Tinkering or orchestrating? The value of country-level asset management capability and entrepreneurship outcomes

Abstract

Drawing on entrepreneurship policy literature and resource orchestration theory, we ask whether asset management capabilities of countries explain differences in entrepreneurship outcomes? We define the term asset management capability as the orchestration of inputs and outputs to improve entrepreneurial activity. Using time-series data of 512 inputs and outputs in 219 countries (2000-2018), we model for non-linear dynamic latent variables, allow for inefficiencies and slack, deconfound the model to improve predictive inference, and use cross-validation. The results illustrate systematic variations in asset management capabilities across countries and have implications for entrepreneurship and policymakers.

Keywords: Asset Management; Resource orchestration; Entrepreneurship; Competitive Advantages; Predictive Models.

1. Introduction

Government programs promoting entrepreneurship range from R&D spending and technology transfer to training programs and third-party guarantee loans. The programs focus on various stages of the entrepreneurship pipeline from entrepreneurship education to providing bridge loans to struggling small businesses. However, studies have increasingly questioned the efficacy of such government spending and whether the resulting entrepreneurial activity results in desired benefits (e.g., Shane, 2009). Though government spending towards entrepreneurship aims to curb market failure the broader question is whether the government is capable of having a 'conversion' ability of inputs of assets towards entrepreneurship in realizing desired entrepreneurial outcomes. Similar to the managers of the organization who exhibit asset management necessary to combine and leverage resources, similarly, policymakers from a wide range of asset inputs must collectively leverage assets at the national level to improve entrepreneurial activity. The assets can range from infrastructures that promote business activity to institutional resource outlays (e.g., national entrepreneurship educational programs or export promotion policies). Past studies have considered these assets on a piecemeal basis, and in this study, we make an attempt by taking a broader perspective on the ability of the policymakers to convert these inputs to realize higher entrepreneurial activity, referred to as asset management capability at the country level in this study. We do not focus on the individual firm factors, as their resource management capabilities are widely studied in the strategic management and entrepreneurship literature (Bitencourt et al., 2020; Markman et al., 2019).

With a focus on country-level policymakers, considering variations in asset management capabilities (AMC)—the capacity of policymakers in a country to orchestrate inputs and outputs to improve entrepreneurial activity—could provide a deeper understanding of the operative process of converting country-level inputs into outputs. Despite the central role of policymaking in priming entrepreneurship, slowing innovation rates (Park et al., 2021), and growing concerns on whether policy inputs do indeed increase entrepreneurship (e.g., Dimos and Pugh, 2016). AMC is an important consideration in understanding how complexities, uncertainties, and difficulties of managing entrepreneurship-related inputs manifest into outcomes. The answer is not straightforward, as much of the academic discourse on policy takes the approach of macro- and micro-level effect of the law change, however, the conversion process of policy inputs to policy outputs, the AMC, is an important consideration for macro-level policy research (cf. Bradley et al., 2021). Though the academic and policy discourse focuses on "do something" and "do more" (Bradley et al., 2021), the AMC perspective focuses on the "do how" approach, and perhaps explains why despite similar inputs, countries vary in entrepreneurship outcomes. AMC could be a potential common denominator to Baumol and Strom (2007) productive and unproductive entrepreneurship, partially driven by differences in AMC. Similarly, the North (1990) explains the variations in formal and institutional conditions facilitating entrepreneurship but does not explain why countries with similar institutional inputs have variegated entrepreneurship outcomes. AMC is an approach to explaining the collective policymaker capabilities in managing assets dedicated to entrepreneurship. Though policymakers may engage in "quick fix" laws under the pressure of "do something" the core concern is how well policymakers exhibit asset management capabilities to improve entrepreneurial outcomes.

Building from entrepreneurship policy literature and resource orchestration theory (Sirmon et al., 2011; Teece, 2016), to ask whether countries with better AMCs have higher rates of entrepreneurship? Policymakers engage in asset management by sensing, devising, and exploiting opportunities across resource and policy combinations (Teece, 2012). Resource orchestration as a systemic activity aims to improve asset productivity (Sirmon et al., 2011) through "resource orchestration (i.e. asset alignment, coalignment, realignment, and redeployment) necessary to … maximize complementarities" (Teece, 2012, page 1398). We consider AMC as a more relevant capability given their tasks as 'puppetmasters' instead of strategists focused on complex resource bundling (Hayek, 1978). Though mainstream entrepreneurship research has widely acknowledged the role of policymakers in driving entrepreneurial activity (Gilbert et al., 2004; Hart, 2003), announcement and implementation of such policies may not be sufficient and AMC may provide explanations on why heterogeneity in the efficacy of entrepreneurship policies persists under available resource pools and infrastructure (Smallbone, 2016). AMC could add the next cobblestone towards reaching a better understanding of the value of orchestrating inputs at the country level to improve entrepreneurial outcomes (cf. Tang and Liou, 2010).

Using the logic from Teece (2016), AMC allows policymakers to fulfill the role of managers through the lens of dynamic capabilities. Orchestration allows for coordination, allocation, and adjustments that policymakers must manage to enhance idiosyncratic, co-specialized, co-developed, and path-dependent resource combinations that are endogenously determined by policymakers' knowledge, governance modes, and structures (Sirmon et al., 2011; Teece, 2016). The dynamic capabilities framework considers managers as the core actors who recognize and bring change under uncertainty. An understanding of AMC can contribute to developing more realistic macroeconomic models and providing a better understanding to policymakers on resource and policy management, a collective and aggregative skill that may explain relative entrepreneurial activity (Cimoli et al., 2008). AMC adds a dynamic element to the entrepreneurship policy research by trying to explain how policymakers can be entrepreneurial in managing country-related inputs and outputs over time. Asset management capabilities help delve into recognizing how allocation and management of resources under uncertainty is important to driving proto-models for explaining the value of asset management at the country level.

Next, we discuss empirical considerations in modeling and testing AMC. Much of the discourse on orchestration focuses on how resources contribute to competitive advantages (Dutta et al., 2005; Fainshmidt et al., 2017; Tang and Liou, 2010; Yu et al., 2014). Extending these rich theoretical discourses, we introduce AMC in a country as a formal variable in the model. The variable is unobserved but it can be estimated given the observed input and output fundamental indicators. We investigate these interdependencies in a global framework using panel data (1998–2018) from the World Bank and draw on their systematic investigations to use constructs that allow the contextualization of several prominent themes based on 512 indicators on entrepreneurship, innovation, business climate competitiveness, and a more broad view of “inputs” and “outputs” in the transformation process which is at the heart of economic outcomes and growth.

To address predictiveity concerns, we use deconfounding (Abadie and Cattaneo, 2018). That is, we predicate our analysis on inputs and outputs that are estimated endogenously from the model (to avoid problems of inconsistent estimators due to measurement errors of the underlying principal component constructs). We model for the following conditions. We define an overall efficiency measure that serves as the main performance indicator but we also introduce slacks or inefficiencies in the construction of input or decision variables. These slacks reflect directly differences in the formation and quality of internal resources, and they also depend on the AMC construct. All inefficiency or slack variables are interrelated so, AMC has a role in the process formation of the quality and quantity of all assets and resources. Shocks in the transformation function as well as input and output formation, are correlated, providing an additional channel for productivity to affect business performance. In the following section, we present the theoretical background, followed by the formal model. Thereafter, we present an empirical test of the model and conclude.

2. Theoretical Background

The entrepreneurship policy literature aims to understand how policy-making and resource allocations in a society can improve entrepreneurial engagement and outcomes (Hart, 2003; Holtz-Eakin, 2000). The rationale for entrepreneurship policy as an intervention is to maintain a vibrant economy that allows for 'churn' through creative destruction driven by innovation and competition. The expected long-term effects of entrepreneurship policy are productivity, GDP, and employment growth (Smallbone, 2016). The focus of much of the research has been on policies ranging from financing to information and advising and from entrepreneurship education to infrastructure (e.g., Bennett, 2019; Giraudo et al., 2019). The policy process summarized in Sutcliffe and Court (2005)—agenda setting, formulation, implementation, and monitoring—is by nature a conversion process of a multitude of country-level inputs to realize the output of entrepreneurship but more importantly also receiving feedback from the output that allows for dynamic adjustments.

AMC differs from the business as a usual paradigm for the bureaucratic managerial systems (Nistotskaya and Cingolani, 2016). AMC can be an important capability to create and capture value through scanning, learning, creation, and interpretation to proactively create environments that promote entrepreneurial activity. The resource orchestration conceptualization is rooted in the dynamic capabilities framework. Organizational capability is the "capacity to perform a particular activity in a reliable and at least minimally satisfactory manner" (Helfat and Winter, 2011, page 1244). AMC allows policymakers to "create, extend, or modify its resource base" (Helfat, 2007, page 4) to improve its performance from existing resource conditions (Teece et al., 1997). AMC is modeled as a circular loop where second-order feedback from entrepreneurial activity informs the inputs in the next period. We take this dynamic lens of the ability to orchestrate inputs and outputs as a key element of entrepreneurship policy. AMC encompasses activities through which policy makers orchestrate inputs to configure resources through alignment, coalignment, realignment, and redeployment (Helfat and Winter, 2011; Sirmon et al., 2011; Teece, 2012). As a dynamic capability, asset management capability allows for orchestrating inputs at the country level to address and shape changes in the environment.

