure per student, tertiary (% of GDP per capita)	32.73322	14.7261	3.053555	99.47382