"National Systems of Innovation: A Structural Model Analysis of Efficacity—The Case of Ghana"

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Abstract

Within the context of the knowledge-based economy a systemic perspective on innovation, as the salient feature of economic development, is increasingly necessary and is of strategic policy value (Bartels *et al*., 2012). The National System of Innovation (NSI) of a country is vital for accelerating competitiveness and enhancing economic performance (Bartels and Voss, 2005) This is crucial for developing economies wishing to catch up with advanced industrialised countries (Arocena and Sutz, 2000). Innovation and NSI previously perceived linearly is now considered as a systemic network and this view yields much improved policy craft (Balzat, 2002). In order to allocate limited resources efficaciously through targeted policy, mapping, measuring and thereby managing the interactions of the core Actors and barriers to innovation within the NSI is necessary (Bartels *et al*., 2009). This paper examines the NSI through Structural Equation Modelling (SEM) using empirical data on the Ghana NSI (GNSI). The theoretical approach used to model GNSI is Systems of Innovation (SI) specifically the 'Triple Helix' (TH) (Leydesdorff and Etzkowitz, 1998) and its extension to the 'Triple Helix' Type 4 (TH4) (Bartels and Koria, 2012; Koria *et al*., 2014). This extension articulates NSI core actors as: Government, Medium- and High-Technology Industries (MHTI)[6], Knowledge-based Institutions (KBIs), and Arbitrageurs[7] operating in a medium of diffused Information and Communication Technology (ICT). The approach herein encapsulates the concurrent application of a single Data Acquisition Survey Instrument (DASI) to the four core Actors in the NSI. We find that first that the construct GNSI Efficacity is determined by Actor Connectedness but not by Barriers to Innovation. Secondly, we find that GNSI Efficacity is measureable by Factors that influence Incentives, Innovation Capacity, and Standards. Thirdly, Actor Connectedness is measureable by Factors that influence Actor Intra- and Inter-linkages. Fourthly, Barriers to Innovation are measureable by Factors that influence ICT Capability/Capacity, Markets, Fiscal Policy, and Organisational Risks.

Key Words: National System of Innovation, Structural Equation Modelling, Factor Analysis, Evidence-based innovation policy, Economic and industrial development.

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1. Introduction

This paper analyses the National System of Innovation (NSI) through Exploratory Factor Analysis (EFA) and Structural Equation Modelling (SEM), using empirical data on the Ghana NSI (GNSI), regarding mapping and measuring the NSI for policy insights. This enables the formulation of coherent, evidence-based science, technology and innovation policy. It presents a four-dimensional ICT-intense methodology for mapping, measuring and hence monitoring and managing NSI (Koria and Koseigi, 2011; Koria *et al*., 2012). Our methodology takes departure from Leydesdorff and Etzkowitz (1996) Triple Helix (TH) framework which we elaborate as a Triple Helix Type 4 (TH4) Model.

First, our approach incorporates specifically the nucleus of the NSI comprising four core Actors [Government (GOV), Industry (specifically Medium- and High-technology Industries (MHTI)), Knowledge-based Institutions (KBIs), Arbitrageurs (ARBs)]. Secondly, it articulates the concurrent application of a single Data Acquisition Survey Instrument (DASI) to Respondents from the four core Actors in the NSI[8]. Thirdly, it reflects the four phases of innovation policy[9] in which a significant part is played by Arbitrageurs [Knowledge-brokers (KBs), Financial Institutions (FIs) and Venture Capital (VC)] (Hargadon, 1998; Baygan and Freudenberg, 2000; Zook, 2003; Howells, 2006; Samila and Sorenson, 2010.). Identifying the dynamic nucleus of the NSI as the Intra- and Inter-relationships of the four Actors advances the TH of Etzkowitz and Leydesdorff (2000), which does not traditionally feature Arbitrageurs as a separate Actor, as a TH4 embedded within an environment of diffused information communications technology (ICT) (Koria *et al*., 2014).

Innovation is the engine of capitalism and National Systems of Innovation or National Innovation Systems (NSI or NIS)[10] are vital to long-term economic growth and competitiveness (Furman *et al*., 2002; Furman and Hayes, 2004); and the effectiveness and efficiency (encapsulated by efficacity) of NSI is increasingly of strategic policy concern for advanced industrialised, as well as developing, countries (Groenewegen and van der Steen, 2006; Taskin and Zaim, 1997; Aghion *et al*., 2012; Samara *et al*., 2012; Ushakov, 2012). This concern is emphasised by the innovation divide (Sachs, 2003) and the ever-widening 'digital divide' or 'digital inequality' (DiMaggio and Hargittai, 2001; White *et al*., 2011). The first formal conceptualisation of NSI is attributable to Adam Smith in his 1776 analysis of "knowledge creation in relation to directly productive activities but also specialised services of scientists" (Lundvall *et al*., 2002. pp. 5). The more modern conceptualisation is by List. Freeman (1995, p. 5) indicates that "Friedrich List's conception of 'The National System of Political Economy' (1841), … might … have been called 'The National

[8] Actors and Respondents are used interchangeably in the Paper.

[9] Phase 1 - the government directly intervenes in business sector R&D and innovation. Phase 2 - involves strengthening of targeted business sectors. Phase 3 - the targeting of VC and rapid growth of R&D and innovation activities are priorities. Phase 4 - the emphasis shifts to restructuring and further targeting of specific sectors while addressing specific system and market failures (Avnimelech and Teubal, 2006).

[10] These two phrases are consistently present in text and citations over time within the literature (see Bartels *et al*., 2012; Munk and Vintergaard, 2004; Arocena and Sutz, 2000b; Rockefeller Foundation, 2003; OECD, 2002, 1999; Lundvall, 1992, 1995, 2007; Nelson, R. R.,1993; Nelson, E. R., (ed.) 1963, for example). Although interchangeable, we prefer to use the term National System(s) of Innovation. The semantic difference is important – our preference places emphasis on the system(s) of innovation manifest at the national level of economic policy co-ordination and organisation.

System of Innovation'. The main concern of List was with the problem of Germany overtaking England and, for underdeveloped countries (as Germany then was in relation to England), he advocated not only protection of infant industries but a broad range of policies designed to accelerate, or to make possible, industrialization and economic growth. Most of these policies were concerned with learning about new technology and applying it."

We map and measure the NSI by applying simultaneously a singular DASI to the nucleus of Actors and then subject the data to EFA and SEM. Our TH4 approach features a distinctive characteristic which is absent from the traditional Triple Helix model, defined by The Institute for Triple Helix Innovation, as "Academia, government, and industry constitute the three helices that engage in triple helix innovation." (The Institute for Triple Helix Innovation)[11]. We argue firstly that the centrality of Arbitrageurs to innovation, in the crucial role of providing funds, links, intermediation, knowledge resources and technical knowledge, is indispensable and hence they must be specifically included in the nucleus of the NSI (Stern *et al*., 2000; Gaba and Bhattacharya, 2011; Delgado *et al*., 2012;) as, according to Kahn *et al*. (2014, p. 2) "The financing of innovation has been identified as an important structural bottleneck that has yet to be solved. Coping with this challenge involves considering both the role of the state and public organisations and the role of private financial institutions." Secondly we argue, according to the diffusion of innovation paradigm (Rogers, 2003), that it is MHTI (ISIC Rev.3), comprising innovators, early adopters and the early majority, which embody the requisite economies of scale and scope, as well as the economically significant capability and capacity to innovate (even though innovation takes place in Low-tech industries)[12]. Furthermore, MHTI represent a disproportionately high percentage of GDP contribution and, in developing countries, are much more ICT-connected than Low-tech industry. Thirdly, we aver that diffused ICT is crucially important for intensifying the Intra- and Inter-relationships of, and facilitating the flow of knowledge and resources between, NSI Actors (Hilbert *et al*., 2010; Koria *et al*., 2012; Bartels and Koria, 2014[13]).

This paper attempts to assist in filling the empirical and measurement gap in the literature (Smith, 2005; Adams *et al*., 2006), and concentrates on the systemic aspect of NSI rather than on a single aspect of the innovation process in firms, as a large part of the current empirical work does (Stock *et al*., 2002). To our knowledge most studies focus on an industry level analysis (Filippetti and Archibugi 2011; Chaminade *et al*., 2012; Adams *et al*., 2013), while this paper analyses the relationship between the Actors; Government, Knowledge Based Institutions, Business Enterprises and Arbitrageurs.

The rest of the paper is organised as follows: Section 2 — Literature Review — examines the seminal literature, elaborates nuances in the NSI conceptualisation while highlighting

[11] Taxonomy of Triple Helix Innovation, The Institute for Triple Helix Innovation, University of Hawai'i, www.triplehelixinstitute.org
[12] This is not to deny innovation in services (Hipp *et al*., 2000; Preissl, 2000; Commission of the European Communities, 2007) however this is beyond the scope of this paper.
[13] Forthcoming in African Journal of Science, Technology, Innovation and Development.

measurement challenges. Section 3 — Modelling — presents the SEM and the hypotheses. Section 4 — Methodology — elucidates our methodological approach for mapping and measuring NSI using innovation and innovativeness variables with respect to EFA and SEM. Section 5 — EFA Analysis and Results — presents the EFA analytics. Section 6 — SEM Analysis and Results — presents the approach to the SEM analytics and presents the results of modelling and model respecification. Section 7 — Findings and Discussion — illustrates the results from the GNSI in terms of the modelled relationships of NSI Actors. Section 8 — Conclusions — presents the overall conclusions and issues for further research.

2. Literature Review

The literature on innovation and NSI is extensively developed with a provenance in the works of List (1841) in terms of the national system of political economy; Marshall (1920) in spatial terms of industrial districts; and Schumpeter (1935), Solow (1957), Veblen (1906), Arrow (1962), Abramovitz (1986), and Romer (1990, 1994) in terms of the role of science and technical change (i.e. innovation) in economic growth (Ahlstrom, 2010).

The evolution of the more recent conceptualisation of NSI, since its introduction in the early 1980s with a focus on long term investment and economic development (Freeman 2004), has increasingly recognised the role of investments in organisational capital and their improvement as the key for advancing economic development. Given the socio-technical nature and systemic properties of innovation (Geels, 2004; Fagerberg, 2005; Fagerberg and Srholec, 2008) the concept of the NSI is best appreciated as one taxon, arguably the central one, among several within the broader notion of Systems of Innovation (SI) (Edquist, 1997, 2005a, 2005b). Even in the earliest stages the literature accepted the complex adaptive and eco-systemic nature of NSI and the importance of linkages within, and between, actors and assets in science, technology, trade and industry (Freeman 2004) enabling resource transactions (exchange functions in human, physical and organisational capital) and resource transformations (functions in innovativeness) in the economy.

It is increasingly recognised that the effectiveness and efficiency (encapsulated by efficacity) of NSI is heavily influenced significantly by the density (number of linkages), directionality (balance of uni-, bi-directional linkages), distribution (spread of linkages), and symmetry/asymmetry of Intra- and Inter-organisational relationships within, and between, actors (Leydesdorff, 2001; Bartels and Koria, 2012; Koria *et al*., 2014) and according to Morris-King (2014, p. ii) "innovation is principally driven by concentrations of mature academic research institutions and is mediated by consistent government support and highly active industrial partners."

The debate on sources of economic growth (Maddison, 2006) has extended the architecture of NSI literature to encapsulate: the economics of innovation and technology; systems of innovation (operationally differentiated at nested and networked vertical and horizontal levels including, on the one hand, local, sub-regional, national, supra-regional and global and on the other hand sector, and technological)[14]; industrial dynamics; organisational and structural change; national innovation capacity (Bartels *et al*., 2012; Chang and Lin, 2012); and technology transfer. Greenacre, Gross and Speirs (2012) review NSI literature revealing the key elements, *inter alia*, as hierarchical and horizontal innovation.

The architecture of systems of innovation is therefore nested and can be considered firstly as hierarchical organisation with the local form, at the core, encapsulated successively by the metropolitan, regional (sub-national), national, regional (supra-national), spatial and global systems respectively. Secondly, there is the horizontal aspect of sector and technological systems of innovation in each of the nested layers. The construct systems of innovation is therefore characterised by emergent features of dynamic complex adaptive systems. Thus according to Levin (2002, p.17) "microscopic interactions and evolutionary processes give rise to macroscopic phenomena through nonlinear interactions, … subject to path dependence, with … multiple stable states, chaotic dynamics and frozen accidents." The international business aspect, manifest as transfers of innovations and technology through internalisation (Michie, 1998; Buckley and Casson, 2002; Dunning, 2003; Buckley and Carter, 2004; Buckley and Hashai, 2004) across the organisational boundaries of Multinational Enterprises (MNEs) via Foreign Direct Investment (FDI), is equally of great consequence and a critical research concern. However, the dynamics of innovation within FDI and inside MNEs are beyond the scope of the present paper.

The expanded architecture and intensifying relevance of NSI is illustrated by ever-widening research and practitioner coverage. The 1996 DRUID Conference on 'The Nature of Knowledge' articulated only three sequential sessions[15]. The DRUID 2014 Conference on 'Entrepreneurship, Organization, Innovation' presented 72 parallel paper sessions ranging from 1 — Team Formation and Performance to 72 — Disruptions in Skills and Leadership[16].

Given this expanding inventory and territory it is no wonder that Gatignon *et al*., (2001, p. 2) suggests that "Innovation and technical change are at the core of dynamic organizational capabilities … Yet after more than 30 years of research on innovation and organisational outcomes, fundamental concepts and units of analysis are often confused and/or ambiguous." A useful definition of NSI that assists in policy and which should include interacting structural elements that shape the innovation processes as well as system process linkages that conform innovation and economic performance (Lundvall 2007) is therefore difficult to arrive at. Hence

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[14] Including Global Systems of Innovation (Archibugi and Iammarino, 1999; Klinger and Lederman, 2006), Continental Innovation Systems (Freeman, 2002), Regional Innovation Systems (Meesus *et al*., 1999), Metropolitan Innovation Systems (Fisher *et al*., 2001) and Spatial Innovation Systems (Audretsch and Feldman, 1996, 1999,; Oinas and Malecki, 2002), Sectoral Innovation Systems (Malerba ,2002; Tidd, 2006), Technological Innovation Systems (Carlsson and Stankiewicz, 1995).

[15] New trends in the Research on Industrial Dynamics; Changes in the Production and use of Knowledge with focus on the Codification Trend; and Industrial policy in the Learning Economy. See Danish Research Unit for Industrial Dynamics 19-20 June 1996 http://www.druid.dk/fileadmin/images/dokumenter/Conferences/Summer1996/PROGRAMME.pdf

[16] See Danish Research Unit for Industrial Dynamics 16-18 June 2014 http://druid8.sit.aau.dk/druid/infosite/file/2014%20society/DRUID2014_Final_program%2018June2014.pdf

there are many definitions of NSI (Freeman, 1987; Lundvall, 1992; Nelson and Rosenberg., 1993; Edquist and Lundvall, 1993; Niosi *et al*., 1993; Patel and Pavitt, 1994; Metcalfe, 1995; OECD, 1992, 1997, 2005; Malerba, 2002; Balzat and Hanusch, 2004; Achim & Popescu, 2009; Sakaraya, 2011; Bartels *et al*., 2012). Nevertheless, despite recurrent commonalities which are: networks of actors, assets, organisations and institutions (North, 1991); complex reciprocating interactions and relationships; spatial knowledge diffusion and technical change; enterprises, universities and government, each NSI is idiosyncratic. However, a valid critique of the definitions is the absence of specific reference to intermediaries, that is, Arbitrageurs as indicated above (Howells, 2006).

Arguably, two analytical frameworks dominate the NSI literature. The first by Andersen and Lundvall (1988) is of the NSI as a system of: (i) backward linkages in flows of information; (ii) learning by doing and searching; (iii) distinctions between industrial subsystems at different stages in terms of life cycle; and (iv) the open economy (Lundvall *et al*., 2002). The second, by Leydesdorff and Etzkowitz (1996. p. 279) is the NSI as a "the Triple Helix of university-industry-government relations." Fundamentally, the processes at the heart of the structure of NSI involve learning and Actors' relationships. The TH framework has evolved (Leydesdorff and Etzkowitz, 1998; Etzkowitz, 2002; Leydesdorff, 2005) to represent an approach to the study of networks and linkages within, and between, the core Actors in the NSI and emphasises the role of KBIs for innovation in increasingly knowledge-based economies. This model is arguably analytically different from the Andersen and Lundvall (1988) approach to NSI (Lundvall, 1988, 1992; Nelson, 1993) wherein the emphasis is on firms and Actors are strongly influenced by the market and technological innovations (Nelson and Winter, 1982). Two distinct paths in evolution of NSI literature evolution are therefore evident. The first is oriented to learning (Lundvall, Ed., 1992); the second to systems (Nelson, 1993). The two traditions, while distinctive in their respective emphases, nevertheless refer consistently to one another (Teixeira, 2013).

Thus (Lundvall, 1992, p. 2) suggests a definition of NSI focusing on the development of technology and user-producer interactions as " … the elements and relationships which interact in the production, diffusion, and use of new, and economically useful, knowledge are either located within or rooted inside the borders of a nation state". Bartels *et al*., (2012, p. 6) suggest a more comprehensive definition, in policy, systemic and organisational capital terms, as "the envelope of conforming policies as well as private and public organisations, their distributed institutional relations, and their coherent social and capital formations, that determine the vector of technological change, learning and application in the national economy."

The two definitions above, separated by two decades of research, encompass micro-level interactive production elements and relationships, as well as macro-level policies that determine technological change, learning and application. They are contoured by interdisciplinary approaches within long-term economic performance (von Tunzelmann, 1997), national competitiveness (Porter, 1990) and growth accounting (Solow, 1960; Arrow, 1962; Jovanovic and

Rob, 1989; Greenwood and Jovanovic, 1998). These approaches bring sharply into relief the indispensability of technological innovation and organisational capital in industrial dynamics and development (ul-Haque, 2007; Squicciarini and Le Mouel, 2012). This implies that NSI consist of linkages between Actors, assets, organisations and institutions that enhance the stocks of intellectual capital and facilitate transactional exchange of knowledge flows, at both formal and informal levels (Buckley and Carter, 2004) and transformational activities of invention (Dunning, 2003).

Considering NSI as an envelope of conforming policies (Bartels *et al*., 2012) implies a further development in the structure and processes of NSI to include the effects of diffused ICT and arbitrageurs as the spread of ICT and digital information has trigged a new mode of development (Perez, 1983: Freeman and Louça, 2001). The digital divide is not solely a matter of access, it is rather attributable to issues of storage, the ability to compute and transmit information; and to contextualize the quantity of hardware as well as the corresponding performance in relation to the four Actors in our extended TH4 model of NSI (Government, Knowledge based institutions, Industry and Arbitrageurs).

According to Lundvall (2007) and our survey of the literature there is a paucity of empirical work on NSI and what there is generally has a sectoral level focus. It is crucial to appreciate that the core of the innovation system is nested in institutions that shape people and relationships between people (Lundvall, 2007; Manjón and Merino, 2012). There is empirical evidence of the contribution of knowledge transfers (albeit analysing exclusively university-industry relationships) to higher productivity and economic growth (Mansfield, 1991; Cohen *et al*., 2002; Mueller, 2006). Nonetheless data show that the overwhelming majority of firms does not collaborate with universities (Bodas Freitas *et al*., 2013).

As indicated by Leydesdorff and Etzkowitz (1996) the strength and quality of interactions between the core Actors determine the effectiveness and efficiency in the NSI and hence in creating and disseminating knowledge (Asheim and Gertler, 2005). The spatial concentration of economic relations and dynamics of knowledge are ultimately based on intellectual assets (Cohen *et al*., 2000). A direct consequence is that well-structured and functional NSI are prevalent in industrialised economies, even if several developing countries aspire to increase innovation to develop their economies[17]. Therefore, the empirics of NSI carry significant implications for developing countries (Bartels and Lederer, 2009). However, given the uniqueness of each NSI, the adoption and adaptation have to take place through local cultural and institutional lenses (Arocena and Sutz, 2000) and it is important to avoid copying the latest policy fashion, since there exist “good ways” that could be “better than others” (Arocena and Sutz, 2000, p. 59).

[17] See African Union summit 2007 on science and technology for Africa’s development.

The NSI performance can therefore be analyzed at meta, macro and meso levels. At meta level, Blanc and Sierra (1999) and Carlsson (2006) highlight the increasing internationalisation of alliances and interrelations between the actors. Within these networks, an important role is played by KBIs and MNEs engaged in research-based techno-scientific collaborations. These are the networks are examined in the Leydesdorff's (2001) 'neo evolutionary' TH. At macro level, decentralisation and social capital are the core subjects of Bjørnskov and Svendsen (2002) study on Scandinavian economic performance. The focus of meso level and cluster NSI performance analysis is oriented to the importance of the knowledge base, organisational nature, institutional characteristics and involvement in innovation (Asheim and Coenen, 2004; Munk and Vintergaard, 2004).

Becheikh *et al*., (2006) find innovation to be measured by direct – innovation count, firm-based surveys – and indirect – research and development (R&D) and patent data – indicators. These 'imperfect' measures are characterised by disadvantages reported in Becheikh *et al*., (2006, Table 2, p. 649). Consequently, other variables have been adopted to measure innovation. These tend to be a composite of the variables mentioned above or multi-item measurements of innovation obtained through factor analysis. Thus we find variables that measure: firm characteristics, global and management functions; firms' culture and structure; and firms' assets and strategies (Becheikh *et al*., 2006) applied to measuring innovation in firms. However, these indicators do not map and measure the 'system' of innovation manifest either in firms or at the national level of the economy because they are not applied simultaneously to all Actors in the NSI. It is this feature of applying a singular DASI to all four Actors in the NSI which distinguishes our approach from others, including the Frascati and Oslo Manuals.