2.1. Asset management capability assessment—a theoretical background

Asset management can lead to competitive advantages and the formation of unique resources that will be helpful in the sustainability of these competitive and comparative advantages (Božič and Cvelbar, 2016; Cai and Yang, 2014; Talluri et al., 2003). The bulk of the literature on AMC focuses how unique resources contribute to competitive advantages (Ahmed et al., 2014; Dutta et al., 2005; Hemmati et al., 2016; Ramanathan et al., 2016; Yu et al., 2014). Veiga et al. (2021) proposed a conceptual framework for constructing inputs and outputs to study the performance frontier (e.g., Gong et al., 2019; Liu et al., 2018). How exactly they contribute to this process is, for the most part, unclear and despite the narratives, it remains to be examined how this can be quantified–which is the main purpose of this study. Previous work has emphasized the need for the use of quantitative tools to assess comparative advantages and business performance metrics to improve AMCs (Veiga et al., 2021). Moreover, from previous work on competitive advantages in the context of the performance or best practice frontiers (Božič & Cvelbar, 2016; Cai & Yang, 2014; Talluri, Vickery, & Droge, 2003), achieving the efficient frontier requires orchestration of resources. Veiga et al. (2021) correctly emphasize that a "one size fits all" strategy is infeasible as different structures and hierarchies call for different asset management strategies (Chang et al., 2015; Miller and Ross, 2003). Relative to Veiga et al. (2021) we provide three key extensions.

First, we allow for the joint production of inputs and outputs. Compared to individual policy making AMC occurs in an ecosystem (Acs et al., 2018; Acs et al., 2017) where multiple coevolving inputs and outputs are jointly considered. Moving from the static consideration of entrepreneurial ecosystems a process-based approach is necessary to explore ecosystem dynamics (Spigel and Harrison, 2018). Simultaneous consideration of inputs and outputs through the lens of AMC is important to modeling allocation and resource interaction processes at the country level. Based on the recent review of the entrepreneurial ecosystem, joint consideration of the inputs and outputs is in line with the expectations of understanding interaction logic (understanding structure and associated interactions), resource logic (understanding resource allocations driving entrepreneurship outcomes), and the governance principles that allow for entrepreneurial growth (Cao and Shi, 2021).

Second, it is important to note that resource inputs to the entrepreneurial systems may be discrete and have varying levels of interactions with the other inputs. The typically used proxies for AMC may produce variables with errors so, incorporation of each unit separately into production function regressions is desired. If the core of AMC is resource orchestration then the observable, non-combined resource inputs would be desirable. Instead of considering combinations of inputs to entrepreneurship at the country level or selectively using a set of inputs (and therefore, not including others) we include all the available observable inputs (512 inputs from the World Bank data).

Third, our goal is to also improve predictive ability (Imbens and Rubin, 2015; Pearl, 2009; Peters et al., 2013, 2017; Pfister et al., 2019). Our approach to examining predictive ability is to use deconfounding (Wang and Blei, 2019)[1]. Using instrumental variables in our context is very difficult as it is almost impossible to find exogenous or pre-determined variables. Our approach to this problem is to estimate all relationships of the model jointly in a likelihood-based framework. For example, we do not extract factors or principal components from the input and output indicators in isolation, that is exogenous, into the model itself. Input and output factors, as well as, AMC are derived and estimated endogenously while, at the same time, we test for the model's predictive interpretability in the light of the data and the particular operative structure we adopt–which is, in itself, a testable hypothesis. We aim to explore the "black box" which involves the transformation of fundamental input-output fundamentals into performance along various dimensions. Based on the above discussion we model and test whether differences in asset management capabilities explain differences in driving entrepreneurship outcomes.

3. Model

3.1.1 Model overview

Our model for the production side is summarized in Figure 1 and shows how inputs and outputs are generated based on lower-level indicators. In equations (2)-(3) or (4)-(5) we assume that we have a factor-like structure which we consider reasonable when there multiple indicators for a single input or a single output. Asset management capability is measured by a factor ξ included in the transformation from inputs to outputs in equation (8). In equation (9) or (10) we include the possibility of inefficiency in the transformation of indicators and Asset management capabilities (AMC) to inputs, and we argue that inefficiency and AMC cannot be independent. AMC is both a factor of production but also an "environmental" or contextual variable (also known as a determinant) of inefficiency. We argue that most models are misspecified and we want to avoid

[1]The main problem is that when we examine the relationship between two variables X and Y they appear to be falsely correlated because they both depend on a confounding variable or set of variables Z. Deconfounding proxies Z and tries to determine whether the relationship can still admit a predictive interpretation.

gross misspecifications. We resort to an approach known as deconfounding a given model. Deconfounding is, essentially, a procedure by which factors are constructed (perhaps as nonlinear functions of the data) and we examine, in turn, whether parameter estimates across subsamples are less severe, and the forecasting ability of the model in different subsamples remains approximately the same. If these conditions are not met a model cannot have a structural or causal interpretation and, therefore, it is highly likely to be spurious. We examine whether these factors can be related to AMC and we answer in the affirmative.

We will present the model in increasing stages of complexity so that the main ideas are described first and, in turn, aspects of functional strategies, resource-specific advantages, etc., are introduced as it becomes necessary. The technology is as follows: There are K unobserved inputs denoted $X_1^*, \ldots, X_K^*$; There are M unobserved outputs denoted $Y_1^*, \ldots, Y_M^*$; Each input, X_k^* has d_k indicators denoted, $I_1, \ldots, I_{d_k} (1 \leq k \leq K)$; and Each output, Y_m^* has d_m indicators denoted, $O_1, \ldots, O_{d_m} (1 \leq m \leq M)$.

A schematic representation appears in Figure 1(a). Our model is a more structured alternative relative to the state-of-the-art approach (Veiga et al., 2021) which (i) first uses factor analysis to extract inputs and outputs from observed fundamental indicators $I_1, \ldots, I_{d_I}$ and $O_1, \ldots, O_{d_O}$, and (ii) uses regression analysis involving these factors or their principal components. Inputs are transformed to outputs according to a technology of the form:

$$g(\boldsymbol{Y}^*; \boldsymbol{\beta}) = f(\boldsymbol{X}^*; \boldsymbol{\beta}) + v - u, \tag{1}$$

where $\boldsymbol{X}^* = [X_1^*, \ldots, X_K^*]'$ and $\boldsymbol{Y}^* = [Y_1^*, \ldots, Y_M^*]'$ are the vectors of inputs and outputs, $f(\cdot; \boldsymbol{\beta})$ and $g(\cdot; \boldsymbol{\beta})$ are transformation functions which depend on a vector parameter $\boldsymbol{\beta} \in \mathbb{B} \subset \mathbb{R}^p$, v denotes a twosided error term, and $u \geq 0$ represents technical inefficiency. Technical efficiency is, by definition, $r = e^{-u} \in (0,1]$. Full production efficiency ($r = 1$) requires $u = 0$.[2]

The transformation function represents the curved arrow in Figure 1(a). Inputs are produced according to the following model:

$$X_k^* = \sum_{j=1}^{d_k} \lambda_{kj}^{(x)} I_j + v_{X,k}, 1 \leq k \leq K. \tag{2}$$

Outputs are produced according to the following model:

$$Y_m^* = \sum_{l=1}^{d_m} \lambda_{mj}^{(y)} O_l, + v_{Y,m}, 1 \leq m \leq M, \tag{3}$$

where $\lambda_{kj}^{(x)}$ is the factor loading of input indicator I_j on input X_k, $\lambda_{mj}^{(y)}$ is the factor loading of output indicator O_l on output Y_m^*, and $v_{X,k}, v_{Y,m}$ denote error terms that reflect output-specific productivity shocks.[3] In matrix notation we have

$$\boldsymbol{X}^* = \Lambda^{(X)} \mathbb{I} + \boldsymbol{v}_X, \tag{4}$$

$$\boldsymbol{Y}^* = \Lambda^{(Y)} \mathbb{O} + \boldsymbol{v}_Y, \tag{5}$$

where $\Lambda^{(Y)} = [\lambda_{mj}^{(y)}]$, $\Lambda^{(X)} = [\lambda_{kl}^{(X)}]$. $\mathbb{I}$ and $\mathbb{O}$ are the vectors of all inputs and output indicators, whose dimensionality is, respectively, $d_I = \sum_{k=1}^{K} d_k$ and $d_O = \sum_{m=1}^{M} d_m$, and $\Lambda^{(x)}, \Lambda^{(y)}$, are $K \times d_I$ and $M \times d_O$ matrices of loading coefficients. We denote $\boldsymbol{v}_X = [v_{X,1}, \dots, v_{X,K}]'$ and $\boldsymbol{v}_Y = [v_{Y,1}, \dots, v_{Y,MK}]'$ the vector of error terms.

