
Innovation Offshoring, Institutional Context and Innovation Performance: A Meta-Analysis

ABSTRACT

Innovation offshoring (IO) has become a widespread management practice. Yet, evidence on the performance implications is inconsistent, and scattered across disciplines and contexts. We argue that the benefits firms can derive from IO depend on the institutional environment at home. Drawing on recent work on institutional theory in international business, we explore institutions that facilitate reverse knowledge transfer and/or institutional arbitrage with respect to innovation-related activities. The results of our meta-analysis that synthesizes evidence from 48 samples show that IO is related positively to innovation performance. As predicted, this relationship is moderated by differences in the institutional environments across countries. Specifically, when national innovation systems are weak at home, IO appears to enable institutional arbitrage strategy whereas Confucian cultures enable more effective reverse knowledge transfer. However, contrary to our expectations, the beneficial effects of IO appear to have diminished over time.

Keywords: innovation offshoring, innovation performance, institutional theory, meta-analytic regression
INTRODUCTION

Innovation offshoring (IO) – the foreign sourcing of knowledge-intensive activities as inputs to the innovation process – has become a widespread management practice. Modern information technologies, shrinking trade barriers, converging consumer tastes, and specialized human capital developments all contribute to the growth of IO (Hutzschenreuter et al., 2011; Lewin and Volberda, 2011). By sourcing innovation input abroad, firms may be able to reduce costs, increase their flexibility, and access expertise abroad, allowing them to differentiate their innovations and to enhance their competitive advantages (Doh et al., 2009; Lewin et al., 2009). However, critics of IO argue that the shift of critical capabilities to foreign countries (Kotabe et al., 2007) might lead to a loss of control over these capabilities which may be detrimental to the offshoring firm.

Scholars from different disciplines have investigated outcomes of offshoring in general and IO specifically (for overviews see Rilla and Squicciarini, 2011; Schmeisser, 2013). While early research on offshoring mainly focused on its cost advantages (Musteen and Ahsan, 2013), more recent research takes into account strategic outcomes such as innovation performance (cf. Lahiri, 2010; Kotabe et al., 2007; Nieto and Rodriguez, 2011; Steinberg et al., 2017) – an important driver of financial performance (Rosenbusch et al., 2011; Rousseau et al., 2016). However, as research on the relationship between IO and innovation performance is scattered across disciplines and contexts, we have limited understanding how and to what extent IO relates to innovation performance, and which external conditions facilitate or hinder the success of IO.

Recent research on the moderators of the IO–innovation performance relationship mainly focuses on the offshoring firm; examining, for example, top management team characteristics (Mihalache et al., 2012), absorptive capacity (Kotabe et al., 2011; van Wijk et al., 2008), or the capabilities of the firm’s subsidiaries (Almeida and Phene, 2004). However, the IO–innovation performance relationship may also depend on external factors such as the institutional environments in
which the offshoring firm is operating (Lam, 2003). Recent studies show that host-country environments play an important role for the location and organizational forms of offshore innovation (Doh et al., 2009; Sartor and Beamish, 2014). International business research also points to the crucial influence of home-country institutions on the strategies and performance of multinational firms more generally (e.g., Wan and Hoskisson, 2003; Marano et al., 2016). Additionally, time may affect IO and its outcomes as institutional environments have co-evolved with the emergence and growth of multinational corporations globally (Cantwell et al., 2010).

Home-country institutions and time likely influence the relationship between IO and innovation performance in two main ways. First, a critical element of IO is the reverse transfer of knowledge from overseas research and development (R&D) units and its integration with the parent organization (Kotabe et al., 2007; van Wijk et al., 2008; Yang et al., 2008). Institutions can either facilitate or hinder knowledge transfer from foreign sources to the parent company and the translation of knowledge into the firm’s innovation process (Kshetri, 2007). IO changes the direction of knowledge transfer from conventional parent-to-subunit knowledge flows to reverse subunit-to-parent knowledge flows. As a result, economic actors may consider the location of innovation activity to other countries as not legitimate due to social norms, and thus inhibit the successful implementation of such a relocation (Meyer and Thein, 2014). Applied to IO, this argument implies that when institutions, including social norms, are supportive of learning from abroad, IO is more likely to benefit the parent firm. We focus on Asian Confucianism, which is associated with more cooperative organizational cultures (Ghauri and Fang, 2001; Lam, 2003), to test this line of argument. Moreover, we predict that social norms have become more favourable to IO over time thus enabling greater benefits to be reaped from it.

Second, home country institutions may affect the relative attractiveness of conducting innovation activities at home rather than abroad. In particular, variations in regulatory institutions can create incentives for ‘institutional arbitrage’, whereby activities are located where costs of compliance

with local institutions are lowest (Jackson and Deeg, 2008; Li and Zhou, 2017; Weng and Peng, 2018).

Applied to IO, this argument suggests that firms would gain more from IO when institutions at home are less supportive to innovation than institutions abroad. Based on the notion of national innovation systems (Lundvall, 2010), we focus on institutions supporting innovation and the rule of law to test this line of argument.