The undeniable importance of innovation such that "knowledge, its accumulation and distribution, through institutions of human and social capital, plays an increasingly crucial role as a key economic factor" (Koria *et al*., 2012, p. 1) has evoked the empirical measurement of innovation variables and NSI (Castellacci and Natera, 2012; Guan and Chen, 2012) as well as 'functions of innovation systems' (Hekkert *et al*., 2007). Mostly the dependent variable (innovation) is regressed – through OLS regression – on explanatory independent variables. Becheikh *et al*., (2006) indicate that the literature suggests about sixty explanatory variables of innovation dichotomised into; firm specific factors (i.e. advantages idiosyncratic to the firm), and context or industry factors (i.e. related to the firm's environment) (Hawawini *et al*., 2003).

The empirical literature on NSI and innovation focuses overwhelmingly on industry and firms (Buesa *et al*., 2010; Chaminade, 2011). Relatively few works concentrate on industry and KBIs (OECD, 1997) and even fewer studies measure the three Actors in the traditional TH framework (Chanthes, 2012). Empirical work dedicated to measuring the four Actors in the TH4 is even rarer (Guston, 2001; Fisher and Atkinson-Grosjean, 2002; Cooke, 2004; Howells, 2006; Koria and Köszegi, 2011; Bartels and Koria, 2012; Koria *et al*., 2012). Becheikh *et al*., (2006) find that of statistical and econometric techniques used to study innovation only 6% is SEM. The contextual determinants of innovation, related to the encapsulating environment of the firm, suggest that the following dimensions are crucial to a better understanding of NSI (Becheikh *et al*., 2006): the firm's industry; the spatiality (local to global location); Actor Intra- and Inter-relations; knowledge and technology transfers; government policies on science, technology and innovation; institutions and the predominant organisational culture.

The incident effect of industry and regional characteristics on innovation and NSI is acknowledged (Cooke *et al*., 1998; Doloreux and Parto, 2005; Iammarino, 2005). With respect to the industry dimension, three key factors are evident: technological dynamism; demand growth; and industry structure (Porter, 1990; Zahra, 1993; Evangelista *et al*., 1997; Crépon *et al*., 1998; Porter, 1998; Quadros *et al*., 2001;). Regarding industry structure, industry concentration may have a negative (Blundell *et al*., 1999) or a positive impact on innovation (Smolny, 2003), in contrast to Baptista and Swann (1998) who conclude no significant relationship between concentration and innovation.

Regarding the regional dimension, spatial variables such as geographic location and proximity have a significant effect on the firm's innovative capacity in terms of science infrastructure and industrial technology output (Asheim and Isaksen, 1997; Blind and Grupp, 1999). Within the regional context, proximity enables interaction effectiveness and efficiency (Arundel and Geuna, 2004; Morgan, 2004; Ponds *et al*., 2007).

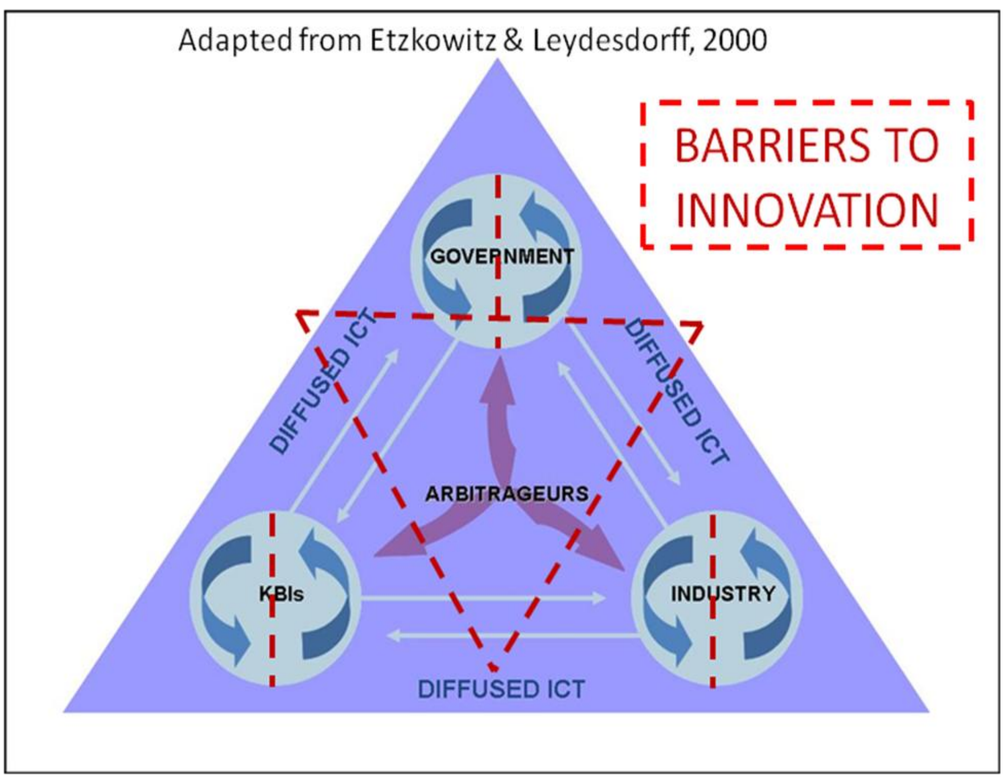
Finally, and most crucially, proximity interactions and networking among Actors are seen as determinants of innovation. The systemic approach to innovation rests on the notion of non-linear and multidisciplinary dynamics and connectedness between Actors, assets, organisations and institutions within a coherent policy space (Balzat and Hanusch, 2003). The correlation between innovation and cooperative networking is indicated by Fritsch and Meschede (2001), and Keizer *et al*., (2002). Analysis by Landry *et al*., (2002) of the relative probability that a firm innovates or not regressed on business, information and research networks finds that the greater the networks of the firm, the higher the likelihood to innovate. The acquisition of knowledge and technologies; government and public policies of the economy in which the firm is located are also contextual determinants of innovation (Pavitt and Walker, 1976; Mowery, 1983; Ahuja and Katila, 2001; Intarakumnerd *et al*., 2002; Bartels *et al*., 2012; Blind, 2012) although Love and Roper (2001) find insignificant effect).

With a systems of innovation approach, we emphasize spatiality in terms of Intra- and Inter-Actor linkages as encapsulating the location, proximity, connectedness, networking determinants of innovation and innovativeness in the NSI. Additionally, in our TH4 framework, we emphasize Actor importance; barriers to innovation; the diffusion of ICT as a facilitator of linkages; and the role of government in terms of firstly, policy instrument success and, secondly governance (Kuhlmann, 2001; Kuhlmann and Edler, 2003; D'Este *et al*., 2012).

The four Actors, as previously mentioned, are; Government, Medium- and High-tech Industries, KBIs, and Arbitrageurs (Financial Institutions, Knowledge-brokers and Venture Capitalists). It is increasingly evident that the efficacity or in other words, the capacity and capability, or the effectiveness and efficiency, of the NSI is, *ceteris paribus*, more reliant on relationships rather than physical assets (OECD, 1999; Ritter and Gemünden, 2003, 2004).

However, regarding the TH framework, in the context of developing countries the three Actors are relatively separate in their roles, with little overlap in functional relationships, thus precluding the benefits of inter-relational exchange. This is compounded by the lack of technology transfer or licensing offices within KBIs and the absence of Arbitrageurs. The TH4 (Koria and Köszegi, 2011; Bartels and Koria, 2012; Koria *et al*., 2012; Leydesdorff, 2012; Koria *et al*., 2014) introduces the fourth Actor (Arbitrageurs), indicating the need for access to financial and information resources for effective and efficient NSI performance. The four Actors of the TH4 are construed to operate in an environment of diffused ICT as illustrated in figure 1 below. The TH4 represents the underlying framework used in this paper to present the rationale and analytical approach in examining the GNSI.

Figure 1 – Triple Helix Type 4



Source: Koria, Bartels, Koeszegi & Carniero, 2012

3. Modelling

We aver that the TH4 is powerfully analytical and encapsulates the vertical and horizontal dimensions of NSI (Greenacre, Gross and Speirs, 2012). Furthermore, it encompasses the financial (Unger and Zagler, 2003), scientific-technological (Etzkowitz and Leydesdorff, 2000) and production-industrial (Lee and Kim, 2001) components of NSI. The TH4 thus enables the accurate mapping and measuring of (N)SI (Bartels and Koria, 2012; Koria *et al*., 2014).

The SEM, Figure 2 below, is the baseline model depicting the GNSI in terms of efficacity, barriers to innovation and Actor connectedness. It hypothesises that the structural model of the GNSI Efficacity is determined by (Actor) Connectedness (H1) and Barriers to Innovation (H2).

The measurement model of the SEM posits that: (i) GNSI Efficacity is measured by the Factors; Fiscal and Monetary Incentives (E1), Knowledge-based Innovation Capability (E2) (H3); (ii) (Actor) Connectedness is measured by Factors; KBIs — Intermediary Inter-linkages (C1), Actor Intra-linkages (C2), ICT Diffusion (C3), Government — Intermediary Inter-linkages (C4), Arbitrageurs — Business Enterprises Inter-linkages (C5) (H4); (iii) Barriers to Innovation are measured by Factors; ICT Capability/Capacity (B1), Unsophisticated Markets (B2), Deficient Fiscal Policy (B3), Reduced Organisational Risks (B4), and Deficient Human Capital (B5) (H5); and (iv) there is a non-recursive relationship between (Actor) Connectedness and Barriers to Innovation (H6).

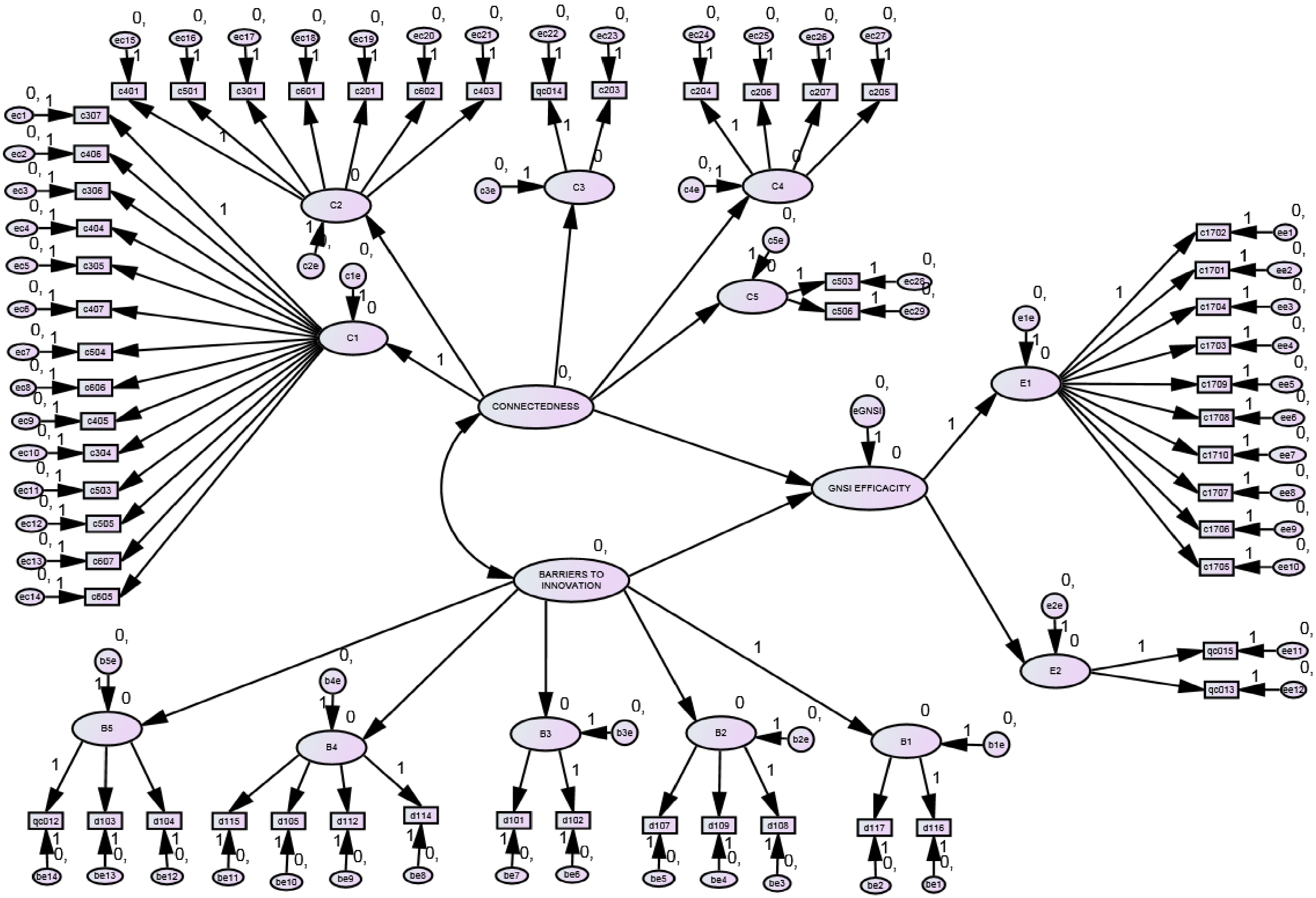


Figure 2: Path Diagram for GNSI Model (Baseline Model 1)

In the SEM path diagrams, arrows represent equations (and their direction indicates dependent and independent variables), ovals indicate latent constructs and rectangles indicate observed variables (in the DASI). We posit that the factors influence observable variables of NSI which are SI specific (i.e. content, internal and idiosyncratic to the NSI) and context specific (i.e. external and related to the environment of the NSI) (Becheikh *et al*., 2006).

4. Methodology

The crucially important differentiating characteristic of our methodology from other methodologies, including the Frascati and Oslo Manuals, is the fact that our survey applies contemporaneously the same DASI to the three core Actors of the NSI as well as to a fourth Actor, Arbitrageurs, acknowledged to play a crucial role of intermediation between sources of knowledge and commercialisation of knowledge. Furthermore, the DASI is applied using ICT.

We perform EFA and SEM on data acquired by the DASI on the GNSI. To the knowledge of the Authors this is the first to map and measure the NSI of a country – i.e. the Intra- and Inter-relationships between policy decision makers (GOV), Medium and High-Technology Industries (MHTI), Knowledge-based Institutions (KBIs), and Arbitrageurs (ARBs) (Bartels and Koria, 2012; Koria and Koszegi; 2011; Koria *et al*., 2012). It is important to note that in order to arrive at the most satisfactory depiction of the GNSI in terms of Efficacity, Barriers to Innovation and Actor Connectedness the models are subject to respecification based on the judicious evaluation of results of EFA, SEM, NSI literature, theory and empirics.

4.1 Exploratory Factor Analysis (EFA)

4.1.1 EFA Methodology

4.1.1.1 Factor Extraction

The Data was subjected to EFA in order to isolate latent influencers of observed variables (Bartels and Koria, 2012). EFA condenses observed variables into factors in a pattern matrix (clusters of inter-correlated variables). The factors represent the underlying structure responsible for the variation of variables in the data and thus in the population and universe (Kim and Mueller, 1978). We select EFA as no *a priori* constraints are imposed on the data structure (Bartels *et al*., 2009). EFA is based on the following assumptions:

1) There is a correlation pattern between the examined variables. This assumption implies that the data correlation matrix R is not an identity matrix[18], and it can be tested through Bartlett's test of sphericity. Variables' inter-correlation is also measured by the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (MSA). This index ranges from 0 to 1 and measures how well a variable is predicted by the other variables in the dataset. An MSA of at least 0.5 is required to carry out a meaningful EFA (Hair *et al*., 2010).

[18] Each variable is not only correlated with itself.

2) The vector of observed variables, $\boldsymbol{x}$, is a linear combination of several latent factors. More specifically, we have:
   $\boldsymbol{x} = \Lambda \boldsymbol{s_c}$ (Widaman, 2007)
   Where $\boldsymbol{s_c}$ is the vector of factor scores (i.e. the values that the latent variables assume for every observation), and Λ is the matrix of the coefficients of $\boldsymbol{s_c}$, [i.e. the matrix of (unrotated) factor loadings].
3) The mean of the variables in $\boldsymbol{x}$ is standardised to zero.
4) Factors are not uncorrelated.
5) High ratio of cases to variables. In our example we have 234 cases and 27, 14 and 11 variables with respect to the EFA[19].
6) Normal distribution of variables.
7) High random sample size. In our case our sample size of 234 is deemed "fair' to "good' by Comrey and Lee (1992).
8) Interval or ratio scales of measurement. In our case we use Likert scales with five intervals (Labovitz, 1967, 1970, 1971, 1972, 1975; Jamieson, 2004).

We assume that $\boldsymbol{x}$ is fully determined by the factors, with no (or negligible) margin of error. This assumption is justified by prior knowledge of the variables and by the high reliability, validity and quality of our data, derived by the use of Lime Survey, which increases response rates and reduces the need for data entry (Bartels *et al*, 2012)[20].

The Factor Extraction employed herein is Principal Component Factoring (PCF) (Abdi and Williams, 2010). This methodology assumes that $\boldsymbol{x}$ is fully determined by the latent factors and calculates Λ so as to maximize the amount of total observed variance in the data driven by each latent construct. PCF requires a criterion to determine the number of components extracted. We employ the Kaiser criterion; components with Eigen values lower than one are dropped, as this implies that they do not explain a sufficient amount of data variance. It must be borne in mind, however, that the decision on the amount of factors to retain ultimately depends on understanding the NSI phenomenon and on previous analyses (Jöreskog, 2007).

4.1.1.2 Factor Rotation

The matrix of unrotated factor loadings Λ can be difficult to interpret. This problem is solved through factor rotation (Jennrich, 2007). Factor rotation comprises a transformation of the loading matrix Λ with the aim of obtaining a matrix of rotated loadings Λ_R such that each factor has variables' loadings (i.e. each factor influences reliably a distinct set of variables). There are two typologies of rotation:

1) Orthogonal Rotation, used when factors are hypothesized not to be inter-correlated; and
2) Oblique Rotation, used when factors are assumed to be inter-correlated.

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[19] Heuristics indicate that the ratio of cases (N) to variables (p) range anywhere from 3:1, 6:1, 10:1, 15:1, or 20:1 (Williams *et al*., 2012) and Hogarty *et al*., (2005, p.222) find in testing different ratio that "our results show that there was not a minimum level of N or N:p ratio to achieve good factor recovery across conditions examined".

[20] Our response rate is 52.7% (234 responses out of 444 target respondents in the convenient sample). In surveys directed towards senior management the general response rate is at 30%. See Harzing (2006).

Given the correlation matrix R, the matrix of unrotated loadings Λ and the covariance matrix of factor scores Φ, oblique rotation consists in estimating a matrix of rotated loadings Λ_R such that $R = \Lambda\Lambda^T = \Lambda_R \Phi \Lambda_R^T$ and Λ_R minimizes a function $Q(\Lambda_R)$, denominated "rotation criterion". The rotation criterion selected for this analysis is the Direct Oblimin Criterion[21]. This oblique rotation is chosen as factors are expected to be inter-correlated, based on NSI Theory. When interpreting and reporting results, we ignore variables with loadings on factors lower than 0.55 (i.e. with less than 30.25% of their variance explained by the factor), in order to maintain high statistical significance (Bartels *et al*., 2009).

After rotation, factors are named, taking into consideration relevant theory and variables with the highest factor loadings. Finally, EFA results are validated by calculating Cronbach's Alpha, a measure of inter-correlation between variables, and an indication of how consistently they are reflected by the latent construct. The following table shows cutoff values for this measure.

Table 1: Cutoff values for Cronbach's Alpha (Bartels and Koria, 2012; p. 46)

Cronbach's Alpha	Internal Consistency/Reliability
α≥0.9	Excellent
0.8≤α<0.9	Good
0.7≤α<0.8	Acceptable
0.6≤α<0.7	Questionable
0.5≤α<0.6	Poor
α<0.5	Unacceptable

5. EFA Analysis and Results

5.1 EFA Results

EFA results are reported in tables as follows: the column "factor number" indicates the descending rank order of the importance of the factor, based on the amount of total variance explained. The column "factor name" provides a description for the grouped variables influenced by the factor. The column "factor loading" indicates the correlation between factors and variables, i.e. the extent to which the factor influences the variable.

5.1.1 EFA Results: Barriers to Innovation

Barriers to Innovation were measured by Respondents judging the level of constraining variables[22]. Table 2 below details EFA results for this group of variables. EFA results[23] are meaningful, as both the KMO (with "meritorious[24]" value) and Bartlett's test support the presence of significant correlation between the variables. All factors have good to acceptable Cronbach's

[21] With the parameter Delta set to zero.
[22] On the Likert Scale of 1 – Very High Constraint, 2 - High Constraint, 3 – Neutral, 4 – Low Constraint, 5 – Very Low Constraint.
[23] It must be noted that analysis result change slightly when replicating the analysis on single actor groups (Bartels and Koria, 2012).
[24] Hair *et al*., 2010.

Alpha values, except for Factor 5 (Deficient Human Capital), which has unacceptable consistency despite its theoretical relevance.

5.1.2 EFA Results: GNSI Inter and Intra-Linkages

Actor Intra- and Inter-linkages were measured by Respondents judging the strength of the linkages between the four core Actors of the GNSI[25]. Table 3 below details EFA results for this group of variables. EFA results are meaningful, as both the KMO (with "meritorious[26]" value) and Bartlett's test support significant correlation pattern between the variables. All factors have good to acceptable Cronbach's Alpha, except for Factor 3 (ICT Diffusion), which has Unacceptable consistency despite its theoretical relevance.

With respect to the interpretation of EFA results, we notice that data variability is mainly driven by Factor 1, representing the strength of connections between KBI and Intermediaries, notably FI and ARB. The strength of Actor Intra-linkages (Factor 2) is also an important driver of data dynamics, while other Factors, although theoretically relevant (such as the strength of GOV's linkages with other Actors), have minimal influence on total variance. For the sake of analytical rigour, and as theory and preliminary inspection of the data leads us to expect a higher number of factors, as well as due to the inter-correlation between items regarding the strength of linkages of the same Actor category, we repeated EFA forcing the extraction of seven factors, in order to gain a finer resolution regarding our initial model. The results are in table 4 below.