[2]We can write the transformation function as $g(\boldsymbol{Y}^*; \boldsymbol{\beta}_1) = f(\boldsymbol{X}^*; \boldsymbol{\beta}_2) + v - u$ and define $\boldsymbol{\beta} = [\boldsymbol{\beta}'_1, \boldsymbol{\beta}'_2]'$, so that each of the two functions has its own parameters. For a general background on transformation functions, see Kumbhakar and Lovell (2000, pp. 28-40). These functions are based on the production set $P = \{(\boldsymbol{X}^*, \boldsymbol{Y}^*) | \boldsymbol{X}^* \text{canproduce} \boldsymbol{Y}^*\}$. The production set has various functional representations of the form $D(\boldsymbol{X}^*, \boldsymbol{Y}^*) \leq 1$, where $D(\cdot,\cdot)$ can be an input-oriented or output-oriented distance function. Full efficiency requires that $D(\boldsymbol{X}^*, \boldsymbol{Y}^*) = 1$. Output distance functions are homogeneous of degree one in outputs and input distance functions are homogeneous of degree one in inputs.

[3]In principle, certain fundamentals can affect both inputs and output and, in this case, they can be thought of as throughput fundamentals or indicators.

The main contextual variable is asset management capabilities (AMC) is factor ξ. The factor is unobservable, consistent with empirical studies. Despite the difficulties in its measurement, it is related to how resources are produced, how they acquire and add value to business performance, and how they contribute to efficiency and productivity. Formally, we replace (4) by

$$\boldsymbol{X}^* = \Lambda^{(X)}\mathbb{I} + \boldsymbol{\gamma}\xi + \boldsymbol{v}_X, \tag{6}$$

where $\boldsymbol{\gamma} = [\gamma_1, \dots, \gamma_K]'$ is a $K \times 1$ vector of loadings of AMC on decisions or assets $\boldsymbol{X}^*$. Based on (2) we also have

$$X_k^* = \sum_{j=1}^{d_k} \lambda_{kj}^{(X)} I_j + \gamma_k\xi + v_{X,k}, 1 \leq k \leq K, \tag{7}$$

Asset management is also important in converting decisions of assets into performance so we modify (1) as follows.

$$g(\boldsymbol{Y}^*; \boldsymbol{\beta}) = f(\boldsymbol{X}^*, \xi; \boldsymbol{\beta}) + v - u, \tag{8}$$

where now asset management appears explicitly in the transformation function as a factor of production. For simplicity in notation, we keep the same symbols for f and g.

Efficient asset management transforms input indicators to inputs as best as possible given the "asset management capability". To introduce the notion of potential inefficiencies in this transformation we modify (2) and (7) as follows.

$$X_k^* = \sum_{j=1}^{d_k} \lambda_{kj}^{(X)} I_j + \gamma_k\xi + v_{X,k} - u_{X,k}, 1 \leq k \leq K, \tag{9}$$

or

$$\boldsymbol{X}^* = \Lambda^{(X)}\mathbb{I} + \boldsymbol{\gamma}\xi + \boldsymbol{v}_X - \boldsymbol{u}_X, \tag{10}$$

where $u_k^{(X)} \geq 0$ denotes inefficiency in the production of the kth input $(1 \leq k \leq K)$, $\boldsymbol{u}_X = [u_{X,1}, \dots, u_{X,K}]'$. ξ and $\boldsymbol{u}_X$ cannot be independent as AMC should reduce waste in the transformation of input indicators to inputs and, in principle, the transformation of inputs to outputs as well, through (8).

Inefficiencies in (9) are related to ξ. First, we define efficiencies as

$$r = e^{-u}, r_k = e^{-u_{X,k}}, 1 \leq k \leq K, \tag{11}$$

and we consider the "log-odds ratios"

$$p = \ln \quad \frac{r}{1-r}, p_k = \ln \quad \frac{r_k}{1-r_k}, 1 \leq k \leq K, \tag{12}$$

also known as Fisher transformations so that effectively p and p_k are defined along the real line. Effectively, $r = \frac{e^p}{1+e^p}$ and

$$u = -p + \ln\left(1 + e^p\right), u_{X,k} = -p_k + \ln\left(1 + e^{p_k}\right), \frac{r_k}{1-r_k}, 1 \leq k \leq K. \tag{13}$$

We define the transformation because it is more convenient to have quantities related to inefficiencies which we can, however, define in $\mathbb{R}$. Our proposed model is as follows:

$$\boldsymbol{p} = \begin{bmatrix} p \\ p_1 \\ \vdots \\ p_K \end{bmatrix} = \boldsymbol{\delta}\xi + \boldsymbol{e}, \tag{14}$$

where $\boldsymbol{\delta} \in \mathbb{R}^{K+1}$ is a vector of loadings of AMC on inefficiency odds, and $\boldsymbol{e} = [e_1, \dots, e_{K+1}]'$ is an error term. Despite the simplicity of the model, notice that

(i) asset managerial capabilities, ξ, load on inefficiency odds through (14).

(ii) ξ determines input / decision production through (9) or (10).

(iii) ξ enters directly as a factor of production and determinant of overall technical inefficiency in (8). First, we introduce an index "i" for the particular observation ($1 \leq i \leq n$, where n is the sample size) so that, for example, inputs and outputs can be indexed by i, viz. $X_{i,k}^*$, $Y_{i,m}^*$, ξ_i etc.

Our assumptions for the remaining random elements of the model are quite general and they are as follows.

$$\begin{gathered}(a)\boldsymbol{v} = [v, \boldsymbol{v}_X', \boldsymbol{v}_Y']' \sim \mathrm{i.i.d}\, \mathcal{N}(\mathbf{0}, \Sigma), \\ (b)\boldsymbol{e} \sim \mathrm{i.i.d}\, \mathcal{N}(\mathbf{0}, \Omega),\end{gathered} \tag{15}$$

where Σ and Ω are covariance matrices. The assumption about inefficiency odds seems to be novel, as in stochastic frontiers, researchers place distributions on u, $\boldsymbol{u}_X$ and $\boldsymbol{u}_Y$, usually half-normal, exponential, etc. (e.g. Kumbhakar and Lovell, 2000). Our most likely view about ξ is simply that

$$\xi_i \sim \mathrm{i.i.d}\, \mathcal{N}(0,1), 1 \leq i \leq n. \tag{16}$$

The normalization of the variance to unity is common in factor analysis and structural equation modeling. Finally, we can define our parameter vector $\boldsymbol{\theta} \in \Theta \subseteq \mathbb{R}^d$ which includes loading matrices $\Lambda^{(X)}$ and $\Lambda^{(Y)}$, technological parameters $\boldsymbol{\beta}$, loadings $\boldsymbol{\delta}$, and the scale parameters Σ and Ω in (15). It remains to specify the technology of transforming decisions or inputs to outputs or performance measures in (8). We use linear transformation functions of the form

$$\begin{gathered} g(\boldsymbol{Y}_i^*; \boldsymbol{\beta}) = \sum_{m=1}^{M} \beta_{m,1}\, Y_{i,m}^*, \\ f(\boldsymbol{X}_i^*; \boldsymbol{\beta}) = \sum_{k=1}^{K} \beta_{k,2}\, X_{i,k}^* + \psi \xi_i, \\ 1 \leq i \leq n. \end{gathered} \tag{17}$$

For purposes of normalization, we can select $\sum_{m=1}^{M} \beta_{m,1} = 1$ which, effectively, means that we have an output-oriented distance function representation of the technology (Kumbhakar and Lovell, 2003).[4] We omit an intercept from the second equation of (17) to allow for the condition that zero inputs should produce no outputs. The coefficient ψ is particularly important as it measures the contribution of asset management as a function of production. The relations between AMC and inefficiencies are defined in (12) and (14).

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[4]A technology can be represented, equivalently, by either and output-oriented or an input-oriented distance function.

It is, perhaps, important to understand the particular context of production and asset management in Figure 1(a). The transformation of inputs to outputs, shown by the arrow, is related to (8) or, originally, to (1). This transformation depends or is contextualized by the presence of asset management capabilities, ξ which is both a factor of production but also an "environmental" or contextual variable (also known as determinant) of inefficiency, u. Inefficiency is a measure of how far from the frontier is any given country so, it represents our overall assessment of its position relative to other country. Unique advantages or resources, better asset management practices, organizational practices, etc., are reflected in inefficiency which, moreover, depends on our *measure of asset management capabilities*, ξ.

This dependence is shown in the first equation of (14). Other than that, the important role of asset management is organizing the process of production of inputs from underlying fundamental or higher-order resources as in (9) or (10). The technical possibilities of this transformation are summarized by the elements of $\Lambda^{(X)}$. Asset management has a critical role in this transformation as it affects directly the transformation (through elements of $\boldsymbol{\gamma}$) but also as a determinant of input-specific inefficiencies ($\boldsymbol{u}_X$). This equips asset management with a dual role both as a direct factor of production (in various stages) and as a catalyst in materializing competitive advantages of assets which are reflected in the formation of inputs via their inefficiencies. So, ξ has a role in (i) determining production as a direct factor in both (9) and (8), (ii) determining the quality of transformation of underlying fundamentals to inputs through the inefficiency terms in (9). The dual role of asset management takes place in both stages of production (production of inputs and, in turn, production of outputs and overall performance).

To understand better the workings of AMC (ξ) in the model, see Figure 1(b).[5]

[5]The posterior of the model is presented in Technical Appendix A. To implement statistical inference we use Markov Chain Monte Carlo (MCMC) using 150,000 passes omitting the first 50,000 during the burn-in phase to account for possible start-up effects. Convergence and performance of MCMC is monitored using the standard Geweke (1992) diagnostics.

As we emphasized before, there is a dual role for AMC, as a factor of production in both the production of inputs $\boldsymbol{X}^*$ and final production through the transformation function; inefficiencies u and $\boldsymbol{u}_X$ are correlated (see the dotted curve in Figure 1(b); and, finally, AMC act as a catalyst in determining and configuring the various slacks or inefficiencies in the model. Therefore, the various stages of operation are *mediated* by AMC and they *depend explicitly* on AMC. Even though performance or outputs, $\boldsymbol{Y}^*$, are not "produced" directly through AMC, there is, of course, an effect of AMC on outputs, not only through overall performance inefficiency, u, but through two other channels. First, the role of AMC in producing inputs which, in turn, produce outputs (the mediating role of ξ in the main production indicated by the yellow circle in Figure 1(b)), and, second, through the effect of slacks u and $\boldsymbol{u}_X$. Therefore, changes in AMC, qualitative or quantitative, affect the entire system of operation and not only the formative aspects of inputs or decisions. Of course, they also affect or mediate the outcomes of operation, which are summarized in performance metrics or outputs ($\boldsymbol{Y}^*$). Therefore, the role of AMC is more pronounced in this model (which is, of course, a testable hypothesis) as there are various channels through which they determine or mediate the relationship between the different operative structures.

Although u can serve as an overall index of performance, input slacks ($\boldsymbol{u}_X$) are also significant, and both measurably depend on AMC. These slacks are important outcomes of AMC as it is made explicit in (14) (in terms of inefficiency odds). Improving business performance, in this context, means optimizing AMC so that (i) input slacks ($\boldsymbol{u}_X$) are as small as possible, (ii) overall slack (u) is as small as possible, and (iii) AMC has an essential role in operations either as a direct factor of production (parameter ψ in (8)) in the transformation function or as a mediator of the operative structure that transforms inputs into outputs through other structural elements of the system.

3.1.2. Policy implications and possible feedback effects on AMC

In terms of policy implications, based on Figure 1(b), it is clear that shocks in productivity or inefficiency can have an effect on operations as well as other inefficiency constructs. For example, shocks in $\boldsymbol{u}_X$ affect on $\boldsymbol{X}^*$ through which there are additional effects on $\boldsymbol{Y}^*$ and u. Exogenous shocks in u alone, affect the configuration of outputs ($\boldsymbol{Y}^*$) but have no other effects, and the same is true for shocks in overall productivity (v). Input-specific productivity shocks will, of course, have additional effects on $\boldsymbol{Y}^*$**.** Naturally, changes in AMC (ξ) have systemic effects that are more extensive as can be seen from Figure 1(b).

Due to the nature of the cross-sectional data, it is not possible to examine time variation with dynamic models (Melnyk et al., 2014; Veiga et al., 2021). In a dynamic model, it would have been possible to assume that ξ has an autoregressive structure and / or depends on lagged slacks and inefficiencies to estimate possible feedback from resource management to AMC itself. In a static model, this is, of course, not possible, however, there is a way to examine such possible effects. More details on implementation and underlying notions are presented in Appendix D.

4. Deconfounding

To examine the predictive interpretability of a given model, it is necessary to make sure that the fundamental relationships of the model are predictive rather than due to the dependence of a set of confounding variables. In linear regression, for example, two unrelated variables X and Y may appear strongly correlated if they both depend on common causes Z which have been omitted from the model. If they were included, then X and Y would no longer appear to be associated. The deconfounding approach of Wang and Blei (2019) relies on proxying the effects of confounding variables (if any) by finding one more or more common factor in the data and using these factors as proxies for the underlying confounding variables. In our context, from the underlying data $D_i = [\mathbb{I}_i', \mathbb{O}_i]'$, Wang and Blei (2019) suggest finding a (possibly nonlinear) factor using a model of the form:

$$D_i = \Phi(\zeta_i; \boldsymbol{\varphi}) + \varepsilon_i, 1 \leq i \leq n, \tag{18}$$

where $\Phi(\cdot; \boldsymbol{\varphi})$ represents a nonlinear function dependent on a parameter vector $\boldsymbol{\varphi}, \boldsymbol{\varepsilon}_i$ is a vector error term, and ζ_i represents the common factors. With a single factor and a linear model we have

$$D_i = \boldsymbol{\varphi}\zeta_i + \varepsilon_i. \tag{19}$$

From this perspective, our AMC ξ_i acts as a de-confounder although it has a specific meaning in the context of the model. The difference is that ξ_i loads only on the inputs ($\boldsymbol{X}_i^*$) and the fundamentals ($\mathbb{I}_i$ but not $\mathbb{O}_i$) in a very specific way according to the way inputs are produced through underlying input fundamentals. Instead, the deconfounding model in (18) takes a more agnostic view and determines factors ζ_i which load indiscriminately on input and output fundamentals to proxy for confounding. Therefore, deconfounding variables and AMC have a different interpretation, although AMC may well serve to deconfound the model as, in theory, AMC has an essential structural role in operations and operative strategies. We use both the linear model in (19) as well as quadratic factor models of the form

$$D_i = \boldsymbol{\varphi}_{(1)}\xi_i + \frac{1}{2}\boldsymbol{\varphi}_{(2)}\xi_i^2 + \varepsilon_i, 1 \leq i \leq n, \tag{20}$$

where $\boldsymbol{\varphi}_{(1)}$ and $\boldsymbol{\varphi}_{(2)}$ are vectors of unknown parameters. The linear and quadratic factor models can be easily generalized to allow for more than one factor, and the number of factors can be determined via the marginal likelihood or "evidence" criterion (DiCiccio et al., 1997; Kass and Raftery, 1995; O'Hagan, 1995).[6]

Given deconfounding "throughputs" ζ_i, our models are rewritten so that they depend linearly on the deconfounding variables. In turn, MCMC has performed again, and the results with and without

[6]For a model with parameters $\boldsymbol{\theta}$,data D, likelihood $L(\boldsymbol{\theta}; D)$ and prior $p(\boldsymbol{\theta})$, the marginal likelihood is $\mathcal{M}(D) = \int L(\boldsymbol{\theta}; D)p(\boldsymbol{\theta})\,\mathrm{d}\boldsymbol{\theta}$, the integrating constant of the posterior. For two models, say "1" and "2" (estimated with the same data with possibly different parameters and, therefore, likelihood functions and priors) the Bayes factor in favor of model "1" and against model "2" is $\mathcal{B}_{1:2} = \frac{\mathcal{M}_1(D)}{\mathcal{M}_2(D)}$

the deconfounding factors are compared, the latter being more reliable provided the new model passes certain predictive tests in hold-out or cross-validating subsets of the data. If the model needs deconfounding, then the results in the previous subsection have to be re-examined via the deconfounded model.

5. Can AMC be related to deconfounding?

The (possibly vector) deconfounding factor ζ_i may be related to the AMC index (ξ_i) as both are factors, albeit derived in different ways and they have different substantive interpretations. Nevertheless, there is no theoretical assurance that AMC operates as in the linear factor model (10), and deconfounding as in (18) or (19) may reveal nonlinear aspects of AMC. The issue, of course, arises only when deconfounding is necessary. In this case, the question becomes whether $[\xi_i, \zeta_i]$ are multiple indicators for AMC standing for its linear and nonlinear components, respectively. This interpretation depends critically on the posterior relationship between ξ_i and ζ_i; as they are estimated based on the same data, in principle, they are not independent, and their relationship reflects interpretations or discursive formations that can be given to ζ_i in the light of information about ξ_i. If ξ_i and ζ_i are a posteriori independent, such formations are not possible and ξ_i continues to have the AMC interpretation that it has been given theoretically.

If they are a posteriori dependent, then the question becomes which part of ζ_i was missing from AMC (ξ_i) and which part of ζ_i reflects purely technical or statistical deconfounding (for example, missing variables, specification errors, etc.). One solution is to look at the part of the variation of ζ_i that can be explained by ξ_i and nonlinear functions of ξ_i. This will be the part that can be attributed to a "better" measure of ξ_i, while the remaining would correspond to proxying for confounding, specification errors, etc. So, deconfounding can operate in terms of improving the AMC indicator and it would also allow, at the same time, to examine the effect of specification errors which, however, are taken into account into final estimation and statistical inference about operative and resource inefficiencies. Our extension to panel data is described in Appendix D.