[25] On the Likert Scale of 1 – Very Strong, 2 - Strong, 3 – Neutral, 4 – Weak, 5 – Very Weak.
[26] Hair *et al*., 2010.

All Respondents – Barriers to Innovation									
Factor Number	**Name of Factor**	**Variables**	**Factor Loading**	**Cronbach's Alpha**	**Total Variance Explained (TVE)**	**KMO**	**Bartlet's Test of Sphericity**		
							Chi Squared	**Df**	**Significance**
1 (B1)	ICT Capability/Capacity	• Rate of Access to ITC [qd001d116] • ICT Capacity [qd001d117]	0.875 0.870	0.918	31.810	0.815	1671.852	153	0.000
2 (B2)	Unsophisticated Markets	• Lack of Demanding Customers [qd001d108] • Lack of Innovative Customers [qd001d109] • Lack of Competition [qd001d107]	0.893 0.846 0.686	0.752	9.715				
3 (B3)	Deficient Fiscal Policy	• Lack of Finance [qd001d102] • Lack of Explicit Policy Support [qd001d101]	0.807 0.797	0.603	8.154				
4 (B4)	Reduced Organisational Risks	• Excessive Perceived Economic Risk [qd001d114] • Organisational Rigidities [qd001d112] • Hierarchical Organisations [qd001d105] • Restrictive Public Governmental Regulations [qd001d115]	-0.801 -0.725 -0.684 -0.672	0.758	6.670				
5 (B5)	Deficient Human Capital	• Adequacy of Human Resources [qc012] • Lack of Technically Trained Manpower [qd001d103] • Quality of Technically Trained Manpower [qd001d104]	0.810 -0.780 -0.572	0.245	6.414				
				Cumulative total (CTVE)	**62.763**				

Table 2: EFA on Barriers to Innovation

All Respondents - Connectedness									
Factor Number	**Name of Factor**	**Variables**	**Factor Loading**	**Cronbach's Alpha**	**Total Variance Explained (TVE)**	**KMO**	**Bartlet's Test of Sphericity**		
							Chi Squared	**Df**	**Significance**
1 (C1)	KBI/Intermediary Inter-Linkages	• Linkages HE-ARB [qc003c307] • Linkages RI-FI [qc004c406] • Linkages HE-FI [qc003c306] • Linkages RI-BE [qc004c404] • Linkages HE-ISTC [qc003c305] • Linkages RI-ARB [qc004c407] • Linkages BE-RI [qc005c504] • Linkages ARB-RI [qc006c606] • Linkages RI-ISTC [qc004c405] • Linkages HE-BE [qc003c304] • Linkages BE-HE [qc005c503] • Linkages BE-ISTC [qc005c505] • Linkages ARB-ISTC [qc006c607] • Linkages ARB-HE [qc006c605]	0.860 0.854 0.841 0.810 0.801 0.799 0.794 0.768 0.764 0.759 0.754 0.735 0.732 0.666	0.966	47.971	0.939	7906.449	630	0.000
2 (C2)	Actor Intra-Linkages	• Linkages RI-RI [qc004c401] • Linkages BE-BE [qc005-c501] • Linkages HE-HE [qc003c301] • Linkages ARB/FI-ARB [qc006c601] • Linkages GOV-GOV [qc002c201] • Linkages ARB/FI-FI [qc006c602] • Linkages RI-HE [qc004c403]	0.884 0.822 0.788 0.764 0.580 0.579 0.572	0.901	10.910				
3 (C3)	ICT Diffusion	• Level of ICT Diffusion [qc014] • Linkages GOV-RI [qc002c203]	0.685 0.570	.459	6.311				
4 (C4)	GOV/Intermediary Inter-Linkages	• Linkages GOV-BE [qc002c204] • Linkages GOV-FI [qc002c206] • Linkages GOV-ARB [qc002c207] • Linkage GOV-ISTC [qc002c205]	-0.774 -0.773 -0.701 -0.782	0.904	3.880				
5 (C5)	ARB/BE Inter-Linkages	• Linkages ARB/FI-BE [qc006c603] • Linkages BE-FI [qc005c506]	0.686 0.561	0.766	2.815				
				Cumulative total (CTVE)	**71.888**				

Table 3: EFA on Connectedness

All Respondents: Connectedness (Forced)									
Factor Number	Factor Name	Variables	Factor Loading	Cronbach's Alpha	Total Variance Explained	KMO	Bartlett's test of Sphericity		
							Chi squared	df	Significance
1 (C1)	KBI/ Intermediary Intrlinkages	• Linkages HE-FI [qc003c306]	0.843	0.944	47.971	0.939	7906.449	630	0.000
		• Linkages HE-ARB [qc003c307]	0.759						
		• Linkages HE-ISTC [qc003c305]	0.720						
		• Linkages RI-FI [qc004c406]	0.688						
		• Linkages RI-ISTC [qc004c405]	0.652						
		• Linkages HE-BE [qc003c304]	0.602						
		• Linkages RI-BE [qc004c404]	0.566						
2 (C2)	Actor Intra-Linkages	• Linkages RI-RI [qc004c401]	0.886	0.875	10.910				
		• Linkages HE-HE [qc003c301]	0.813						
		• Linkages BE-BE [qc005-c501]	0.779						
		• Linkages GOV-GOV [qc002c201]	0.703						
3 (C3)	GOV/KBI Inter-Linkages	• Linkages GOV-RI [qc002c203]	0.855	0.917	6.311				
		• Linkages GOV-HE [qc002c202]	0.780						
		• Linkages RI-GOV [qc004c402]	0.707						
		• Linkages HE-GOV [qc003c302]	0.706						
		• Linkages HE-RI [qc003c303]	0.626						
		• Linkages RI-HE [qc004c403]	0.595						
4 (C4)	GOV/BE-Inermediary Inter-Linkages	• Linkages GOV-BE [qc002c204]	-0.719	0.880	3.880				
		• Linkages GOV-FI [qc002c206]	-0.685						
		• Linkages GOV-ARB [qc002c207]	-0.652						
5 (C5)	BE/Intermediary Inter-Linkages	• Linkages BE-FI [qc005c506]	0.833	0.842	2.815				
		• Linkages BE-ARB [qc005c507]	0.742						
		• Linkages FI- BE [qc006c603]	0.636						
6	ICT Diffusion	• ICT Diffusion [qc014]	0.989		2.450				
7 **(C6)**	ARB/KBI Inter-Linkages	• Linkages ARB-RI [qc006c606]	-0.791	0.917	2.160				
		• Linkages ARB-HE [qc006c605]	-0.780						
		• Linkages ARB-ISTC [qc006c607]	-0.685						
		• Linkages ARB-GOV [qc006c604]	-0.646						
				Cumulative Total (CTVE)	**76.498**				

Table 4: EFA on Connectedness with forced number of factors

As in the previous analysis, the KMO and Bartlett's test support significant inter-correlation between variables. All Factors have good to excellent Cronbach's Alpha. Despite the changes in factor composition, interpretation of EFA results is not altered as KBI/Intermediary Inter-linkages still account for most of the total variance, followed by Actor Intra-linkages, while other factors although theoretically relevant, have relatively low levels of influence on total variance.

5.1.3 EFA Results: Measures of GNSI Efficacity

GNSI Efficacity is measured by factors that influence variables that indicate:

1. Effectiveness of Policies promoting Innovation
2. Links of RI to the Production System
3. Level of Innovativeness in Ghanaian BE.

Survey items related to this measurement construct were subjected to EFA: the results are detailed in table 5 below. Our KMO value and Bartlett's test support significant correlation between observed variables. Factor 1 (Fiscal and Monetary Policy Incentives), the main driver of total variance has an excellent Cronbach's Alpha, while the Cronbach's Alpha of Factor 2 (Knowledge Based Innovation Capability) is "questionable" (Bartels and Koria, 2012): nevertheless the factor is retained for its theoretical relevance. These results are not fully convincing because items measuring very different innovation-promoting policies are lumped together and because these results do not coincide with those of previous analyses[27] where different factors influence, respectively, the fiscal and monetary incentives, as well as standards setting and regulation.

Therefore, again for the sake of analytical rigour, we rerun the EFA, forcing the extraction of three factors, in order to gain a finer resolution regarding our initial model with respect to obtaining results analogous to those in Bartels and Koria (2012). The results are detailed in table 6 below.

As in the previous analysis, the KMO and Bartlett's test support significant inter-correlation between variables. Factors 1 and 3 have excellent internal consistency, while the Cronbach's Alpha of Factor 2 remains questionable. We nevertheless retain the factor because of its theoretical relevance.

[27] See table 9.18, p. 61, Bartels and Koria (2012).

All respondents GNSI Efficacity									
Factor Number	**Name of Factor**	**Variables**	**Factor Loading**	**Cronbach's Alpha**	**Total Variance Explained (TVE)**	**KMO**	**Bartlet's Test of Sphericity**		
							Chi Squared	**Df**	**Significance**
1 (E1)	Fiscal and monetary Incentives	• Tax Breaks [qc017c1702] • Research Grants [qc017c1701] • Government Backed Venture Capital [qc017c1704] • Subsidised Loans [qc017c1703 • Labour Mobility [qc017c1709] • Regulation [qc017c1708] • ICT Access [qc017c1710] • Standards Setting [qc017c1707] • Government Procurement [qc017c1706] • Donor Funds [qc017c1705]	0.889 0.884 0.871 0.855 0.836 0.805 0.803 0.789 0.775 0.750	0.95	58.759	0.929	2099.037	66	0.000
2 (E2)	Knowledge-Based Innovation Capability	• Level of Innovativeness BE [qc015] • Linkages RI-Production [qc013]	0.841 0.822	0.608	11.116				
				Cumulative total (CTVE)	**69.874**				

Table 5: EFA on GNSI Efficacity

All respondents GNSI Efficacity Forced									
Factor Number	**Name of Factor**	**Variables**	**Factor Loading**	**Cronbach's Alpha**	**Total Variance Explained (TVE)**	**KMO**	**Bartlet's Test of Sphericity**		
							Chi Squared	**Df**	**Significance**
1 (E1)	Fiscal and Monetary Incentives	• Research Grants • Tax Breaks • Government Backed Venture Capital • Subsidised Loans • Donor Funds	0.889 0.856 0.845 0.822 0.595	0.919	58.759	0.929	2099.037	66	0.000
2 (E2)	Knowledge-Based Innovation Capability	• Linkages RI-Production • Level of Innovativeness BE	0.894 0.759	0.608	11.116				
3 (E3)	Standards and Regulatory Incentives	• Standards Setting • Regulation • ICT Access • Labour Mobility	- 0.857 - 0.810 - 0.587 - 0.579	0.911	6.047				
				Cumulative total (CTVE)	**75.922**				

Table 6: EFA on GNSI Efficacity with forced number of factors

6. SEM Analysis and Results

6.1 Introduction to SEM

6.1.1 Advantages of SEM

Our theoretical model of the GNSI Efficacity is estimated and tested through SEM. This statistical technique uses the sample covariance matrix between observed variables as a starting point for model estimation. It presents the following advantages (Walker and Maddan, 2008; Bentler and Savalei, 2010):

1) It provides a framework for estimating and testing complex theoretical models, incorporating multiple dependent and independent variables. This allows contemporaneous estimation of all relevant model parameters.
2) It allows the analysis of latent constructs, measured by clusters of observed variables, and of their relationship with other latent constructs (the ensemble of such relationships is referred to as the structural model). It also accounts for measurement error in the relationship between latent factors and their observed indicators (the measurement model).
3) It validates the use of observed variables as indicators for latent constructs and allows assessment of whether the relationships between these constructs are consistent with theory. This allows validation of the use of the indicators for policy formulation and for monitoring policy outcomes (Kaplan and Elliott, 1997; Bollen and Pearl, 2013).

6.1.2 Motivations for SEM use

Our model has several characteristics that make the use of SEM ideal for estimation. First, the model is complex, with many variables having direct and indirect effects on GNSI Efficacity. Only SEM allows simultaneous estimation and testing of all model equations. Secondly, in our dataset many observed variables measure latent constructs: most statistical techniques use observed variables as perfect substitutes for latent factors. They are therefore unable to account for measurement errors or for the reliability of indicators (Bentler and Savalei, 2010). SEM, by estimating the relationship[28] between factors and their indicators, is one of the few techniques able to do so. The inclusion of the measurement model for latent factors also allows a clearer interpretation of regression coefficients, as opposed to the use of estimated factor scores in regression (Walker and Maddan, 2008).

6.1.3 Fundamental assumptions of SEM

The meaning and validity of SEM results depend on the data and on several assumptions, both on the data and on the analysed phenomenon (Bartels *et al.*, 2006). SEM thus assumes a confirmatory function; if the model is found to fit the data, the theory and the assumptions underlying the model acquire validity. Model validity can then be increased further if the model is successfully applied to a different sample (this process is denominated Cross-Validation) (Barrett, 2007; Bollen and Pearl, 2013).

6.1.3.1 Assumptions regarding the Data

Standard SEM estimation relies on the following statistical assumptions (Kline, 2011):

[28] Also defined as Measurement Models.

1) Random Sampling: each individual in the population[29] has the same probability of belonging to the sample. As population composition and response rates vary with Actor category, our sample compromises this assumption. However, balancing the sample would lead to a loss of information. Furthermore, such a sample would no longer be representative of the population.
2) The data is continuous. This assumption is not strictly respected in our dataset, which is constituted by categorical Likert scale scores. However, our data can be treated as continuous, as our scale has more than four categories (Labovitz, 1970, 1971; Bentler and Chou, 1987; Owuor, 2001).
3) The data follows a multivariate normal distribution. This is not strictly adhered to by our sample, as responses may be concentrated at the extremes of the Likert scale.
4) Observations are independent from one another. This assumption is relaxed in our sample, as item scores may be influenced by Actor category.
5) Observed exogenous variables are measured without error. The use of Lime Survey increases data reliability by reducing the need for data entry (Koria and Koszegi, 2011).

6.1.3.2 Assumptions regarding the Model

Model specification in SEM is guided by the following assumptions (Kline, 2011):

1) Existence of a significant correlation between dependent and independent variables.
2) Assumptions (grounded in theory) on the direction of causality. These are necessary because, given, for example, the variables (either latent or observed) X and Y, both a model where X causes Y and another one where Y causes X are compatible with their sample covariance matrix S (Bollen and Pearl, 2013). This issue is known as Covariance Equivalence (Spirtes *et al*., 1998). The directionality assumptions underlying our model are based on NSI theory.
3) Linear relationship between the variables.
4) Isolation (Kline, 2011): when assuming a causal link from X to Y, we are assuming that there is no other plausible explanation (such as the presence of extraneous and/or confounding variables) for their covariation. This implies that the correlation between X and Y holds after including in the model other variables that might have an effect on Y. With respect to this study, NSI theory rules out the presence of extraneous/confounding variables.

6.1.3.3 Assumptions regarding Latent Constructs

Another fundamental assumption required regards the nature of latent constructs. They can be:

a) Reflective: observed variables are measures of a thematically one-dimensional (Petter *et al*., 2007) latent construct. Therefore, changes in the construct bring about changes in the values of its indicator variables. Indicators are interchangeable and inter-correlated. (Jarvis *et al*., 2003).
b) Formative: the construct is a multidimensional composite of its indicators (Petter *et al*., 2007), like an index measure (Jarvis *et al*., 2003). This implies that changes in a single indicator bring about a change in the latent construct. Therefore indicator variables are not interchangeable;

[29] That is the universe of potential respondents.

removing one of them changes meaning and value of the construct. Indicator variables of formative constructs can be uncorrelated (Jarvis *et al*., 2003).

The same classification can also be applied to second order latent constructs, that is, constructs having other latent factors as indicators.

Montecarlo simulations by Jarvis *et al*. (2003) and Petter *et al*. (2007) have shown that specifying formative constructs as reflective ones causes serious model misspecification and bias in estimates and fit indices (Jarvis *et al*., 2003; Petter *et al*., 2007). The high reliability of our first order latent constructs, their inter-correlation and their one-dimensionality, evinced by analysing their indicators, leads us, together with NSI theory, to conclude that they are reflective.

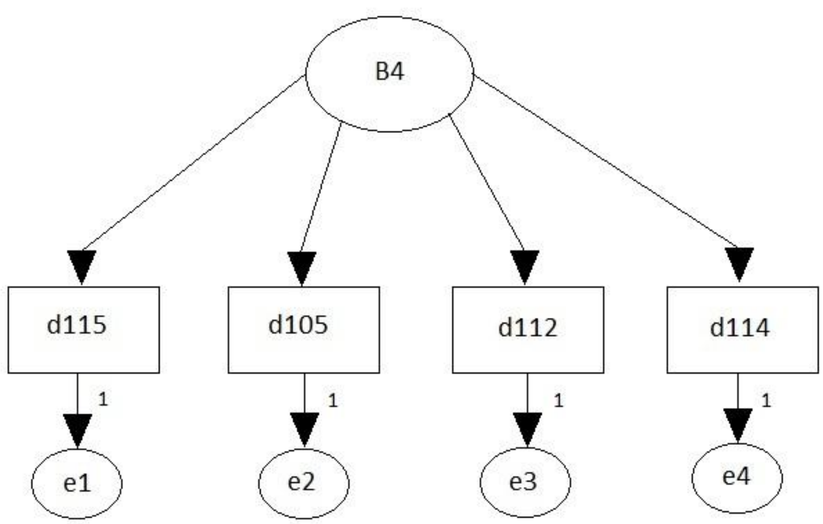
With respect to the second order constructs, the reflective nature of the construct "GNSI Efficacity" is compatible with NSI theory, as is the one of the construct "Barriers to Innovation". Finally, the second order construct "Connectedness" measures the strength of links between NSI Actors and is thus one-dimensional; it can therefore be specified as reflective.

6.2 SEM Estimation

6.2.1 Mathematical Principles of SEM

We illustrate the mathematical principles of SEM estimation through an example, based on Bentler and Savalei (2010). We want to estimate with SEM the measurement model for Factor "Reduced Organizational Risks" (B4), which we assume influences the scores of item variables d115, d105, d112 and d114. The model can be represented through a path diagram (Figure 3). In path diagrams, arrows represent equations (and their direction indicates dependent and independent variables), ovals indicate latent constructs and rectangles indicate observed variables.

Figure 3: Measurement model for factor B4: "Organizational Risks"



Mathematically, the model consists of four equations: each of the item scores is a function of the latent factor, of a constant and of an error term. We assume that the error terms enter the equations with a coefficient fixed to one.

$d115 = \alpha_1 + \lambda_1 B4 + e_1$
$d105 = \alpha_2 + \lambda_2 B4 + e_2$
$d112 = \alpha_3 + \lambda_3 B4 + e_3$
$d114 = \alpha_4 + \lambda_4 B4 + e_4$

Given the variance of our latent factor, Ψ, and the rules of covariance algebra (and assuming that errors are not correlated), the population covariance matrix of our observed indicators (Σ), can be represented thus:

$$\Sigma = \begin{bmatrix} \lambda_1^2\Psi & \lambda_2\Psi & \lambda_3\Psi & \lambda_4\Psi \\ \lambda_2\Psi & \lambda_2^2\Psi & \lambda_3\lambda_2\Psi & \lambda_4\lambda_2\Psi \\ \lambda_3\Psi & \lambda_3\lambda_2\Psi & \lambda_3^2\Psi & \lambda_4\lambda_3\Psi \\ \lambda_4\Psi & \lambda_4\lambda_2\Psi & \lambda_4\lambda_3\Psi & \lambda_4^2\Psi \end{bmatrix}$$

This matrix is uninformative, as B4 and Ψ are unobserved. To estimate it, we need to fix the value of one of the factor loadings to one. Bentler and Savalei (2010) recommend choosing for this purpose 'a good indicator' of the construct. We therefore fix to one the coefficient of the indicator with the highest factor loading[30]. In this case we choose λ_4, the factor loading of item d114. We then obtain the following results:

$Var(d114) = \sigma_4^2 = \Psi$

We can then write Σ as:

$$\Sigma = \begin{bmatrix} \lambda_1^2\sigma_4^2 & \lambda_2\sigma_4^2 & \lambda_3\sigma_4^2 & \sigma_4^2 \\ \lambda_2\sigma_4^2 & \lambda_2^2\sigma_4^2 & \lambda_3\lambda_2\sigma_4^2 & \lambda_2\sigma_4^2 \\ \lambda_3\sigma_4^2 & \lambda_3\lambda_2\sigma_4^2 & \lambda_3^2\sigma_4^2 & \lambda_3\sigma_4^2 \\ \sigma_4^2 & \lambda_2\sigma_4^2 & \lambda_3\sigma_4^2 & \sigma_4^2 \end{bmatrix}$$

Since we observe S, the sample covariance matrix between the indicators, and s_4^2, the sample variance of d114, we can now estimate the parameters λ_1, λ_2 and λ_3.

6.2.2 SEM Estimation Methods

The various SEM estimation methods all have the aim of estimating parameters so to minimize the difference between the sample covariance matrix S and $\hat{\Sigma}$, the covariance matrix implied by the model (which is a function of the observed variances and covariances between indicators and of the estimated parameters).

[30] Loadings are fixed to one even if they are negative in EFA. We choose this course of action because: (i) it is the norm in SEM and (ii) it does not affect the covariance matrix of observed variables and thus the estimation. Finally, even if the sign of coefficients change, the substantive meaning of the estimates does not change; stating that an increase in "Reduced Organisational Risks" causes a decrease in item scores is equivalent to stating that an increase in "Organizational Risks" causes an increase in scores. We are basically observing the same phenomenon through different, but equivalent, perspectives. With respect to second order factors, we fix to one the loading of the factor explaining the highest proportion of the total variance.