6. Data and amendments to the panel data model

We use data from World Bank's TCdata360 which "is an initiative of the World Bank Group's Macroeconomics, Trade & Investment Global Practice, which helps countries achieve the Bank Group's twin goals, ending extreme poverty and boosting shared prosperity, through rapid and broad-based economic growth, centered on strong contributions from the private sector" (https://tcdata360.worldbank.org). As the data is aggregate at the country level, it allows us to examine AMC and management skills of the private sector from a global macroeconomic perspective which, effectively, connects AMC to actual economic policies (Patel and Tsionas, 2021). So, the context is a global economic environment into which different stakeholders, besides the private sector, of course, have an interest in asset management and AMC to improve overall economic conditions. Competitive advantages in this discursive formation are transformed to global competitive advantages with considerable scope for economic policy to improve best practices relative to the world economy. Our sample includes 512 inputs and outputs in 219 countries (2000-2018). The broad set of 512 indicators of the World Bank's TCdata360 initiative is reported in Table 1(a) along with the number of underlying constructs reported in parentheses. The full list of indicators is provided in Appendix B. Descriptive statistics are presented in the Online Appendix B. Each broad indicator depends on a large number of underlying fundamentals which are summarized in the Online Appendix B. The data cover the period 2000-2018 and the list of countries is reported in the Online Appendix B (see also https://tcdata360.worldbank.org/countries#).

Before listing the variables (full list in Appendix B), two important caveats are necessary to discuss. First, we note that of the 512 inputs and outputs in 219 countries (2000-2018) we did not use filters or selected specific variables. This approach is consistent with the proposed empirical model and avoids the problem of selectively including variables specific to a theoretical model (Atinc and Simmering, 2021; Hünermund and Louw, 2020). Due to the more practical goal of our contribution, we selected all the variables that provided a sufficiently balanced panel. Much continuous data collection efforts on detailed country-level indicators started at the World Bank after 2000. Although GDP, unemployment, and population-level measures are available since the 1960s richer measures are sparse.

Second, though we use the data provided by the World Bank, readers must note the data compilation methods and aggregation policies used by the World Bank.[7] Related measurement concerns are that variations in timing and reporting practices across countries can increase measurement errors. Degrees of economic development could add distortions among countries in collecting and reporting data. Due to these inconsistencies, World Bank uses standard definitions, the timing of reporting (fiscal vs. calendar year), and aggregation protocols to ensure fidelity to the data. Given the scale and scope of the data, the World Bank Indicators is the only reliable data available on the global scale. However, we do urge the readers to consider the readers to account for the data collation and aggregation methods used by the World Bank in addressing the findings.

Our outputs are Investment, Private Sector Investment, and Economic Outcomes. Inputs are Trade, Innovation, Manufacturing, and Tourism. Innovation has its inputs and outputs (see Table 1(b)) and is also related to important variables like Entrepreneurship, Firm Dynamics, and Reform Progress in Innovation. We treat these three variables as separate inputs along with Climate Competitiveness. The Social Context variables are Economic & Social Context, Gender, and Climate Competitiveness (which, however, we treat as an input, Gast et al., 2017). Monetary and Fiscal policies are treated as an exogenous "Economic Policy" category.

[7] Source: https://datahelpdesk.worldbank.org/knowledgebase/articles/906531-methodologies

The data allow us to have both Contextual and Policy variables which we denote respectively, by $C^*{}_{it}$ and $\boldsymbol{Z}_{it}^*$–we include a star as these are constructs from their fundamental indicators. One particular characteristic of the model is that innovation, entrepreneurship, and climate competitiveness are both inputs and outputs, albeit not in the same time period, as it takes time for the effect of these inputs to diffuse and have an effect on themselves in a path-dependence paradigm (Dou et al., 2019). The contextual and policy variables are assumed to have a direct effect on AMC which we re-formulate as follows:

$$\xi_{it} = \alpha_{i,\xi} + \rho_i \xi_{i,t-1} + \boldsymbol{p}_{i,t-1}{}' \boldsymbol{\varphi}_i + \boldsymbol{C}^{*'}{}_{it} \boldsymbol{\varphi}_{i,C} + \boldsymbol{Z}{}_{it}^{*'} \boldsymbol{\varphi}_{i,Z} + e_{it,\xi}, \tag{21}$$

where $\boldsymbol{\varphi}_{i,C}$ and $\boldsymbol{\varphi}_{i,C}$ are coefficient vectors. Our discursive formation is that economic policy but, perhaps more importantly, the overall economic and social context, predicate the development of AMC and managerial capabilities–which is, of course, a testable hypothesis using (21). Of course, the contextual and policy variables may have other effects in the system, for example, in economic outcomes such as investment. Such effects are difficult to model and they are still part of wider controversies in economic theory so, we decided not to take a particular stance and relate policy variables with economic outcomes directly as well as through AMC. So, in effect, all outputs are directly related to policy as well as contextual variables. The model is graphically presented in Figure 2.

Part of the attraction of the model is that there are important contextual and policy variables so, changes in ACM are not the only possible changes that we can examine in relation to inefficiencies as well as the process of formation for inputs and outputs. The effects arising from such changes are dynamic and can be traced over time so, different scenarios related to policy or contextual variables may be examined. The need for dynamic formulations has been emphasized before in the asset management literature (Brown and Blackmon, 2005; Melnyk et al., 2014). This is important not only because, conceptually, dynamic models can accommodate better the changes necessary to adapt asset management policies to the operative conditions and market-based signals, but also because such effects can be measured quantitatively to inform policy discussions of asset management.

Part of the appeal for using aggregate data is that such policy effects can be measured and evaluated albeit at the economy-wide level. To another extent, changes in the business climate, policy uncertainty, tax configurations, etc., have a more direct effect and can inform optimal asset management more directly, along with other variables, of course. Innovation is an important part of the model, particularly because we have both innovation inputs and outputs along with indicators for entrepreneurship. As innovation and entrepreneurship are at the heart of formulating an asset management framework, it is important to investigate and quantify the interactions between AMC and entrepreneurship/innovation aspects. Using aggregate data makes this investigation not only more useful (for theoretical formulations and empirical measurement of causes and effects) but also, perhaps, more interesting, as such investigations are properly contextualized in a wider framework that consists of social structures and policy variables.

Next, we present the empirical test. We should note that, at least for the most part, instead of reporting a large number of tables, we resort instead to a graphical approach where marginal posterior densities are presented for parameters and functions or variables of interest emerging from Bayesian analysis. Marginal posterior densities carry all the necessary information for a parameter in terms of location, spread, etc., but also allow a broader view of the small-sample properties which have an impact on estimation. Moreover, multiple posterior densities can be easily compared on the same graph.

8. Discussion

8.1. Empirical findings

As we emphasized before, it is essential to ensure that the model admits a predictive, but not causal, interpretation[8] (Shmueli, 2010; Shmueli et al., 2019; Sperrin et al., 2020). We use an estimation sample containing 75% of the total number of observations and, in turn, we examine the predictive performance of the model in the remaining hold-out or cross-validating sample which contains 25% of the observations. The allocation of observations to estimation and cross-validating samples is performed randomly 1,000 times. Using Bayes factors for model comparison, four factors are needed for the quadratic factor model.[9, 10] Further details are reported in Online Appendix D. Finally, we report posterior moments for the estimation of the transformation function (17) in Table 2.

In the model, entrepreneurship is both an input and output (see Figure 2). The results show that entrepreneurship inefficiency associated with AMC is quite heterogeneous across countries and regions and it seems to be substantial in most instances. The role of climate is also important as documented in other studies (Astebro et al., 2014; Greco et al., 2008) and it is found to be also quite heterogeneous across regions and countries with substantial slacks or inefficiencies which imply that there is a room for improvement in terms of eco-friendly technologies and asset management. The role of entrepreneurship in the process formation of economic outcomes is well established in the literature (Campbell, 2009; Parker, 2018). The underlying measures in the model were Entrepreneurial Culture, Access to Finance, Self-employed, Manufacturing by Business Size,

[8]Posterior means, standard deviations, and their ratios for factor loadings of underlying variables on the various constructs are reported in Online Appendix C. The ratio has the usual *t*- or *z*-statistic interpretation. From each category, we extract a single factor as multiple factors would be hard to interpret. In all cases, a single factor explains at least 80% of the total variation of the underlying variables. Another reason for using a single factor to represent a category is that in what follows, formal deconfounding allows for more than a single linear or nonlinear factor.
[9]The posterior odds in favor of four factors relative to three were 236.15 and against five or six they are 415.20 and 681.15, respectively. The posteriors odds against one, two or three factors were 1,977.42, 873.30 and 717.93, respectively.
[10]This involves an additional MCMC run for each time we perform a cross-validation comparison.

Entrepreneurial Markets, Entrepreneurial Policy, Gender Entrepreneurship, and Entrepreneurial Activity (see Online Appendix B).

In market economies, the realization of competitive advantages works and builds on entry and exit to improve productivity.. The view that emerges from these findings is clear: AMC has important effects on productivity and can contribute to aggregate growth, through various channels including entrepreneurial activity, input and output innovation, climate competitiveness, comparative advantages in international trade. These empirical findings put AMC at the center of a framework that addresses issues of competitiveness, productivity, and entrepreneurship. If AMC has a substantial effect on entrepreneurship (which is both an input and output, i.e. both a decision and an asset) it follows immediately that AMC is a catalyst in building sustainable entrepreneurial cultures and structures.

At first sight, this is a surprising finding as one would expect instead entrepreneurship to be a determinant of good asset management practices. Although the model does not allow a direct link from entrepreneurship to asset management there is, in fact, from entrepreneurial inefficiency to AMC through the panel factor model and this effect is statistically and quantitatively important (see Table 2). In terms of the contextual variables, both Economic & Social Context and Gender have a positive and quantitatively important effect in the AMC process formation. Policy variables seem to be less important as, at least, in the aggregate, we are unable to document "statistically significant" effects with monetary policy having an effect that is marginal "statistically significant". In principle, the country-level effects could be different so, we report their marginal posterior densities for all countries in Figure 3.

Despite the differences across countries, for the most part, fiscal and monetary policies do not seem to contribute much to the formative processes of AMC as the marginal posterior densities are centered around zero. On the contrary, Economic & Social contexts and Gender are quantitatively important determinants of how AMC processes are formed. This is not unexpected as short-term economic policies have significantly less to do compared to the other two contextual variables. Gender equality seems to have an important role in forming the framework of AMC and the same is true for societies with functioning institutions, rule of law among others (reflected in the Economic & Social Context construct). So, the role of "context" is quite significant in discursive formations involving AMC, productivity, and entrepreneurial skills.

8.2. Theoretical implications

We proposed a framework for asset management capabilities, a capability related to processes of inputs and outputs that collectively drive entrepreneurial variation across countries. The analysis aims to understand the relationship of inputs and outputs in driving differences in entrepreneurship-related outcomes. Our study provides a formal quantification of the operative framework for AMC and entrepreneurship, that relies on economic and social context, gender issues, as well as fiscal and monetary policies. The results are carefully predicated on ensuring that the final model we work with has a predictive interpretation, and are not confounded by latent constructs that were used to deconfound the model, allowing us to separate asset management from entrepreneurship, technology, and innovation, the issue of identifying "managerial skill" is, perhaps, redundant, as it is predicated on the stated constructs and processes.

The theoretical mainstay we build upon is from the entrepreneurship policy literature. In his review, Smallbone (2014) shows that the efficacy of entrepreneurship policy is limited and it could be explained by institutional and a variety of policymaker and cultural factors. Our model holds these factors constant using fixed country-year effects. AMC could be an important linchpin to explaining why some entrepreneurship policy is more effective than others. Studies have shown that policies may not affect entrepreneurial activity (Bennett, 2009) and others have called for caution against inefficiency entrepreneurship policy in general. AMC provides a plausible approach in assessing the value of resource orchestration at the country level. It is also important that our empirical findings are consistent with the idea that asset management is, in itself, a form of "managerial entrepreneurship" as it predicates not only economic outcomes per se but also the quality of inputs that go into the production process. This "managerial entrepreneurship" is related to managerial skills although, in this study, we did not attempt to make a distinction between the two, as asset management is not a purely technical issue and managerial skill is not purely entirely outside the process of forming inputs and transforming them to outputs.

The findings demonstrate that asset management has a central role in operative processes of the global economy, including the formative processes of inputs, their transformation to outputs, as well as inefficiencies or slacks in input-specific assets. In turn, these assets, along with variables that represent the contextual framework, exercise quantitatively important effects on AMC. In effect, both asset management effectiveness and the process of its formation, depend critically on inefficiencies resulting from second-best or non-optimal asset management capabilities. Fiscal and monetary policies do not seem to exercise quantitatively important effects on asset management capabilities or the formation of competitive advantages from unique resources (per the resource-based view) but contextual variables like institutions, rule of law, gender, etc., seem to play a significant role in asset management constructs and, perhaps more importantly, their formative processes. Our findings indicate that inefficiencies in the various sources of competitive advantages are highly persistent and interdependent but, at the same time, they depend critically on asset management. We also note that AMC is not by definition a positive consideration. Based on previous cautions against encouraging entrepreneurship by Shane (2009) and Parker (2007), though AMC refers to more effective input-output conversion we caution that AMC must be pursued more so under possibly positive outcomes of self-employment.

The wide range of input and output variables (512 variables), although not exhaustive, are relevant to the ontological and phenomenological aspects of entrepreneurship, broadly defined. This broad definition may also be of help to unify underlying fragmented views of the entrepreneurial process (Radu-Lefebvre et al., 2021). The resource-based view is one of the influential models in production economics and operations research that is related to asset and resource management. It provides an explanation why profitability differences are not rapidly competed away, invoking country-level analogy of access to heterogeneous and immobile resources with limits to competition (Wernerfelt, 1984). There are also implications of the RBV for other fields, including human resource management, economics, entrepreneurship, marketing, and international business (Gerhart and Feng, 2021). We do not test the capabilities directly but use the panoptic approach of zooming out to propose country-level resource orchestration, AMC as an attempt to focus on the 'bundle' element of the resource bundles in RBV. AMC is a more relevant consideration for resource orchestration at the country level (Hayek, 1978).

The relevance of AMC through the lens of resource orchestration is salient in the context of the growing focus on the entrepreneurial ecosystem. Entrepreneurial ecosystem refers to "[s]ituating productive entrepreneurship at the center of research agendas allows for a closer examination of the interdependencies within networks that affect new value creation" in an economy (Wurth et al, 2021, p. 4). We investigate these interdependencies in a global framework using panel data (1998–2018) from the World Bank and draw on the Bank's systematic investigations to use constructs that allow the contextualization of several prominent themes like entrepreneurship, innovation, business climate competitiveness, and a broader view of "inputs" and "outputs" in the transformation process which is at the heart of economic outcomes and growth.

8.3. Methodological implications

AMC as a dynamic process is endogenously determined and, in turn, it affects not only outcomes but also AMC. Entrepreneurship is a complicated phenomenon that draws on different disciplines and epistemological paradigms (Cronin and George, 2020), for example, refer to (Radu-Lefebvre et al., 2021) and Shir and Ryff (2021) among others. Our proposition is that (a) entrepreneurship materializes in a specific context; (b) it is affected by and affects asset management; (c) it depends on several underlying more fundamental underlying constructs, and (d) it is both an input and an output in economic systems.

The formative process of asset management itself depends explicitly on environmental or contextual factors. As the central question is "how entrepreneurial agents can identify and actualize the potentials provided by external changes" (Kimjeon and Davidsson, 2021, page 2) the potential answer, emerging from our findings, is that asset management capabilities have a first-order of importance and that the entrepreneurial process is dynamic in itself. This is not an abstract statement as it is conditioned on a predictive model but, more importantly, on specific determinants of the entrepreneurial process so, the methods and perspectives in the present paper (along, perhaps, with techniques for predictive validity and deconfounding) are likely to be of use in future theoretical or empirical investigations in innovation strategies, entrepreneurship, and asset management. Last but not least, entrepreneurship, asset management, and innovation are found to have important effects on the environment, which paves the way for more eco-friendly technologies, managerial practices, and their applications.

From the econometric perspective, the model is novel as it is a factor model that included nonlinear dynamic latent variables. Such models are difficult to handle by methods such as a maximum likelihood or the generalized method of moments. More importantly, we have shown how proper deconfounding can be carried out in this general class of models to ensure (to the extent afforded by the observed data) the predictive validity of the model. Well-defined statistical procedures are used to perform the deconfounding and, despite the presence of extensive heterogeneity in the data, it is not impossible to arrive at a predictive model.

8.4. Managerial implications

Our findings are not confounded by latent constructs that were used to deconfound the model, allowing us to separate asset management from entrepreneurship, technology, and innovation, the issue of identifying “managerial skill” is, perhaps, redundant, as it is predicated on the stated constructs and processes. Predictive models are characterized by mainly two facts. First, their predictive performance does not deteriorate over different sub-samples of the data, and, second, key quantities of interest or parameters remain approximately invariant as concomitant variables are added to or removed from the model. Thus, predictive models avoid the pitfalls of confounding i.e. the presence of confounding variables that may have an effect of variables of interest without the latter being, necessarily, correlated. Deconfounding the entire model relies on solid statistical procedures and extensive investigation of parameter sensitivity and predictive performance.

Although our conceptual framework is not unlike the one explored in Veigas et al. (2019, 2021), formalization and contextualization are different, as we allow for an explicit role of AMC which can be measured in the light of the data. This leads to a different formalization using, however, more or less the same constructs (although estimated in a rather different way). The contextualization is also different in the sense that functional strategies can be examined in a more detailed way through the quantification of AMC. In this sense, we view the present model as complementary to Veiga et al. (2019, 2021) rather than as a substitute.