6.2.2.1 Maximum Likelihood Estimation (MLE)

If the data follows a multivariate normal distribution, the covariance matrix of the indicators for a single observation will follow the Wishart Distribution[31] (Jöreskog, 1978). If all the observations are independent and identically distributed, the product of the covariance density functions of all observations can be interpreted as the density function of the sample. MLE is an iterative process that calculates parameter estimates such that the probability of observing the actual sample is maximized.

Maximum likelihood estimates are highly meaningful statistically and are asymptotically unbiased, consistent and efficient. However our sample compromises two basic assumptions required for MLE; Multivariate normality and lack of correlation between observations (obviously membership in a particular Actor category conditions responses).

6.2.2.2 Unweighted Least Squares Estimation (ULS)

A possible solution to this problem would be the use of ULS. This method produces parameter estimates such that the squared difference between sample covariances and model-implied covariances is minimized. ULS does not require multivariate normality, but it requires homoscedasticity: that is, all elements of the covariance matrix must have the same variance. Furthermore, this method does not account for inter-correlation between elements of the covariance matrix (Bentler and Savalei, 2010).

Because of these restrictive conditions, ULS is rarely used in the literature, and methods such as Asymptotic Distribution Free Estimation (ADF) and Weighted Least Squares Estimation (WLS) are preferred. These are variants of ULS where various weights are applied to the squared difference between sample covariances and model-implied covariances. These techniques do not require homoscedasticity, but a considerable sample size is needed to obtain consistent estimates in ADF (Bentler and Chou, 1987) and to correctly estimate the weighting matrix in WLS (Hutchinson and Olmos, 1998). ULS, as an alternative to MLE, is supported by Morata-Ramirez and Holgado-Tello (2013) who show through simulations that ULS is best at maximizing model fit when analyzing measurement models where observed indicators are non-normally distributed and measured through Likert scales.

6.2.2.3 Bootstrapping

However, we keep MLE as our main estimation method, as it has been shown to be robust to assumption violation (Bentler and Savalei, 2010). MLE has also been found to perform better than WLS in presence of non-normality and model misspecification (Olsson *et al*., 2000). In order to counter the possible loss of accuracy arising from non-normality and small absolute sample size, we employ bootstrapping to calculate more precise standard errors and confidence intervals to test the significance of our estimates[32].

[31] The Wishart Distribution is the multidimensional equivalent of the Chi Square Distribution. See Haff (1979).
[32] Available from the Authors but not reported due to space limitations.

Bootstrapping relies on the assumption that the actual statistical distribution of the data (F), is well approximated by the empirical distribution of the data in the sample (F_N). If this holds, drawing a random sample from a population with distribution F is equivalent to drawing a random sample from a population with distribution F_N. Parameter estimates, obtained from random sampling of a population with distribution F_N, have thus the same value of estimates resulting from the actual population. Furthermore, the distribution of those estimates closely approximates the distribution of the parameters in the population. It is then possible to calculate accurate confidence intervals for our parameter estimates (Bollen and Stine, 1990).

Bootstrapping creates an analogue of the population with distribution F_N by replicating observations a very large number of times (Diaconis and Efron, 1986). A thousand samples of size identical to the original are then drawn from the original and the replicated observation. The parameters of interest (in our case SEM coefficients) are then estimated for each sample.
Bootstrapping in AMOS produces two kinds of confidence intervals:

1) Percentile Confidence Intervals: given a particular parameter, its estimates in all the thousand samples are ranked by size. We can then define, for example, the 95% confidence interval for the parameter as the continuum of values ranging from the 25th biggest estimate to the 975th biggest one (Singh and Xie, 2008).
2) Bias Corrected Confidence Intervals: Percentile Confidence Intervals are most accurate when the parameter estimates are symmetrically distributed. Bias Corrected Confidence Intervals incorporate a correction that increases statistical accuracy when parameter estimates are asymmetrically distributed.

6.3 Model Evaluation

The validity of a model is evaluated mainly by examining its fit to data, i.e. how closely the covariance matrix between indicators, implied by its assumption, approximates the sample covariance matrix. Model fit can be evaluated in two ways (Bentler and Savalei, 2010):

1. Statistically, that is through a formal statistical test of equality between the covariance matrix of the sample and the one predicted by the model.
2. Practically, that is through descriptive statistics quantifying how well the covariance matrix implied by the model approximates the observed one.

6.3.1 Testing Statistical Fit

6.3.1.1 The Chi-Square Test of Statistical Fit

If the model fits the data accurately and all standard SEM assumptions are reasonably well satisfied, or at least not violated in the extreme, the test statistic T, which is a positively dependent on sample size and on the observed discrepancy between the estimated covariance matrix and the sample one, follows the Chi Square distribution with k degrees of freedom (Bentler and Savalei, 2010).

$$T \sim \chi^2(k) = \chi^2\left(\frac{p(p+1)}{2-q}\right)$$

Where p is the number of variables in the model and q is the number of estimated parameters.

If there is significant discrepancy between implied and sample covariances, the value of the T statistic will increase, and the probability of observing such a value if the statistic follows the Chi Square distribution (i.e. if the model fits the data) will diminish. The model is rejected if there is less than 5% probability of observing the value of its T statistic when the model fits the data. If the probability of observing such a value is between 5 and 10%, the model is not rejected, but its fit is considered merely adequate (Schermelleh-Engel *et al*., 2003; Bartels *et al*., 2006).

6.3.1.2 Performance of the Chi-Square Test

The Chi Square Test is the only statistical test for model fit (Barrett, 2007). However, its precision depends on the assumption of multivariate normality of the data. Furthermore, the test statistic gets smaller, and thus the probability of not rejecting the model increases, if the number of parameters in the model increases (Schermelleh-Engel *et al*., 2003). The test statistic is also positively dependent on sample size, and thus tends to reject models because of small discrepancies with observed covariances in large samples (Mulaik *et al*., 1989; Barrett, 2007; Bentler and Savalei, 2010). Finally, according to Steiger (2007), this test is unrealistic as T assumes a Chi Square distribution only if there is no discrepancy between implied and sample covariance, and small, trivial discrepancies can be considered inevitable in most models.

6.3.1.3 Bollen-Stine Bootstrapping

To improve performance of the Chi Square test with non-normality and large sample size, Bollen and Stine (1992, 1993) propose the following technique:

1. Modification of the original sample so that the model fits the data.
2. Bootstrapping on the modified sample, calculating the T statistic for each replicated sample, and thus estimating T^*, the bootstrapped distribution of T.

Bollen and Stine (1993) prove that T^* approximates the population distribution that T would have if the null hypothesis were true. We therefore do not reject the model if our original test statistic T is smaller than, or equal to, the average of T obtained from the replicated samples.

6.3.2 Indicators of Practical Fit

The problems of the Chi Square Test, which often lead to model rejection with trivial misspecification, have led to the creation of descriptive fit statistics that provide information on how well the model approximates sample covariance, and thus fits the data. The presentation of these fit indicators follows those by Schermelleh-Engel *et al*., (2003) and Schreiber *et al*., (2006).

6.3.2.1 Absolute/Predictive Fit Indices

1. ***T/df* ratio:** this ratio should be close to one; df is the expected value of T if the model fits the data. In practice, values between two and three are considered indicative of acceptable/adequate fit (Schermelleh-Engel *et al*., 2003; Schreiber *et al*., 2006). It is sensitive

to sample size[33] and to the number of indicators per factor (Marsh *et al.*, 1998), but it performs well in presence of slight misspecification in the measurement model (Beauducel and Wittmann, 2005).

2. **Akaike Information Criterion (AIC):** formulated as: $AIC = T + 2q$. It is a modification of the Chi Square Test Statistic that favours parsimonious models[34]. It is useful in model comparison; the model with the lowest AIC is the one with the best fit (Schermelleh-Engel *et al.*, 2003).

6.3.2.2 Comparative Fit Indices

6.3.2.2.1 Characteristics of Comparative Fit Indices

The purpose of comparative fit indices is quantifying how well the model approximates sample covariance, compared to a more restrictive specification. The starting formula for most of these indices is (Schermelleh-Engel *et al.*, 2003):

$$\frac{T_b - T_t}{T_b}$$

Where T_t is the Chi Square Statistic for the target model (i.e. our specification) and T_b is the Chi Square Statistic for the more restrictive baseline model. For all these indices, values close to one indicate good fit. There are two types of baseline models:

1) The null model (T_n), where all parameters are set to zero.
2) The independence model (T_i), where all variables are assumed to be measured without error and uncorrelated (that is, where only their variances are estimated).

The basic fit index using the null model as a baseline is the Goodness of Fit Index (GFI), which has the formula above. As it is based on the Chi-Square statistic, it is sensitive to over-parametrisation; two modifications of GFI, the Adjusted GFI (AGFI) and the Parsimonious GFI (PGFI), correct for this problem. AGFI uses the Chi-Square/Degrees of Freedom ratio in place of *T*, while PGFI multiplies GFI by the ratio of the degrees of freedom of the target and of the null model (df_t/df_n). Barrett (2007) criticizes the use of the null model as a baseline, since even a misspecified model can represent a great improvement on no model at all.

A second group of indices correct for this by using the independence model as a baseline. The fundamental index of this group is the Normed Fit Index (NFI), which follows the starting formula above. The NFI has, for the same motivations, similar parsimony problems of the GFI; the Parsimonious NFI (PNFI) corrects the problem by multiplying NFI by (df_t/df_n). NFI has other three modifications; the Non-Normed Fit Index[35] (NNFI), the Incremental Fit Index (IFI) and the Relative Fit Index (RFI). The first adjustment has the aim of improving NFI performance for values near 1, the second reduces the variance of NFI and increases its precision by adding $-df_t$ to its denominator, while the RFI accounts for sample size dependency by substituting *T/df* to *T* (Hammervold and Olsson, 2012).

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[33] But some simulation studies, like those of Ding *et al.*, (1995) allege that it is insensitive to sample size if no misspecification is present.
[34] I.e. models with a low number of parameters (q).
[35] Also known as the Tucker-Lewis Index (TLI).

The last Comparative Fit Index, the CFI, is based on a different principle. In case of misfit, the T statistic follows a non-central Chi Square distribution. This distribution is characterised by the non-centrality parameter γ, which is directly proportional to the discrepancy between implied and sample covariance. CFI estimates the change in γ, and thus the improvement in fit, obtained by going from the independence model to the target model[36] (Bentler, 1990; Schermelleh-Engel *et al.*, 2003). Its formula is:

$$CFI = 1 - \frac{max[(T_t - df_t); 0]}{max[(T_t - df_t); (T_i - df_i); 0]} = 1 - \frac{\hat{\gamma}_t}{\hat{\gamma}_i}$$

Where $(T - df)$ is used as an estimator of the non-centrality parameter, since, when the model is true and T follows the usual central Chi Square Distribution, we expect to have, on average, $T = df$.

6.3.2.2.2 Performance of Comparative Fit Indices

Various simulation studies and theoretical analyses show that no index of this class can be used on its own in all circumstances; their results are summed up in table 7 below.

Table 7: Performance Problems of Comparative Fit Indices

Index	Study	Problem
NFI	Ding *et al.*, (1995)	NFI is negatively affected by the number of indicators per factor.
	La Du and Tanaka (1989)	NFI doesn't detect trivial model misspecification.
	Schermelleh-Engel *et al.*, (2003)	NFI is sensitive to sample size.
NNFI	Beauducel and Wittmann (2005)	NNFI is too sensitive to trivial distortions in the measurement model.
	Ding *et al.*, (1995)	NNFI is negatively affected by the number of indicators per factor.
IFI	Beauducel and Wittmann (2005)	IFI is too sensitive to trivial distortions in the measurement model.
RFI	Hutchinson and Olmos (1998)	RFI is too sensitive to non-normality.
GFI	Hu and Bentler (1999)	GFI is too sensitive to variations in sample size and to violations of MLE assumptions.
	Schermellehh-Engel *et al.*, (2003)	GFI improves automatically if the number of model parameters increases.
AGFI	Mulaik *et al.*, (1989)	AGFI can be undefined or have negative values in some situations.

[36] $\hat{\gamma}$ indicates an estimate of γ.

6.3.3 Descriptive Measures of Model Fit

6.3.3.1 The Root Square Mean Error of Approximation (RMSEA)

The main assumption behind the RMSEA is that, since every theoretical model represents an abstraction from reality, it will never be able to fit perfectly a real dataset (Steiger, 2007). This explains the high occurrence of model rejection with the Chi-Square test[37] (which has perfect fit as the null hypothesis). It also implies that, on average, there will always be a positive discrepancy (approximation error) between the population covariance matrix and the one implied by the model. This discrepancy will follow a non-central Chi Square distribution with a non-centrality parameter γ if (MacCallum *et al*., 1996):

a) All the SEM assumptions detailed above hold.

b) Approximation errors have the same magnitude of the estimation errors.

Given $\hat{\gamma}$, an estimator for γ, we have that (Bentler and Savalei, 2010):

$$RMSEA = \sqrt{\frac{\hat{\gamma}_t}{(N-1)df_t}}$$

Given that $\hat{\gamma}$=$(N-1)\hat{F}_0$ (where N is sample size and $\hat{F}_0$ is an estimator of F_o, the discrepancy between the population covariance matrix and the one implied by the model) and F, the discrepancy between the implied covariance matrix and the sample one, it can be proven that

$$F_t - \frac{df_t}{(N-1)}$$

is an unbiased estimator of F_o. The practical formula for RMSEA is thus (Schermelleh-Engel *et al*., 2003):

$$RMSEA = \sqrt{max\left\{\left(\frac{F_t}{df_t} - \frac{1}{N-1}\right), 0\right\}}$$

This formulation avoids negative values, which are unrealistic, since the error of approximation is always expected to be positive. A non-truncated formulation is used to calculate the confidence interval of RMSEA (Steiger, 2000).

RMSEA values of 0.05 and below are considered indicators of good fit, while values between 0.05 and 0.08 indicate an "adequate" (MacCallum *et al*., 1996) or "acceptable" fit. These cutoff values were proposed by Browne and Cudeck (1993), on the basis of the results of various simulation studies (MacCallum *et al*., 1996). MacCallum *et al*. (1996) provides a rationale for the use of confidence intervals for RMSEA; if all the assumptions indicated above are respected, the statistical distribution of the RMSEA is known, thus allowing us to test the consistency of our RMSEA value with the null hypothesis of approximate fit. Multivariate normality is needed for this result to be valid. However, RMSEA and its confidence interval do not lose meaning when applied

[37] Note that Barrett (2007) claims that the Chi-Square test allows for trivial discrepancies by rejecting only the T statistics whose probability of being compatible with the model is smaller than a 5% threshold. Steiger (2007) counters this claim by stressing that the Chi Square test remains flawed because of its unrealistic premise (the null hypothesis of perfect fit).

to our strictly-speaking non-normal sample, since simulation studies have shown that RMSEA is robust to non-normality (Andreassen *et al*., 2006). RMSEA is also not sensitive to trivial misspecification in measurement models (Beauducel and Wittmann, 2005).

6.3.3.2 Root Mean Residual (RMR) and Standardized Root Mean Residual (SRMR)

The RMR and the Standardized[38] RMR represent the average value of an element of the matrix of discrepancies between implied and sample covariances (Schermelleh-Engel *et al*., 2003). RMR and SRMR are purely descriptive measures of fit. They tend to be unduly influenced by outliers (Bentler and Savalei, 2010).

6.3.4 Combined Use of Fit Indices

Following the above, we conclude that each fit index has particular strengths and weaknesses. The use of particular combinations of indices has therefore been proposed, with the aim of increasing analytical precision. A simulation study by Hu and Bentler (1999) is an influential work in the field: they test the adequacy of their combinations of indices through simulations on true and misspecified confirmatory factor analysis models. Their main results are:

- SRMR is sensitive to covariance discrepancies, while other indices are more sensitive to errors in the coefficients.
- In general, values of TLI and CFI close to 0.96 and SRMR close to 0.09 are best in minimising the probability both of model over-rejection and of not rejecting a misspecified model. With sample sizes smaller than 250 the incidence of over-rejection increases, and more lenient cutoffs should be used.

The cutoffs proposed by Hu and Bentler (1999) are popular, but they have been questioned by Marsh *et al*., (2004), for tending to over-reject models with a high number of indicators per factor, and by Fan and Xivo (2005) for not accounting for the severity of model misspecification.

6.3.5 Current Best Practices for Model Evaluation

Despite being very common in applied research, the use of 'Golden Rules', 'rules-of-thumb' or heuristics to determine model fit is strongly discouraged by the literature (Mulaik *et al*., 1989; Mulaik and Millsap, 2000; Fan and Xivo, 2005; Bentler and Savalei, 2010). The current best practice in model evaluation is to examine contemporaneously the values of all available fit indices, also taking into account the validity of the assumptions (both statistical and theoretical) and the theoretical soundness of the results (Marsh *et al*., 2004). Literature Reviews such as Schermelleh-Engel *et al*., (2003) and Schreiber *et al*., (2006), present cutoffs for various indices, which should be seen as orientative criteria for fit evaluation. We report them in table 8

[38]That is, divided the standard deviation of the manifest variables.

Table 8: Cutoff Values for Fit Indices

Fit Measure	Good Fit	Acceptable Fit	Good Fit (Categorical Data)
P-Value (Chi Square)	0.05<p≤1	0.01≤p≤0.05	
T/df	0≤T/df≤2	2<T/df≤3	
RMSEA	0≤RMSEA≤0.05	0.05<RMSEA≤0.08	Smaller than 0.06
P-Value (RMSEA)	0.10<p≤1	0.05≤p≤0.10	
SRMR	0≤SRMR≤0.05	0.05<SRMR≤0.10	
NFI	0.95≤NFI≤1	0.90≤NFI<0.95	
NNFI (TLI)	0.97≤NNFI≤1	0.95≤NNFI<0.97	Close to 0.96
CFI	0.97≤CFI≤1	0.95≤CFI<0.97	Close to 0.95
IFI	0.95<IFI≤1	IFI close to 0.95	
GFI	0.95≤GFI≤1	0.90≤GFI<0.95	
AGFI	0.90≤AGFI≤1	0.85≤AGFI<0.90	
AIC	Smaller than AIC for Comparison Model		

Bentler and Savalei (2010) also recommend direct inspection of the matrix of the standardised discrepancies between implied and sample covariances as a model evaluation tool. According to Hair *et al*., (2010), the presence of standardized discrepancy with a value higher than four indicates nontrivial misfit. Due to the fact that the evaluation of a model's assumptions and of its fit indices always entails a certain level of discretionality, some authors consider model cross-validation in a different sample to be the final test of model validity (Barrett, 2007; Bollen and Pearl, 2013).

6.4 The Model

Our baseline model can be visualized in the path diagram Figure 3: Path Diagram for GNSI Model (Baseline Model 1) below [39].

6.4.1 Issues related to Model Identification

A model is identified if it has enough observed indicators to estimate its parameters. Most of our latent constructs have at least three observed indicators, and are therefore at least just identified. The following Constructs are however under-identified:

1. ICT Capability/Capacity (B1);
2. Deficient Fiscal Policy (B3);
3. Knowledge-Based Innovation Capability (E2);
4. ICT diffusion (C3); and
5. Arbitrageurs — Business Enterprise Inter-Linkages (C5).

[39] Equivalent to Figure 2.

An under-identified model can be estimated only if it is linked to other latent variables. This creates the risk of interpretational confounding; the behavior of the under-identified construct is determined by the factors to which it is linked, and not by its indicators (Hair *et al*., 2010). According to Burt (1976) there is no risk of interpretational confounding if:

1) There is high inter-correlation between the indicators of the under-identified construct.
2) The covariances of the indicators of the under-identified construct with the other indicators, denominated communalities in EFA Theory (Hair *et al*., 2010), are high.

These two conditions hold for most of our under-identified constructs:

- The indicators of B1 and B3 have communalities above 0.78 and 0.57, respectively.
- The indicators of E2 have communalities above 0.67.
- The indicators of C5 have communalities above 0.61.