8.5. Practical implications

Our study has implications for policymakers. The results demonstrate that AMC is an important consideration for policymakers in managing their task environment. Dealing with a multitude of policies and resources AMC helps assess the efficacy of systemic conversion input conversion efforts necessary to allocate and leverage resources. AMC is essential to managing a task environment consisting of macroeconomic, institutional, and resource conditions within the bounds of policymakers as a collective. Because AMC requires consideration of emerging changes, requires sensing and responding, AMC could be central to building a critical capability necessary for the endurance of entrepreneurial activity in a country. AMC can be central to leveraging resource combinations and experimenting with unusual initiatives and "what if" configurations.

AMC may also explain how policy makers in resource-scarce settings can improve entrepreneurial activity under limited resources—by not pursuing systematic activities Conversely, managers in more resource-scarce settings may increase resilience by not pursuing systematic activities to extract more value from resource configurations. Though our study is not aimed at providing developmental paths for assessing resource configurations, we assessed whether it helps to a stronger AMC in explaining the entrepreneurial activity. Consideration of a variety of inputs and the conversion ability at the country level is an important consideration.

8.6. Limitations, directions for future research, and conclusion

Our study has limitations that must be considered in interpreting the effects. First, as noted earlier, AMC, like capabilities is unobserved. As such, though we cannot propose a country-level recipe for AMC, our model considering a wide range of inputs and lowering concerns for predictive ability does demonstrate that AMC is an important consideration for explaining heterogeneity in entrepreneurial outcomes. Second, to allow for replication using publicly available data and using the most comprehensive country-level data of 512 economic inputs and outputs we used the World Bank data. Acknowledging that richer data with even more inputs may add more precision, we expect that the proposed model provides a starting point in helping guide future AMC-related studies.

Our analysis focuses on country-level asset management capability and does not refer to the complex meso-level interactions among firm capabilities and policies. Developing a richer understanding of how firms respond to policies within the milieu of their resources is an important research question for future research. The same policy in the same country may elicit different reactions from firms and these outcomes could further aggregate at the national level. Though data gathering across a variety of firms in different countries is challenging, the between-country policy variations and within-country firm responses is an important area of future research.

Next, though our analysis focuses on the country level and perhaps seems to credit policymakers, we caution that the findings should not be interpreted as such. In addition to the firms, local governments, competitors, universities and research laboratories, and historic formal and informal institutional conditions are some of the factors that enhance AMC. The effects of these enabling conditions are not modeled in this study due to the lack of availability of process data from these factors. As such, AMC may be an upward bias in favoring the role of policymakers.

Despite these limitations, we believe that this study moves forward in the understanding of AMCs for the field and policymakers. Third, though we do not claim that AMC can directly explain if it leads to *better* entrepreneurship outcomes, it provides a starting point to impel discussion on the operative process of converting a variety of inputs to realize a level of entrepreneurial activity. Based on past works we caution that not all entrepreneurship is "good" entrepreneurship (Parker, 2007; Shane, 2009), understanding the orchestration process could help shed light on the operative process of considering a wide range of inputs to entrepreneurship in a country.

We also present the following future research directions. On the one hand, the lack of deterioration of competitive advantages is path-dependent and persistent, it is structural as it depends on inefficiencies in other competitive advantages or assets and decisions but there is hope in the sense that asset management is quite prominent in the model and plays a substantive role. For example, asset management quality sets in motion feedback or dynamic process which impacts on entrepreneurship (a dynamic process itself) which has feedback on asset management capabilities themselves. This interrelationship is critical as it sets in motion a process of growth and sustainable productivity which is predicated on innovation and entrepreneurship predicated on asset management capability.

We do not claim that we have found a *unique* causal model, as multiple models can be consistent with a causal interpretation if they are invariant under interventions in their concomitant variables or terms of predictive performance in a cross-validating context. Therefore, our model is predictive. In terms of the wider entrepreneurship agenda, we believe that we have suggested some important avenues for future research. First, the formal connection between entrepreneurship and asset management which is novel in itself can be investigated further. In this operative framework, the connection between entrepreneurship and asset management is predicated on or mitigated (mediated) by a wider agenda that relates to innovation in inputs and outputs (R&D figuring, of course, prominently), aspects of sectoral dynamics, aspects of international trade and unique competitive advantages but also economic, social, and gender issues. Second, the issue of the role of economic policies in the formative process of entrepreneurship and asset management, seems that deserve further investigation even though it received its fair share of investigation in the present study. Although we do include factors relating to policy uncertainty and business climate changes, it could be interesting how different economic policies (particularly, a monetary policy that determines interest rates) may have a path-dependent (persistent or dynamic) effect on the formative process of innovation, competitive advantages, entrepreneurship, and overall competitiveness.[11]

Third, there is certainly, a theorization that emerges from the model for further investigation. One particularly important aspect of this abstract theorization is that entrepreneurial dynamics depend on asset management dynamics, and inefficiencies in input formation (where inputs include entrepreneurship, innovation, etc.) *may be part of the systemic structure*. Therefore, organizational and managerial culture, as a contextual variable, emerges as a key conditioning process for

[11] This particular aspect is motivated by the Austrian theory of the business cycle due to von Mises and Hayek.

entrepreneurial dynamics but also the *entrepreneurial identity itself*, a feature that has been emphasized in recent research (Radu-Lefebvre et al., 2021; Shir and Ryff, 2021; Kimjeon and Davidsson, 2021). The notion of an *entrepreneurial identity is contextualized in this study,* hopefully in a proper way although further research is needed along this dimension. Undoubtedly enhancing "future accumulation of knowledge about the *strategic and serendipitous influence of environmental changes throughout and beyond the venture creation process*" (Kimjeon and Davidsson, 2021, emphasis added) is, clearly, an item that has been the central focus of the present study and we suggested that key link is asset management in the formative processes of entrepreneurship, innovative activities in inputs and outputs, sustainable competitive advantages and overall business climate.

8.7. Conclusion

Hayek explained the value of policymaking as: "The effect of people's agreeing that there must be central planning, without agreeing on the ends, will be rather as if a group of people was to commit themselves to take a journey together without agreeing where they want to go: with the result that they may all have to make a journey which most of them do not want at all." In the Hayekian sense, there are, of course, different channels through which entrepreneurship affects aggregate economic outcomes and growth (Silverberg and Yildizoglu, 2002). However, AMC involves a discursive formation where entrepreneurship is both a produced and used resource in the wider context of economic and social environments. We hope that the theory and findings presented here spur further examinations of AMCs.

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Table 1. Indicators (512 indicators in total)

Table 1(a). List of broad indicators

Category	Broad Indicators
Trade	Trade Outcomes (32) Trade Barriers (20) Trade Facilitation (18) E-trade (20) Connectivity (12) Competition and Competition Policy (20)
Investment	Reform Progress (Investment) (20) Perceived Constraints (20) Risk and Policy Uncertainty (20) Entry and Investment (21) Cost of Operations (28) FCS Investment Trends (20)
Innovation	Innovation Inputs (22) Innovation Outputs (20) Entrepreneurship (8) Firm Dynamics (35) Reform Progress (Innovation) (20)
Economy	Economic Outcomes (20) Economic & Social Context (20) Monetary and Fiscal Policies (20) Private Sector Investment (16) Gender (20)
Sectors	Climate Competitiveness (20) Manufacturing (20) Tourism (Sector) (20)

Notes: Reported in parentheses is the number of underlying constructs.

Table 1(b). Definition of inputs and outputs

Inputs	Outputs	Context	Policy
1. Trade 2. Innovation inputs 3. Innovation outputs 4. Manufacturing 5. Tourism 6. Entrepreneurship (*t*-1) 7. Firm Dynamics 8. Reform Progress in Innovation 9. Climate Competitiveness (*t*-1)	1. Investment 2. Priv. Sector Investment 3. Economic Outcomes 4. Entrepreneurship 5. Innovation Outputs (*t*-1) 6. Climate Competitiveness	1. Econ. & Social Context 2. Gender	1. Monetary policy 2. Fiscal policy

Table 2. Posterior moments of transformation function parameters

	$\boldsymbol{\beta}_{(1)}$ $g(\boldsymbol{X}^{*};\boldsymbol{\beta})$ coefficients		$\boldsymbol{\beta}_{(2)}$ $f(\boldsymbol{X}^{*};\boldsymbol{\beta})$ coefficients
1. Trade	0.00124 (0.0005)	1. Investment	0.013 (0.004)
2. Innov. Inputs	0.0130 (0.003)	2. Priv. Sector Inv.	0.127 (0.032)
3. Innov. Outputs	0.022 (0.005)	3. Econ. Outcomes	0.361 (0.032)
4. Manufacturing	0.032 (0.013)	4. Entrepreneurship	0.225 (0.010)
5. Tourism	0.052 (0.010)	5. Innov. Outputs	0.414 (0.012)
6. Entrepreneurship (t-1)	0.213 (0.043)	6. Climate Comp.	0.082 (0.014)
7. Firm Dynamics	0.226 (0.025)	7. ξ_{it}	0.372 (0.044)
8. Reform Progress in Innovation	0.082 (0.014)		
9. Climate Competitiveness (t-1)	0.122 (0.043)		

Notes: Posterior standard deviations appear in parentheses.

Figure 1. AMC process

Figure 1(a). Representation of AMC operative process

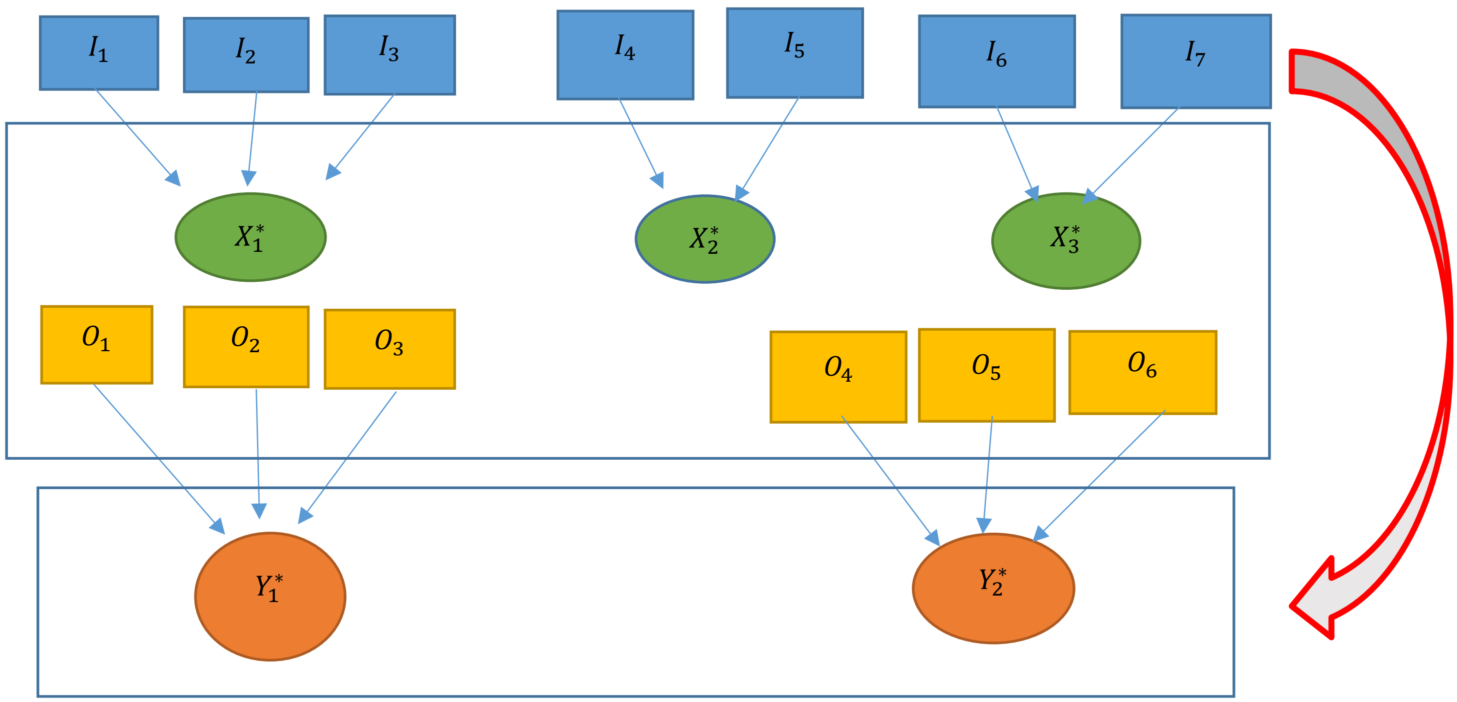

Figure 1(b). Workings of AMC model

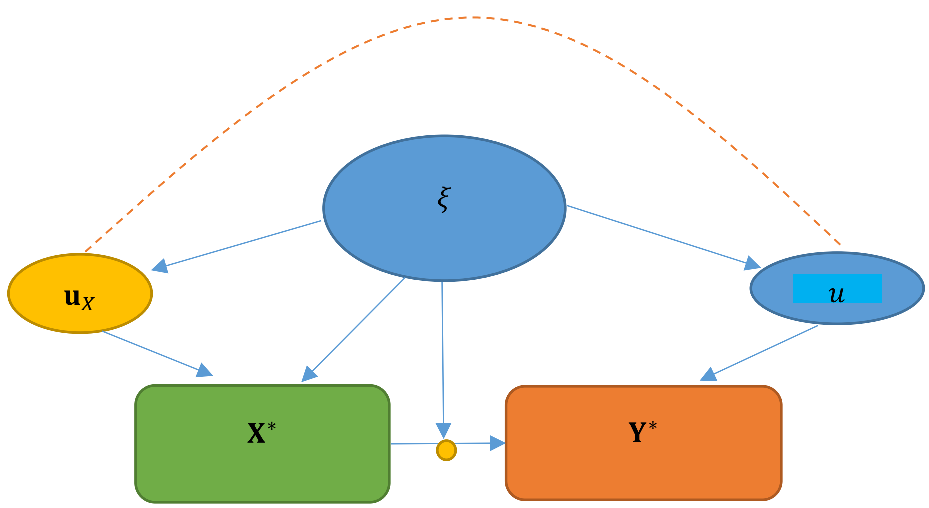

Figure 2. Illustration of the model

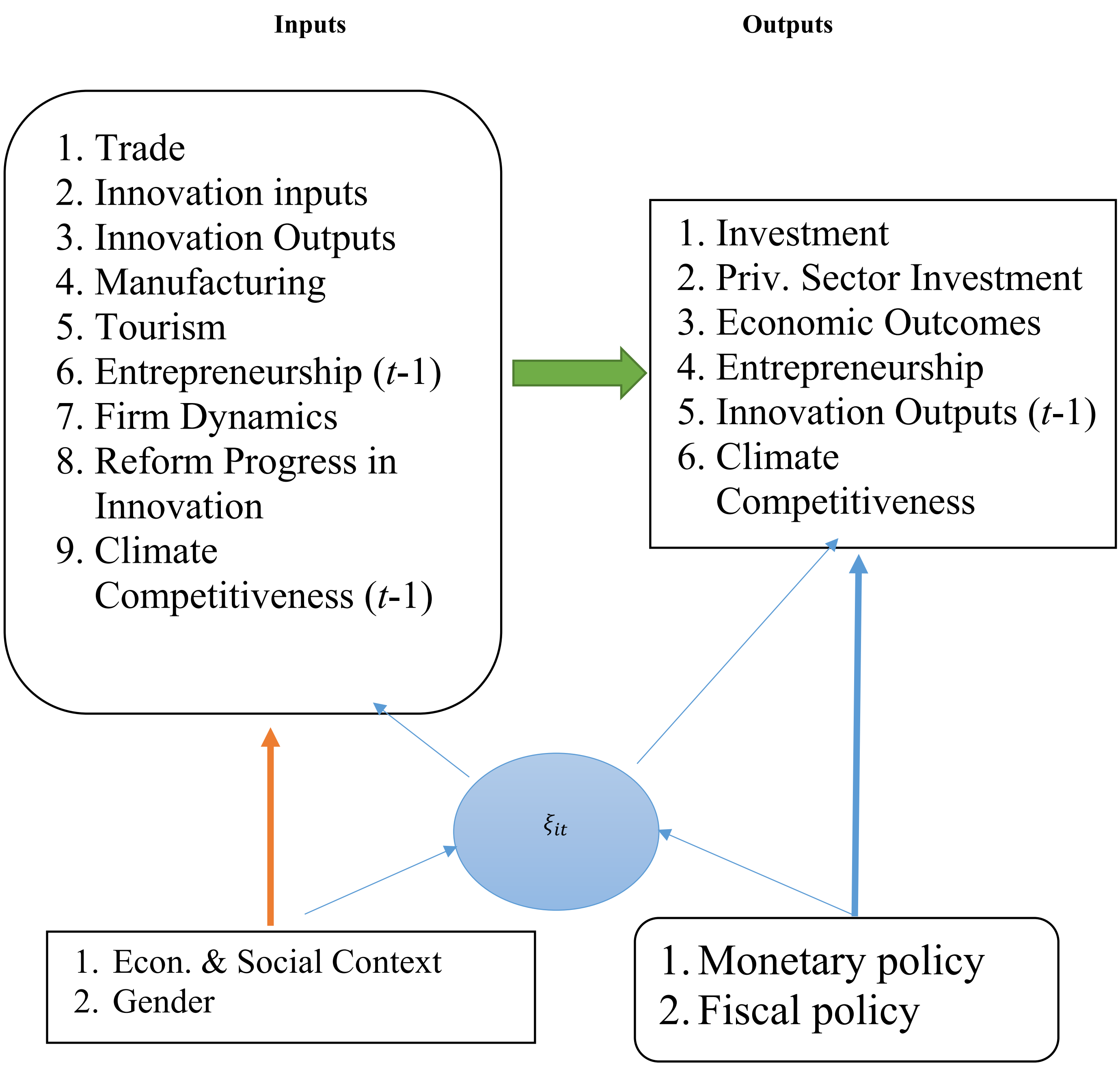

Figure 3. Marginal posterior densities of policy variable effects