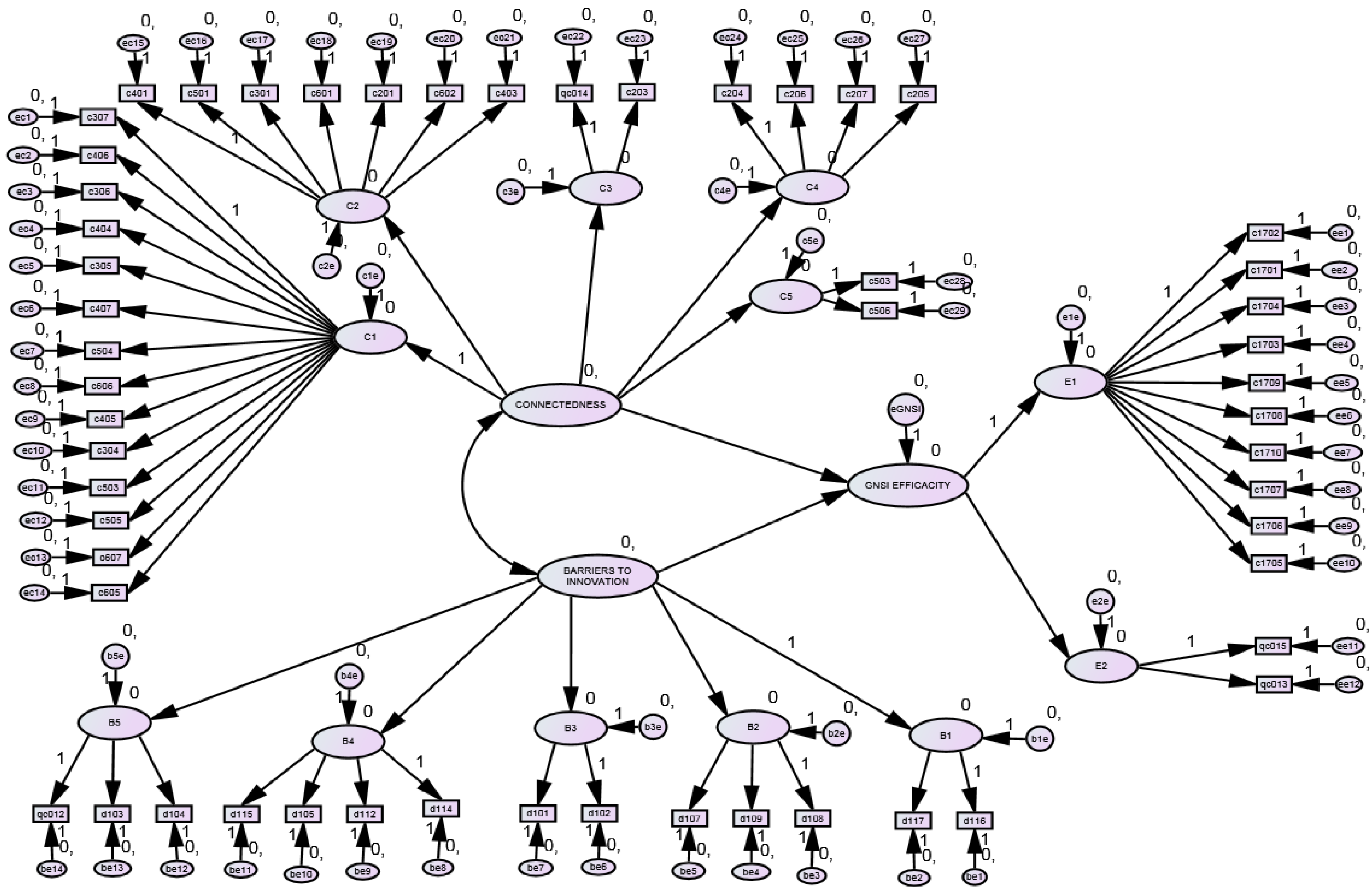

Figure 3: Path Diagram for GNSI Model (Baseline Model 1)

One indicator of C3 (qc014) has a communality of 0.449, but we retain it in the analysis (since the other indicator has a communality of 0.83) in order to test the pattern suggested by EFA results.

6.4.2 Hypotheses on the Measurement Models

We expect factor loadings to be positive and significant in all our measurement models, that is:

1) We expect item scores to increase when the values of the constructs increase.
2) We expect our observed variables to be good indicators of our latent constructs.

We also expect the coefficients for the paths between first order factors and second order factors (namely Connectedness, Barriers to Innovation and GNSI Efficacity) to be positive and significant.

6.4.3 Hypotheses on the Structural Model

From NSI literature, theory and empirics we derive the following hypotheses about the relationships between our second-order latent constructs (structural model):

1) The path coefficient between Connectedness and GNSI Efficacity is positive and significantly different from zero.
2) The path coefficient between Barriers to Innovations and GNSI Efficacity is negative and significantly different from zero.
3) A negative and significant correlation between Connectedness and Barriers to Innovation.

6.5 Estimation and Results

6.5.1 Results

6.5.1.1 Model Coefficients and Covariances

Table 9: Coefficients for the Structural Model and loadings for second order factors

			Estimate	S.E.	C.R.	P
GNSI EFFICACITY	<---	CONNECTEDNESS	0,573	0,117	4,914	***
GNSI EFFICACITY	<---	BARRIERS TO INNOVATION	-0,077	0,074	-1,034	0,301
C1	<---	CONNECTEDNESS	1			
C2	<---	CONNECTEDNESS	0,854	0,111	7,69	***
C4	<---	CONNECTEDNESS	1,214	0,117	10,394	***
C3	<---	CONNECTEDNESS	0,278	0,077	3,618	***
C5	<---	CONNECTEDNESS	0,941	0,118	7,991	***
B4	<---	BARRIERS TO INNOVATION	0,678	0,128	5,276	***
B5	<---	BARRIERS TO INNOVATION	-0,341	0,091	-3,734	***
B2	<---	BARRIERS TO INNOVATION	0,613	0,131	4,661	***
B3	<---	BARRIERS TO INNOVATION	0,342	0,09	3,818	***
B1	<---	BARRIERS TO INNOVATION	1			
E2	<---	GNSI EFFICACITY	0,896	0,204	4,384	***
E1	<---	GNSI EFFICACITY	1			

Table 10: Covariance between Connectedness and Barriers

			Estimate	S.E.	C.R.	P
BARRIERS TO INNOVATION	<-->	CONNECTEDNESS	0,025	0,036	0,709	0,478

The coefficients in the measurement models (omitted here due to space constraints) are consistent with NSI theory and are all significant at the one percent level. The path coefficients between first and second-order latent constructs are also all significant at the one percent level; most of them are consistent with theory, apart for the negative coefficient for factor B5 (Deficient Human Capital), which would lead the negative impact of lack and quality of technically trained manpower to decrease when "Barriers to Innovation" increases. This problem is due to low factor consistency[40]: the behavior of factor B5 is influenced by "Adequacy of Human Resources" (qc012), its indicator with the highest loading, which ranges from one (completely inadequate) to five (highly adequate), while the other two indicators range from one (the variable is a low constraint to innovation) to five (the variable is a very high constraint to innovation).

With respect to the structural model, the positive and significant path between "Connectedness" and "GNSI Efficacity" is consistent with theory. The estimate of the path coefficient between "Barriers to Innovation" and "GNSI efficacity" is negative, as expected, but not significantly different from zero. The covariance between "Connectedness" and "Barriers to Innovation" is also not significant.

In order to control for non-normality and small sample size, we produce bootstrapped standard errors and confidence intervals for our ML estimates: our previous results are confirmed (albeit only at 5% significance level).

6.5.1.2 Model Fit

Table 11: Fit Indices

Maximum Likelihood											
NFI	RFI	IFI	TLI	CFI	RMSEA	P (RMSEA)	SRMR	Chi Sq	T/df Ratio	P Value (Chi)	AIC
0,707	0,681	0,807	0,787	0,808	0,076	0,000	0,084	3335,219	2,357	0,000	3695,219

The Chi Square Test rejects the null hypothesis of good fit. Furthermore, most of our fit indices do not reach the conventional cutoffs for adequate fit, except for the RMSEA and the *T/df* ratio (Schermelleh-Engel *et al*., 2003). With the aim of verifying whether the test result is invalid because of non-normality or sample size, we apply the Bollen-Stine Bootstrap, which confirms model rejection. We therefore inspect the matrix of standardized residuals and notice that, despite the fact that most discrepancies have an absolute value lower than four, there is evidence of nontrivial misfit.

[40]Attested by its Cronbach's Alpha.

In order to verify whether the problem is caused by a violation of the data continuity assumption, we reestimate the model using ULS (Morata-Ramirez and HolgadoTello, 2013). Coefficient estimates from ULS[41] are slightly different than those from MLE; however they are essentially the same in terms of sign and significance. With respect to fit indices, ULS estimation gives improved results, however some indices fall short of conventional cutoffs. Furthermore, following, respectively, Mulaik *et al*., (1989) and Hu and Bentler (1999), we do not attribute high importance to high AGFI and GFI values.

6.5.2 Measurement Model Respecification

We verify whether measurement model misspecification is a cause of misfit by using the results of EFA with forcing of the number of factors to structure an alternative SEM model (Figure 4 below). The measurement model of the respecified SEM posits that: (i) GNSI Efficacity is measured by the Factors; Fiscal and Monetary Incentives (E1), Knowledge-based Innovation Capability (E2), and Standards and Regulatory Incentives (E3)(H3); (ii) (Actor) Connectedness is measured by Factors; KBIs — Intermediary Inter-linkages (C1), Actor Intra-linkages (C2), ICT Diffusion (C3), Government — Intermediary Inter-linkages (C4), Arbitrageurs — Business Enterprise Inter-linkages (C5) and Arbitrageurs — KBIs Inter-linkages (C6) (H4); (iii) Barriers to Innovation are measured by Factors; ICT Capability/Capacity (B1), Unsophisticated Markets (B2), Deficient Fiscal Policy (B3), Reduced Organisational Risks (B4), and Deficient Human Capital (B5) (H5); and (iv) there is a non-recursive relationship between (Actor) Connectedness and Barriers to Innovation (H6).

[41] Bootstrapping was used to obtain standard errors and confidence intervals.

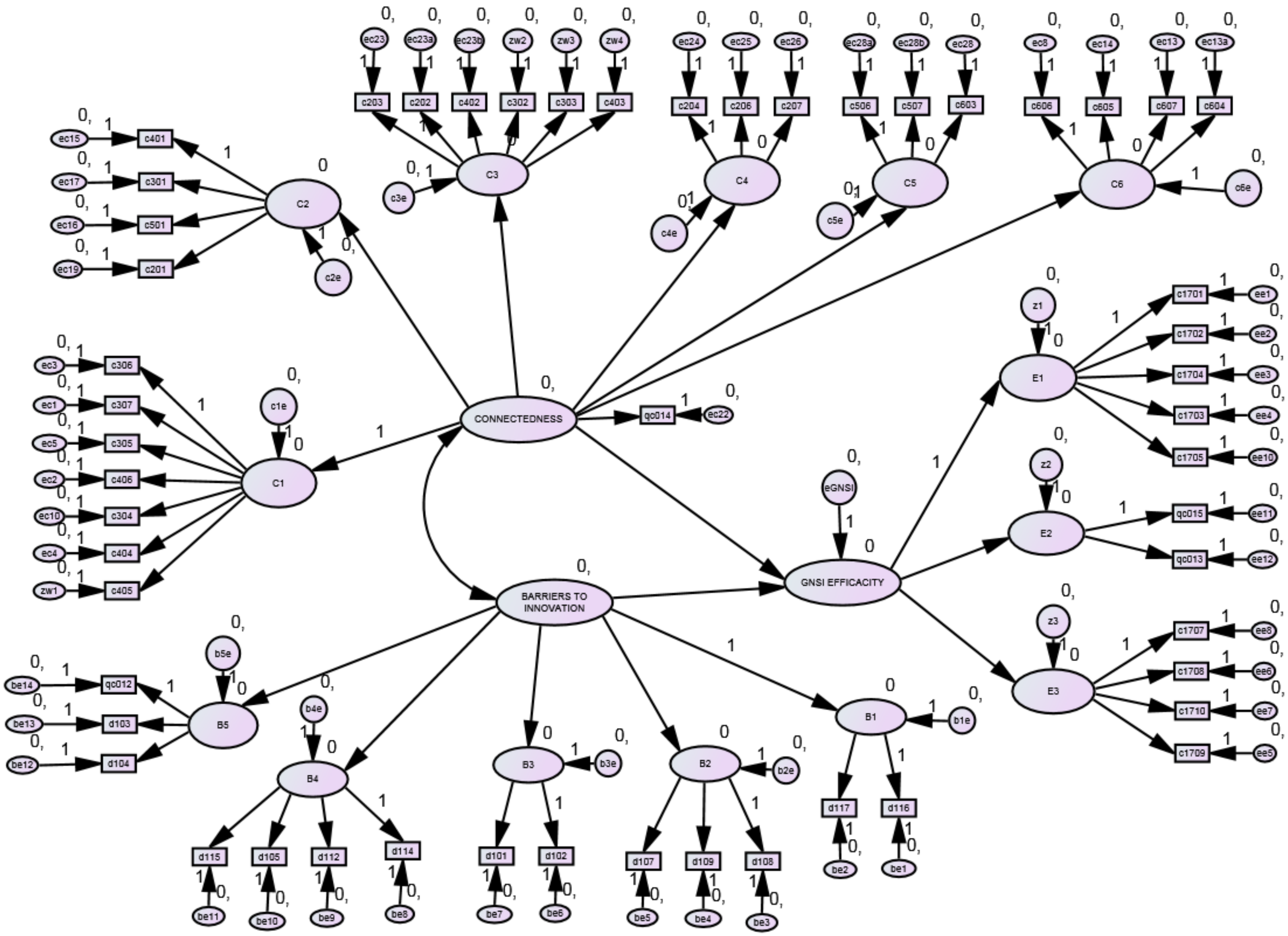

Figure 4: Path Diagram for the second GNSI Model (Model 2)

6.5.2.1 Model Coefficients and Covariances

Table 12: Coefficients for the Structural Model and loadings for second order factors

			Estimate	S.E.	C.R.	P
GNSI EFFICACITY	<---	CONNECTEDNESS	0,461	0,095	4,86	***
GNSI EFFICACITY	<---	BARRIERS TO INNOVATION	0,016	0,104	0,155	0,877
B4	<---	BARRIERS TO INNOVATION	0,673	0,129	5,23	***
B2	<---	BARRIERS TO INNOVATION	0,606	0,131	4,641	***
B3	<---	BARRIERS TO INNOVATION	0,337	0,089	3,798	***
B1	<---	BARRIERS TO INNOVATION	1			
C1	<---	CONNECTEDNESS	1			
B5	<---	BARRIERS TO INNOVATION	-0,334	0,09	-3,721	***
C2	<---	CONNECTEDNESS	0,665	0,089	7,464	***
C3	<---	CONNECTEDNESS	0,935	0,092	10,187	***
C6	<---	CONNECTEDNESS	1,001	0,076	13,216	***
E1	<---	GNSI EFFICACITY	1			
E2	<---	GNSI EFFICACITY	0,29	0,062	4,674	***
E3	<---	GNSI EFFICACITY	1,069	0,112	9,565	***
C4	<---	CONNECTEDNESS	0,913	0,084	10,802	***
C5	<---	CONNECTEDNESS	0,907	0,091	9,956	***

Table 13: Covariance between Connectedness and Barriers

			Estimate	S.E.	C.R.	P
BARRIERS TO INNOVATION	<-->	CONNECTEDNESS	0,027	0,042	0,65	0,515

The coefficients in the measurement models (omitted here) are consistent with NSI theory and are all significant at the one percent level. The path coefficients between first and second-order latent constructs are also all significant at the one percent level and consistent with theory, except for B5. Our previous results for the structural model are confirmed by MLE estimation (at the 5% significance level), bootstrapping and ULS (with slight changes in coefficient values).

6.5.2.2 Model Fit

Table 14: Fit Indices

Maximum Likelihood											
NFI	RFI	IFI	TLI	CFI	RMSEA	P (RMSEA)	SRMR	Chi Sq	T/df Ratio	P Value (Chi)	AIC
0,740	0,726	0,844	0,835	0,843	0,069	0,000	0,094	2747,938	2,101	0,000	3099,938

Bootstrapped ULS						
NFI	PNFI	RFI	GFI	AGFI	PGFI	RMR
0,929	0,882	0,926	0,941	0,936	0,861	0,087

After respecification fit indices for MLE improve, but remain still unsatisfactory, except for RMSEA and the *T/df* ratio, which indicate adequate fit. The inspection of the matrix of standardised residuals reveals the presence of discrepancies with absolute value bigger than four and thus the persistence of misfit.

6.5.3 Measurement Model Further Respecification

6.5.3.1 Elimination of Constructs with Low Reliability

Jackson's (2001) simulation study claims that low factor reliability can negatively affect model fit and the precision of coefficient estimates. We therefore remove from the model Factor B5 (Deficient Human Capital), because of its unacceptable Cronbach's Alpha (0.245), obtaining Model 3. The model is still unsatisfactorily fitting to the data and we only obtain improper solutions[42] for ULS. We nonetheless observe some improvement in fit indices (see table 12). MLE coefficient estimates (with bootstrapped standard errors and confidence intervals) confirm our previous results for both the structural and the measurement models.

6.5.3.2 Elimination of Marginal Latent Constructs

Our model modifications not having significantly reduced misfit calls for further measurement model respecification. The structural model remains unchanged, since it has a solid grounding in NSI literature. With respect to the measurement model for Connectedness, we notice that Factors C1 and C2 measure more than 58.9% of the total variance, while all other Factors have altogether a much lower explanatory power (17.6%). The indicators of those factors, while being only marginally relevant to the model, might introduce misfit through spurious and theoretically irrelevant correlation with other indicators.

We therefore decided to gradually remove these Factors and their indicator variables from the model, starting with the ones with the lowest impact on total variance. This procedure could lead us to accept a misspecified model: some of our fit indices, like RMSEA, AIC and the *T/df* ratio, are parsimony-adjusted and should automatically improve if the number of parameters to estimate decreases. However:

a) All the other indices reported are not parsimony-adjusted and should detect misspecification arising from our procedure[43].
b) According to a simulation study by Olsson *et al*., (2000), RMSEA detects model misspecification arising from the omission of model parameters, despite its parsimony adjustment.

Furthermore, a reduction in estimated parameters implies that fewer elements of the covariance matrix are used for parameter estimation; more sample information can thus be used to compute fit statistics, thus increasing their accuracy and their ability to detect misspecification. Our procedure should therefore facilitate model rejection if misspecification arises.

6.5.3.3 Results

Table 15: Fit Indices after eliminating inconsistent and irrelevant Factors[44].

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[42] I.e. with negative variances. We had this problem for all models not containing Factor B5. We tried to follow normal SEM practice by constraining them to zero, but the problem simply reappeared with other variables. Therefore we decided to neglect the analysis of ULS estimates for the models concerned, also on the basis of our literature on the robustness of MLE to non-normality and on the opportunity of treating discrete variables as continuous ones.

[43] Mulaik *et al*., (1989) show that non-parsimony-adjusted indices tend to improve with lower model parsimony. This increases their ability to detect misspecification arising from our procedure.

[44] Note that in model 6 we obtained an improper solution (negative variance). The problem was solved by setting the variance to zero.

	Maximum Likelihood											
MODEL	NFI	RFI	IFI	TLI	CFI	RMSEA	P (RMSEA)	SRMR	Chi Sq	T/df Ratio	P Value (Chi)	AIC
Model 3 (Model 2 minus B5)	0,752	0,738	0,851	0,842	0,850	0,070	0,000	0,092	2464,172	2,126	0,000	2796,172
Model 4 (Model 3 minus C5, C6 and C7)	0,787	0,773	0,879	0,869	0,878	0,067	0,000	0,082	1645,160	2,044	0,000	1841,160
Model 5 (Model 4 minus C4)	0,806	0,792	0,895	0,887	0,894	0,064	0,000	0,082	1342,646	1,946	0,000	1600,646
Model 6 (Model 5 minus C3)	0,855	0,842	0,942	0,936	0,941	0,050	0,536	0,074	759,328	1,572	0,000	981,328

We notice an improvement in all fit indices, including the non-parsimony-adjusted ones. In model 6 IFI, TLI and RMSEA come close to conventional cutoffs for acceptable fit. With respect to coefficient estimates, MLE estimation and the computation of bootstrapped standard errors and confidence intervals confirm our previous results.

6.5.4 Final Measurement Model (Model 7)

6.5.4.1 Analysis of Modification Indices for Measurement Model 6

In order to improve the model further, we analyze modification indices for model 6. Modification Indices (MI) estimate the improvement in the Chi Square statistic that can be obtained by adding covariances or path coefficient between two variables to the model. Some authors (Hayduk and Glaser, 2000; Barrett, 2007) discourage the use of MI in model respecification, claiming that it denatures the confirmatory character of SEM. Most authors however allow the use of MI, provided that it is parsimonious and consistent with theory (Hair *et al*., 2010).

We analyzed MI for possible covariances between errors in the measurement model (see table 13). We individuated the following covariances, which would affect fit significantly and have a theoretical rationale:

1) The covariance between the error terms of variables c306 and c307 (ec3 and ec1), measuring the strength of linkages between HE and, respectively, ARB and FI. We expect the measurements of the linkages between the same Actor (HE) and other two Actors with an analogous intermediation function to be correlated.
2) The covariance between the error terms of variables c1707 and c1708 (ee8 and ee6), measuring the perceived success, respectively, of regulation and standard setting in promoting innovation. The covariance is justified by substantial affinity and proximity in the targets and in the application of these two policy interventions.

Our final model, incorporating these two covariances, is shown in figure 5 below.

6.5.4.2 Results

6.5.4.2.1 Model Fit

Table 16: Fit Indices for the Final Model 7

Maximum Likelihood											
NFI	RFI	IFI	TLI	CFI	RMSEA	P (RMSEA)	SRMR	Chi Sq	T/df Ratio	P Value (Chi)	AIC
0,863	0,850	0,950	0,945	0,950	0,046	0,832	0,073	717,265	1,491	0,000	943,265

The Chi Square Test rejects the model. However IFI, TLI, CFI and SRMR reach conventional cutoffs for acceptable fit, while RMSEA indicates good fit. Inspection of the matrix of standardised residuals shows that no discrepancy has an absolute value higher than four. This leads us to claim that model fit has to be considered at least adequate.

Table 17 (1st part): Modification Indices for Model Covariances

			M.I.	Par Change
z2	<-->	CONNECTEDNESS	15,582	0,147
c2e	<-->	z1	4,086	0,08
c1e	<-->	z2	19,926	0,166
b3e	<-->	CONNECTEDNESS	18,131	-0,124
b3e	<-->	z2	11,077	-0,084
b3e	<-->	c2e	4,242	0,066
b3e	<-->	c1e	30,632	-0,16
b4e	<-->	c2e	5,735	-0,078
b4e	<-->	c1e	12,014	0,102
be7	<-->	CONNECTEDNESS	4,34	-0,081
be7	<-->	b2e	5,224	-0,094
be6	<-->	CONNECTEDNESS	7,09	-0,089
be6	<-->	z2	9,266	-0,089
be6	<-->	c2e	4,949	0,082
be6	<-->	c1e	19,763	-0,149
ec17	<-->	b2e	4,424	0,081
ec17	<-->	ec19	6,541	0,094
ec16	<-->	be6	4,881	-0,069
ec15	<-->	zw1	4,221	0,047
ec2	<-->	b1e	4,617	0,074
ec2	<-->	be6	7,132	-0,066
ec2	<-->	ec16	6,487	0,075
ec2	<-->	ec15	4,435	-0,052
ec3	<-->	zw1	11,735	-0,07
ec3	<-->	ec1	16,841	0,094
ec3	<-->	ec2	13,157	0,08
ec4	<-->	ec3	8,703	-0,057
ec5	<-->	zw1	9,926	0,064
ec5	<-->	ec16	4,763	-0,061
ec5	<-->	ec2	14,654	-0,083
ec10	<-->	ec2	5,956	-0,057
ec10	<-->	ec4	8,22	0,059
ec10	<-->	ec5	5,884	0,053
be2	<-->	ec4	4,5	-0,04
be2	<-->	ec10	5,368	-0,049
be5	<-->	b1e	5,465	0,124
be4	<-->	ec15	8,783	-0,092
be4	<-->	ec10	6,53	0,075
be3	<-->	c2e	4,647	0,096
be3	<-->	be7	6,123	-0,092
be11	<-->	c2e	12,316	-0,179
be11	<-->	c1e	4,495	0,098
be11	<-->	ec2	4,067	0,069
be11	<-->	be5	5,521	0,124

Table 18 (Part 2): Modification Indices for Model Covariances

			M.I.	Par Change
be9	<-->	ec3	4,186	-0,059
be9	<-->	ec4	4,139	0,054
be9	<-->	be3	5,614	-0,092
ee12	<-->	SS	7,717	0,123
ee12	<-->	c1e	11,839	0,152
ee12	<-->	b3e	8,02	-0,086
ee12	<-->	be6	6,134	-0,086
ee12	<-->	ec4	8,71	0,086
ee12	<-->	be2	4,508	-0,063
ee12	<-->	be3	5,871	-0,102
ee11	<-->	ec1	5,662	0,068
ee11	<-->	ec5	4,057	0,052
ee10	<-->	z3	4,431	0,07
ee10	<-->	z2	5,875	0,09
ee10	<-->	z1	5,93	-0,087
ee10	<-->	ec5	5,989	0,073
ee7	<-->	z3	6,132	-0,076
ee7	<-->	z1	10,485	0,108
ee6	<-->	z1	7,17	-0,066
ee6	<-->	ee8	11,306	0,072
ee5	<-->	BARRIERS TO INNOVATION	6,606	0,069
ee5	<-->	z3	5,565	-0,063
ee5	<-->	z1	10,98	0,096
ee5	<-->	b1e	6,449	0,096
ee5	<-->	b2e	5,038	-0,082
ee5	<-->	b4e	6,27	0,06
ee5	<-->	ee10	4,718	-0,075
ee4	<-->	be9	4,593	-0,071
ee4	<-->	ee10	10,525	-0,112
ee4	<-->	ee5	4,879	0,062
ee3	<-->	b2e	4,249	0,075
ee3	<-->	zw1	4,092	0,048
ee3	<-->	ee11	5,121	-0,068
ee3	<-->	ee10	4,044	0,069
ee2	<-->	b2e	4,852	-0,075
ee2	<-->	ec5	9,613	-0,07
ee2	<-->	be4	6,706	-0,077
ee2	<-->	ee10	4,665	-0,069
ee2	<-->	ee4	18,587	0,109
ee2	<-->	ee3	5,042	-0,057
ee1	<-->	c2e	10,102	0,127
ee1	<-->	ec15	7,029	0,076
ee1	<-->	ee7	5,789	0,082

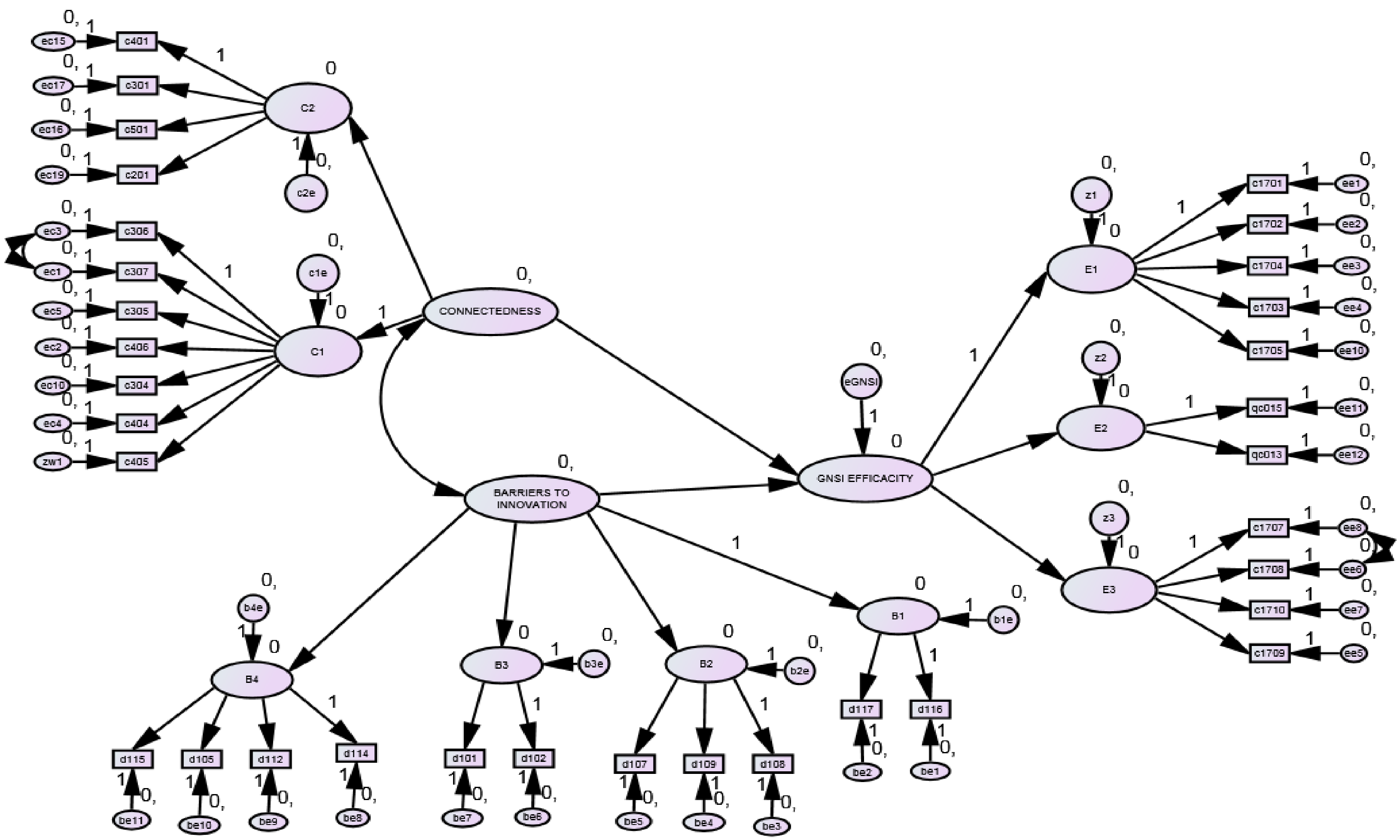

Figure 5: Path Diagram for the Final Model (Model 7)

6.5.4.2.2 Model Coefficients and Covariances

Table 19: Coefficients for the Structural Model and loadings for second order Factors

			Estimate	S.E.	C.R.	P
GNSI EFFICACITY	<---	CONNECTEDNESS	0,652	0,232	2,813	0,005
GNSI EFFICACITY	<---	BARRIERS TO INNOVATION	0,008	0,141	0,057	0,954
B4	<---	BARRIERS TO INNOVATION	0,999	0,258	3,877	***
B2	<---	BARRIERS TO INNOVATION	0,775	0,177	4,385	***
B3	<---	BARRIERS TO INNOVATION	0,42	0,115	3,647	***
B1	<---	BARRIERS TO INNOVATION	1			
C1	<---	CONNECTEDNESS	1			
C2	<---	CONNECTEDNESS	0,792	0,259	3,058	0,002
E1	<---	GNSI EFFICACITY	1			
E2	<---	GNSI EFFICACITY	0,265	0,061	4,379	***
E3	<---	GNSI EFFICACITY	0,999	0,113	8,806	***

Table 20: Estimated Covariances for Model 7

			Estimate	S.E.	C.R.	P
BARRIERS TO INNOVATION	<-->	CONNECTEDNESS	0,028	0,038	0,753	0,452
ec3	<-->	ec1	0,109	0,029	3,819	***
ee6	<-->	ee8	0,162	0,039	4,143	***

The coefficients in the measurement models (omitted here) are consistent with NSI theory and are all significant at the one percent level. The path coefficients between first and second-order latent constructs are also all significant at the one percent level, except for C2, significant at the 5% level, and consistent with theory. Results for the structural model confirm our previous findings, which are shown to be extremely robust to model respecification. Our conclusions do not change with the computation of bootstrapped standard errors and confidence intervals, which can be seen in tables 21 and 22 below; path coefficients between our first and second-order factor are significant at the 5% level, while the path coefficient between Connectedness and GNSI Efficacity is significant at the 10% level.

Table 21: Bootstrapped Bias Corrected Confidence Intervals for the Structural Model

Parameter			Estimate	Lower	Upper	P
GNSI EFFICACITY	<---	CONNECTEDNESS	0,652	0,03	1,148	0,006
GNSI EFFICACITY	<---	BARRIERS TO INNOVATION	0,008	-0,501	0,309	0,918
B4	<---	BARRIERS TO INNOVATION	0,999	0,55	3,463	0,001
B2	<---	BARRIERS TO INNOVATION	0,775	0,353	1,432	0,002
B3	<---	BARRIERS TO INNOVATION	0,42	0,155	0,724	0,002
B1	<---	BARRIERS TO INNOVATION	1	1	1	...
C1	<---	CONNECTEDNESS	1	1	1	...
C2	<---	CONNECTEDNESS	0,792	0,125	1,711	0,003
E1	<---	GNSI EFFICACITY	1	1	1	...
E2	<---	GNSI EFFICACITY	0,265	0,137	0,413	0,002
E3	<---	GNSI EFFICACITY	0,999	0,786	1,426	0,001

Table 22:Bootstrapped Bias Corrected Confidence Intervals for Covariances (Model 7)

Parameter			Estimate	Lower	Upper	P
BARRIERS TO INNOVATION	<-->	CONNECTEDNESS	0,028	-0,067	0,123	0,455
ec3	<-->	ec1	0,109	0,046	0,179	0,003
ee6	<-->	ee8	0,162	0,056	0,316	0,001

7. Findings and Discussion

The fit indices for final model (7), together with the robustness of our structural model to measurement model respecification, make us strongly confident that it is at least an adequate representation of the GNSI.

Our results are:

Normed fit index (NFI)	0.863	(Acceptable fit 0.9≤ 0.95)[1]
Relative fit index (RFI)	0.850	(Acceptable fit ≥ 0.9)[2]
Incremental fit index (IFI)	0.950	(Acceptable fit ≥ 0.95)[1]
Non-nonmed fit index (NNFI [TLI])	0.945	(Acceptable fit 0.95≤ NNFI ≤0.97)[1]
Comparative fit index (CFI)	0.950	(Acceptable fit 0.95≤ CFI ≤0.97)[1]
Root mean square error of approximation (RMSEA)	0.046	(Acceptable fit 0.05≤ RMSEA ≤0.08)[1]
Square root mean residual (SRMR)	0.073	(Acceptable fit 0.05≤ SRMR ≤0.10)[1]
p-value Chi square	0.000	(Acceptable fit 0.01≤ p ≤0.005)[1]
T/δf ratio	1.491	(Good fit 0 ≤ T/δf ≤2)[1]

[1] Schermelleh-Engel *et al.*, (2003)

[2] Bartels *et al.*, (2006)

Therefore our SEM fits acceptably the data. Our hypotheses are supported (or not) as follows:

1. Regarding the Structural Model
    a. The GNSI Efficacity is significantly determined (coeff 0.652, p 0.005) by (Actor) Connectedness. H1 — fully supported.
    b. The GNSI Efficacity is not significantly determined (coeff 0.008, p 0.954) by Barriers to Innovation. H2 — unsupported.
    c. There is no significant non-recursive relationship between (Actor) Connectedness and Barriers to Innovation (coeff 0.028, p 0.452). H6 — unsupported.
2. Regarding the Measurement Model
    a. The measurement model indicates that GNSI Efficacity is significantly measured by:
        i. Factor E2—Knowledge-based Innovation Capability (coeff 0.265, p 0.000); and
        ii. Factor E3—Standards and Regulatory Incentives (coeff 0.999, p 0.000). H3 — mainly supported.
    b. The measurement model indicates that (Actor) Connectedness is measured by:

i. Factor C2—Actor Intra-linkages (coeff 0.792, p 0.002). H4 — partially supported.

c. The measurement model indicates that Barriers to Innovation is measured by:

i. Factor B4—Reduced Organisational Risks (coeff 0.999, p 0.000);

ii. Factor B2—Unsophisticated Markets (coeff 0.775, p 0.000); and

iii. Factor B3—Deficient Fiscal Policy (coeff 0.420, p 0.000). H5 — mainly supported.

The significant structural model findings suggest several indications with respect to policy craft and design for enhancing the GNSI Efficacity (i.e. effectiveness and efficiency in performance terms or capacity and capability in operational terms). First, increasing the GNSI Efficacity requires increasing the coherence of Actor Connectedness. In other words, *ceteris paribus*, Actor Intra-, Inter-linkages need to be strengthened in terms of increasing the density, distribution and symmetric directionality within, and between Actors. Isolation of Actors from one another is inimical to a NSI that is functional at higher levels of performance in enabling innovativeness in the economy on the one hand; and on the other hand allowing the sources of intellectual assets to be linked with the productive system of the economy. This finding supports theory as innovative capacity is related to the concept of centrality (Singh, 2005; Fox *et al.*, 2013) and the ability of agents to create and maintain connections (Jansen, van den Bosch and Volbera, 2006). The externalities of this Connectedness include better decision-making capacity (Teece, 1996), enhanced organisational capital and increased marketisation of research outputs from KBIs (Etzkowitz, 1998). The significant coefficient implies that a 1% increase in Actor Connectedness results in a 0.652% increase in the GNSI Efficacity. Means by which this might be achieved are arrived at through addressing, with policy, the variables that Factors of Actor Connectedness influence such as those in table 4 above.

Secondly, it is unexpected that the GNSI Efficacity is not significantly determined negatively (coeff 0.008, p 0.954) by Barriers to Innovation. This, at first sight, is counter-intuitive. However, notwithstanding the statistical results, reflection on the NSI literature suggests that there may be threshold dynamics at work. In other words, it may not matter how high or low Barriers to Innovation are in the NSI, they are unlikely to be significant in the absence of Actor Connectedness. Barriers to Innovation appear not to matter to GNSI Efficacity when Actors are isolated for reasons such as: (i) threshold issues in that the Factor Barriers to Innovation in the GNSI are dominated by Skills ICT capability/capacity (influencing the variables access to ICT and ICT Capacity) (Bartels and Koria, 2012). This factor influences Connectedness and therefore it is likely that Barriers to Innovation become structurally significant at a certain level of obstruction. (ii) Barriers to Innovation are dynamic, and therefore it may be that institutional barriers on the one hand [e.g. learning deficiencies of Actors, absence of innovation transmission mechanisms and lack of innovation orientation by Actors (Oyelaran-Oyeyinka and Gehl Sampath, 2006)]; and, on the other hand, organisational barriers (e.g. the absence of innovation as a core organisational value, isolated innovation responsibility, and risk averse behaviour) moderate the link between Barriers to Innovation and GNSI Efficacity.

Thirdly, the non-significant positive relationship between (Actor) Connectedness and Barriers to Innovation is counter intuitive, notwithstanding the statistical results. The reason for this could be that Actors are relatively isolated from one another (Bartels and Koria, 2012). This counter intuitive relation[45] though insignificant demands explanation. It could be that, before Barriers to Innovation become significant, a threshold level of Connectedness and interaction between Actors is requisite. In this regard, Bernardes and da Motta e Albuquerque (2003, p. 882) suggest the "there seems to be a threshold level in the scientific production (… in the neighbourhood of 150 scientific papers per million inhabitants), beyond which the efficiency in the use of scientific output by the technological sector increases; there is an inter-temporal dynamics of this threshold, as it changes in time". When intellectual capital or scientific production is seen as a function of Connectedness (Biglan, 1973) it is only after a threshold level of Connectedness is passed that Barriers to Innovation have a significant impact.

The significant measurement model findings again suggest several indications with respect to policy craft and design regarding the fundamentals of the GNSI – Efficacity, Connectedness and Barriers to Innovation. These indications concern using the relevant variables influenced by the significant Factors to benchmark, and thus monitor and manage longitudinally the GNSI. First, the variables influenced by the Factor E2—Knowledge-based Innovation Capability; and Factor E3—Standards and Regulatory Incentives (table 6) can be used with regards to GNSI Efficacity. Secondly, the variables influenced by the Factor C2—Actor Intra-linkages (table 4) can be used for managing Actor Connectedness with respect to Intra-organisational coherence. Thirdly, the variables influenced by the Factor B4—Reduced Organisational Risks; the Factor B2—Unsophisticated Markets; and the Factor B3—Deficient Fiscal Policy (table 2) can be used to reduce Barriers to Innovation.

With respect to developing countries and under conditions of resource constraints, from the relevant Factor and variable coefficients, policy makers have a view of where to apply limited fiscal and monetary resources as well as regulatory, standards and performance requirements and by how much an amount of input resource application to an independent policy variable will result in the output of the dependent policy variable. Illustrative examples make the point. Regarding GNSI Efficacity, a 1% increase in the Factor E2—Knowledge-based Innovation Capability; and the Factor E3—Standards and Regulatory Incentives results respectively in a 0.265% and 0.999% increase in GNSI Efficacity. Again, how this might be achieved is through the variables influenced by the particular Factor (table 6). Similarly, with respect to (Actor) Connectedness, a 1% increase in the Factor C2—Actor Intra-linkages generates a 0.792% increase in (Actor) Connectedness. The variables influenced by the Factor (table 4) could be used to achieve this policy goal. Concerning Barriers to Innovation a 1% increase in the Factor B2—Unsophisticated Markets increases the Barriers to Innovation by 0.775%. The positive correlation implies that a 1% decrease in the Factor B2—Unsophisticated Markets decreases the Barriers to Innovation by 0.775%. Likewise a 1% decrease in the Factor B3—Deficient Fiscal Policy decreases the Barriers to Innovation by 0.420%; and a 1% decrease in the Factor

[45] As Connectedness increases so too Barriers to Innovation and *vice versa*.

B4—Reduced Organisational Risks results in a 0.999% decrease in Barriers to Innovation. The variables influenced by Factors in table 2 assist in achieving this policy outcome.

7.1 Implications and Contribution

The implications of our paper are several. First, the complexity of NSI can be modeled successfully using SEM for insights and therefore policy design. Secondly, the measurement model Factors can be used to bench-mark GNSI Efficacity, (Actor) Connectedness, and Barriers to Innovation. Thirdly, GNSI Efficacity is structurally determined solely by (Actor) Connectedness at least until a threshold level of Barriers to Innovation interfere with NSI effectiveness and efficiency. Fourthly, in developing countries, ensuring that NSI Actors are well-connected is the most important policy goal for increasing innovativeness in the economy; and conversely, the lack of NSI (Actor) Connectedness appears the most significant barrier to innovation and innovativeness — the analogy being the inutility of a disconnected telephone.

The contributions of this paper to theory and empirics requires reference to the seminal work of Leydesdorff and Etzkowitz (1996) further elaborated in Etzkowitz & Leydesdorff (2000) with respect to the political economy of the innovation-knowledge infrastructure and the knowledge-based economy (Leydesdorff, 2012). As mentioned previously the traditional TH Model incorporates formally only three Actors namely Government, University and Industry. This framework developed in the context of industrialised countries needs adjustment in the developing country context. Hence, we advance the TH4 Model in which Arbitrageurs as another distinct Actor and diffused ICT are incorporated. Thus the major contribution of our paper lies firstly in this advance and employing SEM to model successfully the interactively complex NSI of a developing country[46]. Secondly, the fit of our model to the data indicates that the model serves well to inform, configure and calibrate policy instruments [incentives (fiscal, monetary, regulatory, performance requirements and standards setting)] in order to improve NSI Efficacity. Thirdly, there is merit in the model application to other NSI.

8. Conclusions

Our paper has served to demonstrate reliably that the dynamic complexity of NSI can be successfully modeled using SEM to elucidate the determinants of fundamental constructs of NSI in terms of efficacity, linkages, and barriers to innovation. The measurement model enables policy makers concerned with innovation to view the dynamics of innovation systemically and to have valid and reliable variables that can be used to indicate the performance of the NSI. The structural model permits crucial insights: (i) Connectedness through Intra- and Inter-linkages of the core Actors is key to efficacious performance of the NSI; (ii) threshold dynamics appear to be at work in the NSI, in that Barriers to Innovation may become significant only after a certain level of obstruction with respect to Actor Connectedness; (iii) mapping and measuring the system of innovation is a primary necessity for producing evidence-based policy. The robustness of the SEM allows it to be applied to other NSI.

[46] Behboudi, Jalili and Mousakhani (2011) present a SEM of the commercialisation of research in Iran.

Issues for further research concern: (i) performing a comparative SEM analysis for each Actor for an indication of structural similarities; (ii) the application of our methodology to NSI in other economies[47]; and (iii) applying the methodological approach to the vertical and horizontal nested levels of systems of innovation.

[47] To this end the Authors are currently analysing data from the Kenya NSI,

References

Abdi, H., Williams, L.J., 2010, Principal Component Analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*, 2 (2), 433-459.

Abramovitz, M., 1986, Catching Up, Forgoing Ahead, and Falling Behind. *Journal of Economic History*, 46 (2), 385-406.

Achim, I.M., Popescu, T., 2009, The Systemic approach to national innovation systems in a knowledge-based economy. *Annales Universitatis Apulensis: Series Oeconomica*, 11 (2), 946-952.

Adams, P., Fontana, R., Malerba, F., 2013. The magnitude of innovation by demand in a sectoral system: The role of industrial users in semicondutors. *Research Policy*, 42, 1-14.

Adams, R., Bessant, J., Phelps, R., 2006, Innovation management measurement: A review, *International Journal of Management Reviews*, 8 (1), 21-47.

Aghion, P., Dewatripont, M., Du, L., Harrison, A. ,Legros, P., 2012, Industrial Policy and Competition. NBER Working Paper 18048, May. Cambridge, MA, National Bureau of Economic Research.

Ahlstrom, D., 2010, Innovation and Growth: How Business Contributes to Society, *Academy of Management Perspectives*, 24 (3), 11-24.

Ahuja, G., Katila, R., 2001, Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study, *Strategic Management Journal*, 22 (3), 197-220.

Andersen, E.S., Lundvall, B.-Å., 1988, Small national innovation systems facing technological revolutions: an analytical framework. In Freeman, C., Lundvall, B.-Å. (Eds.), Small Countries Facing the Technological Revolution. Pinter, London.

Andreassen T.W., Lorentzen B.G., Olsson U.H., 2006, The Impact of Nonnormality and Estimation Methods in SEM on Satisfaction, *Research in Marketing. Quality and Quantity*, 40 (1), 39-58.

Archibugi, D., Iammarino, S., 1999, The policy implications of the globalization of innovation, *Research Policy*, 28 (2-3), 317-336.

Arocena, R., Sutz, J., 2000, Looking at National Systems of Innovation from the South, *Industry & Innovation*, 7(1), 55-75

Arrow, K.J., 1962, The Economic Implications of Learning by Doing, *Review of Economic Studies*, 29, 155-173.

Arundel, A., Geuna, A., 2004, Proximity and the use of public science by innovative European firms, *Economics of Innovation and New Technology*, 13 (6), 559-580.

Asheim, B.T., Coenen, L., 2004, The Role of Regional Innovation Systems in a Globalizing Economy: Comparing Knowledge Bases and Institutional Frameworks of Nordic Clusters. Working Paper 03/2005, Lund: Centre for Innovation, Research and Competence in the Learning Economy (CIRCLE).

Asheim, B. T., Gertler, M. S., 2005, The geography of innovation: Regional innovation systems, Oxford University Press, Oxford.

Asheim, B.T., Isaksen, A., 1997, Location, agglomeration and innovation: Towards regional innovation systems in Norway?, *European Planning Studies*, 5 (3), 299-330.

Audretsch, D.B., Feldman, M.P., 1996, R&D spillovers and the geography of innovation and production, *American Economic Review*, 86, 630–640.

Audretsch D., Feldman M. P., 1999, Innovation in Cities: Science-Based Diversity, Specialization and Localized Monopoly, *European Economic Review*, 43, 409-429.

Avnimelech G., Teubal M., 2006, Creating venture capital industries that co-evolve with high tech: Insights from an extended industry life cycle perspective of the Israeli experience, *Research Policy*, 35 (10), 1477-1498.

Balzat, M., 2002, The theoretical basis and the empirical treatment of National Innovation Systems. Institute for Economics, University of Augsburg, Paper No 232.

Balzat, M. ,Hanusch, H., 2003, Recent Trends in the Research on National Innovation Systems. Volkswirtschaftliche Diskussionsreihe / Institut für Volkswirtschaftslehre der Universität Augsburg, 254 (downloaded from http://hdl.handle.net/10419/22777).

Balzat, M., Hanusch, H., 2004, Recent trends in the research on national innovation systems, *Journal of Evolutionary Economics*, 14, 197-210.

Baptista, R., Swann, P., 1998, Do firms in clusters innovate more?, *Research Policy*, 27 (5), 525-540.

Barrett, P., 2007, Structural equation modeling: Adjudging model fit, *Personality and Individual Differences*, 42 (5), 815-824.

Bartels, F. L., Giao, H. N. K., Ohlenburg, T. J., 2006, ASEAN Multinational Enterprises: A Structural Model Analysis of Strategic Coherence, *ASEAN Economic Bulletin*, 23 (2), 171-191.

Bartels, F. L, Eicher, M., Bachtrog, C., Rezonja, G., 2009, Foreign Direct Investment in Sub-Saharan Africa: Changing Location-Specific Advantages as Signals of Competitiveness, *The Developing Economies*, 47 (3), 244-78.

Bartels, F. L., Koria, R., 2012, Evidence-Based Policy Making. The Ghana National System of Innovation – Measurement, Analysis & Policy Recommendations, GNSI Report 2012, UNIDO.

Bartels, F. L., Koria, R., 2014, Mapping, Measuring and Managing African National Systems of Innovation for Policy and Development: The Case of The Ghana National System of Innovation, *African Journal of Science, Technology, Innovation and Development* (Forthcoming).

Bartels, F. L, Koria, R., Carneiro, S., 2009, National Systems of Innovation in Selected Emerging Market Economies: an Examination of Actors, Interactions and Constraints, EAMSA (Euro-Asian Management Studies Association), 26th Conference on Globalization of Technology, Innovation and Knowledge. Lausanne, Switzerland, 22-24 Oct. 2009.

Bartels, F. L., Lederer S., 2009, Changing patterns in industrial performance – A UNIDO competitive industrial performance perspective: Implications for industrial development. Working Papers, No. 05/2009, Vienna: Research and Statistics Branch, UNIDO.

Bartels, F. L., Voss, H., Lederer, S., Bachtrog, C., 2012, Determinants of National Innovation Systems: Policy implications for developing countries, *Innovation: Management, Policy & Practice 14*, (1), 2-18.

Baygan, G., Freudenberg, M., 2000, The Internationalization of Venture Capital Activity in OECD Countries: Implications for Measurement and Policy. Science, Technology and Industry Working Papers - 2000/7. Organization for Economic Co-operation and Development (OECD), Paris.

Beauducel, A., Wittmann, W. W., 2005, Simulation Study on Fit Indices in CFA Based on Data with Slightly Distorted Simple Structure, *Structural Equation Modeling*, 12 (1), 41-75.

Becheikh, N., Landry, R., Amara, N., 2006, Lessons from innovation empirical studies in the manufacturing sector: A systematic review of the literature from 1993–2003, *Technovation*, 26 (5-6), 644-664.

Behboudi, M., Jalili, N., Mousakhani M., 2011, Examine the commercialization research outcomes in Iran a structural equation model, *International Journal of Business and Management*, 6 (7), 261-275.

Bentler, P. M., 1990, Comparative Fit Indexes in Structural Models, *Psychological Bulletin*, 107 (2), 238-246.

Bentler, P. M., Chou, C-P., 1987, Practical Issues in Structural Modeling, *Sociological Methods and Research*, 16 (1), 78-111.

Bentler, P. M., Savalei, V., 2010, Structural Equation Modeling, In Corsini Encyclopaedia of Psychology, Eds., I. B. Weiner & W. E. Craighead, Chapter 17, Wiley and Sons, Hoboken, NJ.

Bernardes, A. T., da Motta e Albuquerque, E., 2003, Cross-Over, Thresholds, and Interactions between Science and Technology: Lessons for Less-Developed Countries, *Research Policy*, 32(5), 865-885.

Biglan, A., 1973, Relationships between subject matter characteristics and the structure and output of university departments, *Journal of Applied Psychology*, 57(3), 204.

Blanc, H., Sierra, C., 1999, The internationalization of R&D by multinationals: a trade off between external and internal proximity, *Cambridge Journal of Economics*, 23 (2), 187-206.

Blind, K., 2012, The influence of regulations on innovation: A quantitative assessment for OCED countries, *Research Policy*, 41 (2), 391-400.

Blind, K., Grupp, H., 1999, Interdependencies between the science and technology infrastructure and innovation activities in German regions: empirical findings and policy consequences, *Research Policy*, 28 (5), 451-468.

Blundell, R., Griffith, R., Van Reenen, J., 1999, Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms, *Review of Economic Studies*, 66 (3), 529-554.

Bjørnskov, C., Svendsen, G. T., 2002, Why does the northern light shine so brightly? Decentralisation, social capital and the economy, Aarhus School of Business, Working Paper 15.

Bodas Freitas, I.M., Geuna, A., Rossi, F., 2013. Finding the right partners: Institutional and personal modes of governance of university-industry interactions, *Research Policy*, 42, 50-62.

Bollen, K. A. and Pearl, J., 2013, Eight Myths about Causality and Structural Equation Models, In Handbook of Causal Analysis for Social Research, Ed., S. L. Morgan, Berlin, Springer.

Bollen, K. A., Stine, R., 1990, Direct and Indirect Effects: Classical and Bootstrap Estimates of Variability, *Sociological Methodology*, 20, 115-140.

Bollen, K. A., Stine, R., 1992, Bootstrapping Goodness-of-Fit Measures in Structural Equation Models, *Sociological Methods and Research*, 21 (2), 205-229.

Bollen, K. A., Stine, R., 1993, Bootstrapping Goodness of Fit measures in Structural Equation Models, In Testing Structural Equation Models, Ed., K. A. Bollen & J. S. Long, Thousand Oaks (CA), Sage Publications.

Buckley, P. J., Carter, M. J., 2004, A formal analysis of knowledge combination in multinational enterprises, *Journal of International Business Studies*, 35 (5), 371-384.

Buckley P. J., Casson M., 2002, The Future of the Multinational Enterprise: 25th anniversary Edition, London, Palgrave Macmillan.

Buckley P. J., Hashai N., 2004, A Global Systems View of Firm Boundaries, *Journal of International Business Studies*, 35 (1), 33-45.

Buesa, M., Heijs, J., Baumert, T., 2010, The determinants of regional innovation in Europe: A combined factorial and regression knowledge production function approach, *Research Policy*, 39 (6), 722-735.

Burt, R. S., 1976, Interpretational Confounding of Unobserved Variables in Structural Equation Models, *Sociological Methods and Research*, 5 (1), 3-52.

Browne, M. W., Cudeck, R., 1993, Alternative ways of assessing model fit, In Testing structural equation models, Eds., K. A. Bollen & J. S. Long, Newbury Park, CA, Sage, (pp. 136−162.

Carlsson, B., 2006, Internationalization of innovation system: A survey of literature, *Research Policy*, 35, 56-67.

Carlsson, B., Stankiewicz, R., 1995, On the nature, function and composition of technological systems, In Technological systems and economic performance: The case of factory automation, Ed., B. Carlsson, Kluwer, Dordrecht.

Castellacci, F., Natera, J. M., 2012, The dynamics of national innovation systems: A panel cointegration analysis of the coevolution between innovative capability and absorptive capacity, *Research Policy*, 42 (3), 579-594.

Chaminade, C., 2011, Exploring the role of regional innovation systems and institutions in global innovation networks, Working Paper 2011/15, Centre for Innovation, Research and Competence in the Learning Economy (CIRCLE), Lund University, Sweden (downloaded from http://www4.lu.se/o.o.i.s/9673).

Chaminade, C., Intarakumnerd, P., Sapprasert, K., 2012, Measuring systemic problems in National Innovation Systems. An application to Thailand, *Research Policy*, 41 (8), 1476–1488.

Chang, S. H., Lin, P. H., 2012, A Preliminary study on the structural model of national innovation capability, *Journal of International Management Studies*, 7 (1), 128-137.

Chanthes, S., 2012, Increasing Faculty Research Productivity via a Triple-Helix Modeled University Outreach Project: Empirical Evidence from Thailand, *Procedia – Social and Behavioral Sciences*, 52, 253-258, 10th Triple Helix Conference 2012.

Cohen, W. M., Nelson, R. R., Walsh, J. P., 2000, Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing firms patent (or not), NBER Working Paper No. 7552, NBER, Cambridge, MA.

Cohen, W. M., Nelson, R., Walsh, J. P., 2002, Links and impacts: The influence of public research on industrial R&D, *Management Science*, 49(1), 1-23.

Commission of the European Communities, 2007, Fostering Innovation in Services, Final Report of the Expert Group on Innovation in Services, Brussels, Belgium.

Cooke, P., 2004, The role of research in regional innovation systems: new models meeting knowledge economy demands, *International Journal of Technology Management*, 28 (3-6), 507–533.

Cooke, P., Uranga, M. G., Etxebarria, G., 1998, Regional systems of innovation: an evolutionary perspective, *Environment and Planning*, A 30 (9), 1563-1584.

Comrey A. L., Lee H. B., 1992, A First Course in Factor Analysis, Hillsdale, NJ, Erlbaum.

Crépon, B., Duguet, E., Mairessec, J., 1998, Research, Innovation And Productivity: An Econometric Analysis At The Firm Level, *Economics of Innovation and New Technology*, 7 (2), 115-158.

D'Este, P., Iammarino, S., Savona, M., von Tunzelmann, N., 2012, What hampers innovation? Revealed barriers versus deterring barriers, *Research Policy*, 41, 482-488.

Delgado M., Ketels C., Porter M. E., Stern S., 2012, The Determinants of National Competitiveness, NBER Working Paper No. 18249.

Diaconis, P., Efron, B., 1983, Computer-Intensive Methods in Statistics, *Scientific American*, 248 (5), 116-131.

Ding, L., Velicer, W. F., Harlow, L. L., 1995, Effects of Estimation Methods, Number of Indicators per Factor, and Improper Solutions on Structural Equation Modeling Fit Indices, *Structural Equation Modeling*, 2 (2), 119-144.

DiMaggio P., Hargittai E., 2001, From the 'Digital Divide' to `Digital Inequality': Studying Internet Use As Penetration Increases, Center for Arts and Cultural Policy Studies, Princeton University, Working Paper No 15.

Doloreux, D., Parto, S., 2005, Regional innovation systems: Current discourse and unresolved issues, *Technology in Society*, 27 (2), 133-153.

Dunning J. H., 2003, Some Antecedents of Internalization Theory, *Journal of International Business Studies*, 34 (2), 108-115.

Edquist, C., 1997, Systems of Innovation: Technologies, Institutions and Organizations. Pinter, London.

Edquist C., 2005a, Systems of innovation approaches – Their Emergence and characteristics, in systems of innovation: Technologies, institutions and organizations. Ed., Charles Edquist, Routledge, Oxon.

Edquist C., 2005b, Systems of innovation: Perspectives and challenges, In The Oxford Handbook of Innovation, Eds., Jan Fagerberg, David C. Mowery & Richard R. Nelson, OUP, Oxford.

Edquist, C., Lundvall, B-Å., 1993, Comparing Danish and Swedish systems of innovation, In Charles Edquist, Ed., Systems of innovation, technologies, institutions and organizations. Pinter, London.

Etzkowitz, H., 1998, The norms of entrepreneurial science: cognitive effects of the new university–industry linkages, *Research policy*, 27(8), 823-833.

Etzkowitz, H., 2002, Incubation of incubators: Innovation as a triple helix of university-industry-government networks, *Science and Public Policy*, 29 (2), 115-128.

Etzkowitz, H., Leydesdorff, L., 2000, The dynamics of innovation: from National Systems and "Mode 2" to a Triple Helix of university-industry-government relations, *Research Policy*, 29 (2), 109-123.

Evangelista, R., Perani, G., Rapiti, F., Archibugi, D., 1997, Nature and impact of innovation in manufacturing industry: some evidence from the Italian innovation survey, *Research Policy*, 26 (4-5), 521-536.

Fagerberg J., 2005, Innovation: A guide to the literature, In The Oxford Handbook of Innovation, Eds., Jan Fagerberg, David C. Mowery & Richard R. Nelson, OUP, Oxford.

Fagerberg, J., Srholec, M., 2008, National innovation systems, capabilities and economic development, *Research Policy*, 37 (9), 1417-1435.

Fan, X., Sivo, S.A., 2005, Sensitvity of Fit Indexes to Misspecified Structural or Measurement Components: Rationale of Two-Index Strategy Revisited, *Structural Equation Modeling*, 12 (3), 343-367.

Filippetti, A., Archibugi, D., 2011, Innovation in times of crisis: National Systems of Innovation, structure, and demand, *Research Policy*, 40, 179-192.

Fisher, M., Revilla-Diaz, J., Snickars, F., 2001, Metropolitan innovation system: Theory and evidence from metropolitan regions in Europe, Springer, New York.

Fisher, D., Atkinson-Grosjean, J., 2002, Brokers on the Boundary: Academy-Industry Liaison in Canadian Universities, *Higher Education*, 44 (3-4), 449-467.

Fox G. L., Smith J. S., J. Cronin J., Brusco M., 2013, Weaving webs of innovation, *International Journal of Operations & Production Management*, 33 (1), 5 – 24.

Freeman, C., 1987, Technology Policy and Economic Performance: Lessons from Japan. Printer, London.

Freeman, C., 1995, The 'National System of Innovation' in historical perspective, *Cambridge Journal of Economics*, 19, 5-25.

Freeman, C., 2002, Continental, national and sub-National Innovation Systems – Complementarity and economic growth, *Research Policy*, 31, 191-211.

Freeman, C., 2004, Technological infrastructure and international competitiveness, *Industrial and Corporate Change*, 13, 541-569.

Freeman, C., Louça, F., 2001, As Time Goes By: From the Industrial Revolutions to the Information Revolution, OUP, Oxford

Fritsch, M., Meschede, M., 2001, Product innovation, process innovation, and size, *Review of Industrial Organization*, 19 (3), 335–350.

Furman, J.L., Hayes, R., 2004, Catching up or standing still?: National innovative productivity among 'follower' countries, 1978-1999, *Research Policy*, 33 (9), 1329-1354.

Furman, J.L., Porter, M.E., Stern, S., 2002, The determinants of national innovative capacity, *Research Policy*, 31(6), 899-933.

Gaba V., Bhattacharya S., 2011, Aspirations, Innovation, and Corporate Venture Capital: A Behavioral Perspective, INSEAD Working Paper, 2011/126/OB/TOM.

Gatignon H., Tushman M. L., Smith W., Anderson P., 2001, A Structural Approach to Assessing Innovation: Construct Development of Innovation Locus, Type and Characteristics, INSEAD Working Paper, 21 November, 2001/97/MKT.

Geels F. W., 2004, From sectoral systems of innovation to socio-technical systems: Insights about dynamics and change from sociology and institutional theory, *Research Policy*, 33, 897–920.

Greenacre, P., Gross, R., Speirs, J., 2012, Innovation Theory: A review of the literature, ICEPT Working Paper, ICEPT/WP/2012/011, May.

Greenwood, J., Jovanovic, B., 1998, Accounting for growth, NBER Working Paper No. 6647.

Groenewegen, J., van der Steen, M., 2006, The Evolution of National Innovation Systems, *Journal of Economic Issues*, 40, 277-285.

Guan, J., Chen, K., 2012, Modeling the relative efficiency of national innovation systems, *Research Policy*, 41 (1), 102-115.

Guston, D. H., 2001, Boundary organizations in environmental policy and science: An introduction, *Science, Technology, and Human Values*, 26 (4), 399-408.

Haff, L. R., 1979, An identity for the Wishart distribution with applications, *Journal of Multivariate Analysis*, 9 (4), 531-544.

Hair, J. F, Black, W. C., Babin, B. J., Anderson, R. E., 2010, Multivariate Data Analysis, Pearson Education, Upper Saddle River, NJ.

Hammervold, R., Olsson, U. H., 2012, Testing Structural Equation Models: the Impact of Error Variances in the Data Generating Process, *Quality and Quantity: International Journal of Methodology*, 46 (5), 1547-1570.

Hayduk, L. A., Glaser, D. N., 2000, Jiving the Four-Step, Waltzing around Factor Analysis and Other Serious Fun, *Structural Equation Modeling*, 7 (1), 1-35.

Hargadon, A. B., 1998, Firms as Knowledge Brokers: Lessons in Pursuing Continuous Innovation, *California Management Review*, 40 (3), 209-227.

Harzing, A. W., 2006, Response Styles in Cross-National Survey Research: A 26-country Study, *The International Journal of Cross Cultural Management*, 6(2), 243-266.

Hawawini, G., Subramanian, V., Verdin, P., 2003, Is performance driven by industry-or firm-specific factors? A new look at the evidence, *Strategic Management Journal*, 24 (1), 1-16.

Hekkert, M. P., Suurs, R. A. A., Negro, S. O., Kuhlmann, S., Smits, R. E. H. M., 2007, Functions of innovation systems: A new approach for analysing technological change, *Technological Forecasting & Social Change*, 74, 413-432.

Hilbert, M., López, P., Vásquez, C., 2010, Information societies or "ICT equipment societies?" Measuring the digital information-processing capacity of a society in bits and bytes, *The Information Society*, 26 (3), 157–178.

Hipp, C., Tether, B. S., Miles I., 2000, The Incidence and effects of Innovation in Services: Evidence from Germany, *International Journal of Innovation Management*, 4 (4), 417-453.

Hogarty K, Hines C, Kromrey J, Ferron J, Mumford K., 2005, The Quality of Factor Solutions in Exploratory Factor Analysis: The Influence of Sample Size, Communality, and Overdetermination, *Educational and Psychological Measurement*, 65(2):202-26.

Howells, J., 2006, Intermediation and the role of intermediaries in innovation, *Research Policy*, 35 (5), 715-728.

Hu, L. T, Bentler, P. M., 1999, Cutoff Criteria for Fit Indices in Covariance Structure Analysis: Conventional Criteria versus New Alternatives, *Structural Equation Modeling*, 6 (1), 1-55

Hutchinson, S. R., Olmos, A., 1998, Behavior of Descriptive Fit Indices in Confirmatory Factor Analysis using Ordered Categorical Data, *Structural Equation Modeling*, 5 (4), 344-364.

Iammarino, S., 2005, An evolutionary integrated view of Regional Systems of Innovation: Concepts, measures and historical perspectives, *European Planning Studies*, 13 (4), 497-519.

Intarakumnerd, P., Chairatana, P., Tangchitpiboon, T., 2002, National innovation system in less successful countries: the case of Thailand, *Research Policy*, 31 (8-9), 1445-1457.

Jackson, D. L., 2001, Sample Size and Number of Parameter Estimates in Maximum Likelihood Confirmatory Factor Analysis: a Monte Carlo Investigation, *Structural Equation Modeling*, 8 (2), 205-223.

Jamieson, S., 2004, Likert scales: how to (ab)use them, *Medical Education*, 38 (12), 1217-1218.

Jansen, J., van den Bosch, F., Volbera, H., 2006, Exploratory innovation, exploitative innovation and performance: Effects of organizational antecedents and environmental moderators, *Management Science*, 52(11), 1661-1674.

Jarvis, C. B., MacKenzie, S. B., Podsakoff, P. M., 2003, A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research, *Journal of Consumer Research*, 30 (2), 199-218.

Jennrich, R. I., 2007, Rotation Methods, Algorithms and Standard Errors, In Factor Analysis at 100, Eds., R. Cudeck & R. C. Mac Callum, Routledge, London.

Jöreskog, K. G., 1978, Structural Analysis of Covariance and Correlation Matrices, *Psychometrika*, 43 (4), 443-477.

Jöreskog, K. G., 2007, Factor Analysis and Its Extensions, In Factor Analysis at 100, Eds., R. Cudeck & R. C. Mac Callum, Routledge, London.

Jovanovic, B., Rob, R., 1989, The growth and diffusion of knowledge, *Review of Economic Studies*, 56, 569-582.

Kahn M., Martins de Melo L., Pessoa de Matos M. G., 2014, The Financing of Innovation, pp. 1-20, In Financing Innovation, Eds., Michael Kahn, Luiz Martins de Melo & Marcelo G. Pessoa de Matos, Routledge, Abingdon.

Kaplan, D., Elliott, P. R., 1997, A Model-Based Approach to Validating Education Indicators Using Multilevel Structural Equation Modeling, *Journal of Educational and Behavioral Statistics*, 22 (3), 323-347.

Keizer, J. A., Dijkstra, L., Halman, J. I. M., 2002, Explaining innovative efforts of SMEs: An exploratory survey among SMEs in the mechanical and electrical engineering sector in The Netherlands, *Technovation*, 22 (1), 1-13.

Kim, J. O., Mueller, C. W., 1978, Factor Analysis: Statistical Methods and Practical Issues. Quantitative Applications in Social Sciences Series, 14, Sage Publications, Thousand Oaks (CA).

Kline, R. B., 2011, Principles and Practices of Structural Equation Modeling, Guilford Press, New York.

Klinger, B., Lederman, D., 2006, Diversification, Innovation, and Imitation inside the Global Technological Frontier, World Bank Policy Research Working Paper 3872, April. Washington DC, The World Bank (downloaded from http://web.worldbank.org/WBSITE/EXTERNAL/COUNTRIES/LACEXT/EXTLACOFFICEOFCE/0,,contentMDK:20727935~menuPK:1925860~pagePK:64168445~piPK:64168309~theSitePK:870893,00.html).

Koria, R., Bartels, F. L., Andriano, L., Köszegi, S., 2014, Efficiency and Effectiveness of National Systems of Innovation: The importance of ICT, the Cases of Ghana and Kenya, IST Africa Conference, Mauritius, May 6-9, IST Africa 2014 Conference Proceedings, Paul

Cunningham and Miriam Cunningham, Eds., IIMC International Information Management Corporation..

Koria, R., Bartels, F. L., Koeszegi, S., Carneiro, S., 2012, Free Open Source Software (FOSS) and Survey Methodologies: The case of the Ghana National System of Innovation Survey, IST Africa 2012 Conference Proceedings, Paul Cunningham and Miriam Cunningham (Eds), IIMC International Information Management Corporation.

Koria, R., Köszegi, S., 2011, National Systems of Innovation (NSI): Measurement and implications for science technology and innovation policy in Ghana. UNIDO Conference on Competitiveness & Diversification: Strategic Challenges in a Petroleum-Rich Economy, Accra, Ghana, 14-15 March.

Kuhlmann, S., 2001, Future governance of innovation policy in Europe – three scenarios, *Research Policy*, 30 (6), 953-976.

Kuhlmann, S., Edler, J., 2003, Scenarios of technology and innovation policies in Europe: Investigating future governance, *Technological Forecasting & Social Change*, 70, 619-637.

La Du, T. J., Tanaka, J. S., 1989, Influence of Sample Size, Estimation Method and Model Specification on Goodness of Fit Assessment in Structural Equation Models, *Journal of Applied Psychology*, 74 (4), 625-635.

Labovitz, S., 1967, Some observations on measurement and statistics, *Social Forces*, 46 (2), 151-160.

Labovitz, S., 1970, The assignment of numbers to rank order categories, *American Sociological Review*, 35 (2), 515-524.

Labovitz, S., 1971, In defence of assigning numbers to ranks, *American Sociological Review*, 36 (4), 521-22.

Labovitz, S., 1972, Statistical Usage in Sociology: Sacred Cows and Ritual, *Sociological Methods and Research*, 1 (1), 13-37.

Labovitz, S., 1975, Comment on Henkel's paper: the interplay between measurement and statistics, *Pacific Sociological Review*, 18, 27-35.

Landry, R., Amara, N., Lamari, M., 2002, Does social capital determine innovation? To what extent?, *Technological Forecasting and Social Change*, 69 (7), 681-701.

Lee, K., Lim, C., 2001, Technological regimes, catching-up and leapfrogging: findings from the Korean industries, *Research Policy*, 30, 459–483.

Levin, S., 2002, Complex adaptive systems: Exploring the known, the unknown and the unknowable. *Bulletin of the American Mathematical Society*, 40 (1), 3-19.

Leydesdorff L., 2001, Knowledge-Based Innovation Systems and the Model of a Triple Helix of University-Industry-Government Relations, Paper presented at the Conference New Economic Windows: New Paradigms for the New Millennium, Salerno, Italy, September.

Leydesdorff, L., 2005, The triple helix model and the study of knowledge-based innovation systems, *International Journal of Contemporary Sociology*, 42 (1), 1-16.

Leydesdorff, L., 2012, The Triple Helix, Quadruple Helix, and an N-Tuple of Helices: Explanatory Models for Analyzing the Knowledge-Based Economy?, *Journal of the Knowledge Economy*, 3 (1), 25-35.

Leydesdorff, L., Etzkowitz, H., 1996, Emergence of a triple helix university-industry-government relations, *Science and Public Policy*, 23(5), 279–286.

Leydesdorff, L., Etzkowitz, H., 1998, The triple helix as a model for innovation studies (Conference Report), *Science and Public Policy*, 25 (3), 195–203.

List, F., 1841, The National System of Political Economy, English Edition (1904), Longman, London.

Love, J. H., Roper, S., 2001, Location and network effects on innovation success: Evidence for UK, German and Irish manufacturing plants, *Research Policy*, 30, 313-332.

Lundvall, B-Å., 1988, Innovation as an interactive process: From user–producer interaction to the national system of innovation, In G., Dosi, C., Freeman, R., Nelson, G., Silverberg, L., Soete, Eds., Technical Change and Economic Theory. Pinter, London, 349–369.

Lundvall, B-Å., Ed., 1992, National Systems of Innovation: Towards a theory of Innovation and Interactive Learning, Printer, London.

Lundvall, B-Å., Ed., 1995, National Systems of Innovation: Towards a theory of innovation and interactive learning, Pinter, London.

Lundvall, B-Å., 2007, National Innovation Systems - Analytical Concept and Development Tool, *Industry and Innovation*, 14 (1), 95-119.

Lundvall, B-Å., Johnson, B., Andersen, E. S., Dalum, B., 2002, National systems of production, innovation and competence building, *Research Policy*, 31 (2), 213-231.

MacCallum, R. C., Browne, M. W., Sugawara, H. M., 1996, Power Analysis and Determination of Sample Size for Covariance Structure Modeling, *Psychological Methods*, 1 (2), 130-149.

Maddison, A., 2006, The World Economy, Volume 1: A Millennial Perspective, Volume 2: Historical Statistics, Paris, OECD.

Malerba, F., 2002, Sectoral systems of innovation and production, *Research Policy*, 31, 247-264.

Manjón, J. V. G., Merino, E. R., 2012, Innovation systems and policy design: The European experience, *Innovation: Management Policy & Practice*, 14, 33-42.

Mansfield, E., 1991, Academic research and industrial innovation, *Research Policy*, 20, 1-12.

Marsh, H. W, Hau, K. T., Balla, J. R., Grayson, D., 1998, Is More ever Too Much? The number of Indicators per Factor in Confirmatory Factor Analysis, *Multivariate Behavioral Research*, 33 (2), 181-220.

Marsh, H. W., Hau, K. T., Wen, Z., 2004, In search of Golden Rules: Comment on Hypothesis Testing Approaches to setting Cutoff Values for Fit Indexes and dangers in Overgeneralising Hu and Bentler's (1999) Findings, *Structural Equation Modeling*, 11 (3), 320-341.

Marshall, A., 1920, Principles of Economics, Macmillan: London.

Meesus, M., Oerlemans, L., van Dijck, J., 1999, Regional systems of innovation from within an empirical specification of the relation between technological dynamics and interaction between multiple actors in a Dutch region, ECIS, Working Paper No 99.

Metcalfe, S., 1995, The Economic Foundations of Technology Policy: Equilibrium and Evolutionary Perspectives, In Mullin Consulting Ltd., Ed., Reflections on the process of Reviewing National Policies for Science, Technology and Innovation. Mullin Consulting Ltd, Ontario.

Michie, J., 1998, Introduction. The Internationalisation of the innovation process, *International Journal of the Economics of Business*, 5 (3), 261-277.

Morata-Ramirez, M., Holgado-Tello, F. P., 2013, Construct Validity of Likert Scales through Confirmatory Factor Analysis: A Simulation Study Comparing Different Methods of Estimation Based on Pearson and Polychoric Correlations, *International Journal of Social Science Studies*, 1 (1), 54-61.

Morgan, K., 2004, The exaggerated death of geography: learning, proximity and territorial innovation systems, *Journal of Economic Geography*, 4 (1), 3-21.

Morris-King J. R., 2014, Situated Socio-Cognitive and Ecological Simulation of the Triple-Helix Theory of Regional Innovation Dynamics, PhD Dissertation, Graduate Faculty of Auburn University, Auburn, Alabama, May 3.

Mowery D. C., 1983, Economic theory and government technology policy, *Policy Sciences*, 16 (1), 27-43.

Mueller, P., 2006, Exploring the knowledge filter: how entrepreneurship and university-industry relationships drive economic growth, *Research Policy*, 35, 1499-1508.

Mulaik, S. A. James, L. R., Van Alstine, J. Bennet, N., Lind S., Stilwell C.D., 1989, Evaluation of Goodness of Fit indices for Structural Equation Models, *Psychological Bulletin*, 105 (3), 430-445.

Mulaik, S. A., Millsap, R. E., 2000, Doing the Four-Step Right, *Structural Equation Modeling*, 7 (1), 36-73.

Munk, K. B., Vintergaard, C., 2004, Venture capitalists in systems of innovation, MPP Working Paper No. 1/2004, Dept. of Management, Politics and Philosophy, Copenhagen Business School.

Nelson, E. R., Ed., 1963, National Innovation Systems: A Comparative Analysis, OUP, Oxford.

Nelson, R. R., 1993, National Systems of Innovations: A Comparative Analysis, OUP, Oxford.

Nelson, R. R., Rosenberg, N., 1993, Technical Innovation and National Systems, In Nelson, R. R., Ed., National Systems of Innovation a Comparative Study, OUP, Oxford.

Nelson, R., Winter. S., 1982, An evolutionary theory of economic change, Harvard University Press, Cambridge, Massachusetts.

Niosi, J., Saviotti, P., Bellon, B., Crow, M., 1993, National Systems of Innovation: In search of a workable concept, *Technology in Society*, 15, 207–227.

North, D. C., 1991, Institutions, Institutional Change and Economic Performance. Political Economy of Institutions and Decisions, Washington University, St Louis.

OECD, 1992, Oslo Manual: Guidelines for Collecting and Interpreting Technological Innovation Data, OECD, Paris.

OECD, 1997. Anon., 1997. Oslo Manual: Proposed Guidelines for Collecting and Interpreting Technological Innovation Data [Second (revised) Edition], OECD, Paris.

OECD, 1999, Managing National Innovation Systems, OECD, Paris.

OECD, 2002, Dynamising National Innovation Systems. OECD, Paris.

OECD, 2005, Oslo Manual: Guidelines for Collecting and Interpreting Technological Innovation Data (Third Edition), OECD, Paris.

Oinas, P., Malecki, E. J., 2002, The evolution of technologies in time and space: From national and regional to spatial innovation systems, *International Regional Science Review*, 25 (1), 102-131.

Olsson, U. H., Foss, T., Troye, S. V., Howell, R. D., 2000, The Performance of ML, GLS and WLS in Structural Equation Modeling under Conditions of Misspecification and Nonnormality, *Structural Equation Modeling*, 7 (4), 557-595

Owuor, C. O., 2001, Implications of using Likert data in multiple regression analysis, Doctoral Dissertation, University of British Columbia.

Oyelaran-Oyeyinka, B., Gehl Sampath, P., 2006, Rough road to market: institutional barriers to innovations in Africa (No. 026), United Nations University, Maastricht Economic and Social Research and Training Centre on Innovation and Technology.

Patel, P., Pavitt, K., 1994, National systems of innovation: Why they are important, and how they might be measured and compared, *Economics of Innovation and New Technology*, 3, 77-95.

Pavitt, K., Walker, W., 1976, Government policies towards industrial innovation: a review, *Research Policy*, 5 (1), 11-97.

Perez, C., 1983, Structural change and assimilation of new technologies in the economic and social systems, *Futures*, 15(5), 357-75.

Petter, S., Straub, D., Rai, A., 2007, Specifying Formative Constructs in Information Systems Research, *MIS Quarterly*, 31 (4), 623-656.

Ponds, R., Van Oort, F., Frenken, K., 2007, The geographical and institutional proximity of research collaboration, *Regional Science*, 86 (3), 423–443.

Porter, M., 1990, The Competitive Advantage of Nations, Free Press, New York.

Porter, M., 1998, Clusters and the new economics of competition, *Harvard Business Review*, 76 (6), 77-90.

Preissl, B., 2000, Services Innovation: What Makes it Different? Empirical Evidence from Germany, In J. S. Metcalfe and I. Miles, Eds., Innovation Systems in the Service Economy: Measurement and Case Study Analysis, Kluwer, London, 124-128.

Quadros, R., Furtado, A., Bernardes, R., Franco, E., 2001, Technological Innovation in Brazilian Industry: An Assessment Based on the São Paulo Innovation Survey, *Technological Forecasting and Social Change*, 67 (2-3), 203-219.

Ritter, T., Gemünden, H. G., 2003, Network competence: Its impact on innovation success and its antecedents, *Journal of Business Research*, 56 (9), 745–755.

Ritter, T., Gemünden, H. G., 2004, The impact of a company's business strategy on its technological competence, network competence and innovation success, *Journal of Business Research*, 57 (5), 548-556.

Rockefeller Foundation, 2003, Knowledge flows and knowledge collectives: Understanding the role of science and technology policies in development, Vol. 1, Global Inclusion Program.

Rogers, E. M., 2003, Diffusion of Innovations, 5th Ed., Free Press, New York.

Romer, P. M., 1990, Endogenous Technological Change, *The Journal of Political Economy*, 98 (5), Part 2: The Problem of Development: A Conference of the Institute for the Study of Free Enterprise Systems, S71-S102.

Romer, P. M., 1994, The Origins of Endogenous Growth, *The Journal of Economic Perspectives*, 8 (1), 3-22.

Sachs, J., 2003, The Global Innovation Divide, In A. B. Jaffe, J. Lerner & S. Stern, Eds., NBER, Innovation Policy and the Economy, Vol. 3, pp. 131 - 141, MIT Press Cambridge, MA.

Sakaraya, A. O., 2011, Institutions' and initiatives' role in Turkey's national innovation system, *International Business & Economics Research Journal*, 10 (3), 29-39.

Samara, E., Georgiadis, P., Bakouros, I., 2012, The impact of innovation policies on the performance of national innovation systems: A system dynamics analysis, *Technovation*, 32 (11), 624-638.

Samila, S., Sorenson, O., 2010, Venture capital as a catalyst to commercialization, *Research Policy*, 39 (10), 1348-1360.

Schermelleh-Engel, K., Moosbrugger H., Müller, H., 2003, Evaluating the Fit of Structural Equation Models: Tests of Significance and Descriptive Goodness-of-Fit Measures, *Methods of Psychological Research Online*, 8 (2), 23-74.

Schreiber, J. B., Amaury, N., Stage, F. K., Barlow, E. A, King, J., 2006, Reporting Structural Equation Modeling and Confirmatory Factor Analysis Results: A Review, *The Journal of Educational Research*, 99 (6), 323-337.

Schumpeter, J. A., 1935, The Analysis of Economic Change, *The Review of Economics and Statistics*, 17 (4), 2-10.

Singh, J., 2005, Collaborative networks as determinants of knowledge diffusion patterns, *Management Science*, 51(5), 756-770.

Singh, K., Xie, M., 2008, Bootstrap: a Statistical Method, Rutgers University, Retrieved September 9, 2013 from http://www.stat.rutgers.edu/home/mxie/stat586/handout/Bootstrap1.pdf

Smith, K., 2005, Measuring Innovation, In J. Fagerberg, D. C., Mowery & R. R. Nelson Eds., The Oxford Handbook of Innovation: 148-177, OUP, Oxford.

Smolny, W., 2003, Determinants of innovation behaviour and investment estimates for West-German manufacturing firms, *Economics of Innovation and New Technology*, 12 (5), 449-463.

Spirtes, P. Richardson, T., Meek, C., Scheines, R., Glymour, C., 1998, Using path Diagrams as a Structural Equation Modeling Tool, *Sociological Research Methods*, 27 (2), 182-225.

Solow, R. M., 1957, Technical Change and the Aggregate Production Function, *The Review of Economics and Statistics*, 39 (3), 312-320.

Solow, R., 1960, Investment and technological progress, In K. J., Arrow, S., Kalin & P. Suppes, Eds., 1960, Mathematical methods in the social sciences, 89-104m Stanford University Press, Stanford, CA.

Steiger, J. H., 2000, Point Estimation, Hypothesis Testing , and Interval Estimation using RMSEA: Some Comments and a Reply to Hayduk and Glaser, *Structural Equation Modeling*, 7 (2), 149-162.

Steiger, J. H., 2007, Understanding the Limitation of Global Fit Assessment in Structural Equation Modeling, *Personality and Individual Differences*, 42 (5), 893-898.

Stern S., Porter M. E., Furman J. L., 2000, The Determinants of National Innovative Capacity, NBER Working Paper No. 7876.

Stock, G. N., Greis, N. P., Fischer, W. A., 2002, Firm size and dynamic technological innovation, *Technovation*, 22 (9), 537-549.

Squicciarini, M., Le Mouel, M., 2012, Defining and Measuring Investment in Organisational Capital: Using US Microdata to Develop a Task-based Approach, OECD Science, Technology and Industry Working Papers, 2012/05, OECD Publishing, http://dx.doi.org/10.1787/5k92n2t3045b-en

Taskin, F., Zaim, O., 1997, Catching-up and innovation in high- and low-income countries, *Economics Letters*, 54 (1), 93-100.

Teece, D. J., 1996, Firm organization, industrial structure, and technological innovation, *Journal of Economic Behavior & Organization*, 31(2), 193-224.

Teixeira, A. A., 2013, Evolution, roots and influence of the literature on National Systems of Innovation: a bibliometric account, *Cambridge Journal of Economics*, bet022

Tidd, J., 2006, A review of innovation models. Discussion Paper 1/1, Imperial College London, Tanake Business School.

ul-Haque, I., 2007, Rethinking Industrial Policy, UNCTAD Discussion Papers 183, UNCTAD/OSG/DP/2007/2, April. Geneva, UNCTAD (downloaded from http://unctad.org/en/Pages/Publications/Discussion-Papers-%28Series%29.aspx).

Unger B., Zagler M., 2003, Institutional and organizational determinants of product innovations, *Innovation: The European Journal of Social Science Research*, 16 (3), 293-310.

Ushakov, D. S., 2012, Innovative Capacity as a Modern Factor of Countries Investment Attractiveness Dynamic, *International Journal of Organizational Innovation*, 4 (4), 6-20.

Veblen, T., 1906, The Place of Science in Modern Civilization, *The American Journal of Sociology*, 11 (5), 585-609.

Von Tunzelmann, G. N., 1997, Innovation and Industrialization: A Long-Term Comparison, *Technological Forecasting and Social Change*, 56, 1-23.

Walker, J. T., Maddan, S., 2008, Statistics in Criminology and Criminal Justice, Jones and Bartlett Publishers, Burlington, MA.

Widaman, K. F., 2007, Common Factors versus Components: principals and Principles, Errors and Misconceptions, In Factor Analysis at 100, R. Cudeck & R. C. Mac Callum, Eds., Routledge, London.

White, S. D., Gunasekaran, A., Shea, T. P., Ariguzo, G.C., 2011, Mapping the global digital divide, *International Journal of Business Information Systems*, 7 (2), 207 – 219.

Williams, B., Brown, T., Onsman, A., 2012, Exploratory factor analysis: A five-step guide for novices, *Australasian Journal of Paramedicine*, 8(3), 1-13. Retrieved from http://ro.ecu.edu.au/jephc/vol8/iss3/1

Zahra, S. A., 1993, New product innovation in established companies: Associations with industry and strategy variables, *Entrepreneurship Theory and Practice*, 18 (2), 47-69.

Zook, M. A., 2003, The Knowledge Brokers: Venture Capitalists, Tacit Knowledge and Regional Development. Paper presented at DRUID (Danish Research Unit on Industrial Dynamics), Summer Conference 2003 on Creating and Sharing, Sharing and Transferring Knowledge, The Role of Geography, Institutions and Organizations, Copenhagen, Denmark 12-14 June 2003.