Empirically we follow an evidence-based research approach adopting a comprehensive temporal and cross-country perspective (Mueller et al., 2013). A meta-analysis enables us to synthesize research from various contexts to explore the contingencies in the IO–innovation performance relationship. It is also the “best method to reach consensus” (Combs et al., 2011, p. 194) when primary empirical results are inconsistent. Our meta-analysis combines 46 studies with 48 samples and 113,111 observations from 14 different explicitly mentioned home countries and data relating to the period 1973-2014. Comparing effects of IO on innovation performance measured at different points in time allows to account for differences in institutional environments at different points in time.

Our study contributes in several ways to management research at the intersection of internationalization and innovation. First, as a quantitative literature review, a meta-analysis provides an overview of the state of the art of the research field. When a field is maturing but empirical results remain inconsistent, a meta-analysis can illuminate new research avenues, especially in a field as fragmented as that on IO outcomes. As far as we know, this is the first study to meta-analytically synthesize research on the IO–innovation performance relationship. Second, our study expands theorizing on the strength and direction of the IO–innovation performance relationship by highlighting their context dependence. Specifically, our results indicate that a fine-grained understanding of the consequences of IO needs to incorporate home-country institutions and variations over time in the theoretical framework and methodological design. Thus, our findings support adopting context-
sensitive approaches (c.f. Kostova et al., 2008; Marano et al., 2016; Meyer and Peng, 2016) for research at the intersection of internationalization and innovation.

THEORETICAL BACKGROUND AND HYPOTHESES

IO and Innovation Performance

In line with prior research (e.g., Ahuja and Katila, 2001; Laursen and Salter, 2006), we define innovation performance as the degree to which a firm’s innovation process is successful in terms of producing outcomes that lead to new or significantly improved products or services, processes, new marketing methods, or new organisational methods in business practices, workplace organisation, or external relations (OECD, 2005, p. 46). Such outcomes can be intermediate, such as patents (e.g., Ahuja and Katila, 2001), or they can be the final results of the innovation process, such as new product introductions (e.g., Laursen and Salter, 2006).

Following prior research (e.g., Lewin et al., 2009; Mihalache et al., 2012), we define innovation offshoring (IO) as a management practice that sources innovation input abroad and coordinates innovation activities across borders either within firms or with external partners. IO implies the transfer of knowledge between different geographical locations, which enhances both the diversification (breadth) and enrichment (depth) of firms’ knowledge sources. First, IO enables greater breadth of innovation inputs because foreign knowledge sources likely differ from those in the home country. This is because national innovation systems often differ owing to institutional differences (Lundvall, 2010; Nelson and Rosenberg, 1993). Second, IO can enhance the depth of innovation inputs because it enables access to specialized knowledge and skills in foreign geographic knowledge clusters with comparative advantages in certain industries (Florida, 1997; Kuemmerle, 1999; Lewin et al., 2009). Both knowledge breadth and depth are linked to increased innovation performance (Leiponen and Helfat, 2010). Whereas knowledge breadth associated with IO can lead to new combinations of
resources and therefore Schumpeterian innovation performance (Schumpeter, 1934), access to specialized knowledge through IO helps firms to perform cutting-edge R&D and build core competencies in certain fields in order to increase innovation output and stay ahead of competition (Galunic and Rodan, 1998). Hence, IO can help offshoring firms to differentiate themselves from competitors that do not engage in IO, which confers innovation advantages (Mihalache et al., 2012; Nieto and Rodriguez, 2011).

From a risk perspective, IO is associated with a reduced risk of over-reliance on specialized knowledge suppliers in the home market, be they internal or external to the firm (Willcocks et al., 2011). That can increase flexibility (Hutzschenreuter et al., 2011) which is critical to innovation outcomes (cf. Zhou and Wu, 2010). To avoid technology lock-in, IO can serve as a mechanism to explore and exploit new technologies earlier than competitors (Duysters and Lokshin, 2011).

The increased knowledge breadth and depth as well as the increased flexibility associated with IO should be beneficial for innovation performance. Hence, we propose:

**H1: IO is positively related to innovation performance.**

**Firms’ External Environment as a Contingency**

The effectiveness and efficiency of IO can vary depending on the environment in which offshoring firms and their managers are embedded (Kotabe et al., 2007; Kshetri, 2007). This research adopts an institutional perspective, which allows us to explore how institutions differ across geographic and temporal environments, and how such differences affect the behaviour of economic actors (Wan and Hoskisson, 2003; Kostova et al., 2008). At least three lines of theorizing have influenced contemporary theorizing about institutions in management (Kostova and Marano, 2019; Meyer and Peng, 2016). In economics, North (1990) distinguishes formal and informal institutions setting the rules for economic behaviour. In sociology, Scott (2001) argues that these institutions consist of three pillars
that reflect what economic actors perceive to be appropriate in their own cognition (cognitive pillar), norms and values of the society (normative pillar), and legal regulations (regulative pillar). The comparative capitalisms perspective emphasizes the differences of the inherent logic by which sets of institutions interact in different national contexts (Hall and Soskice, 2001, Jackson and Deeg, 2008).

What these perspectives have in common is that decision makers in international business take into consideration institutional prerogatives of their home environments, as well as those of potential host environments when making decisions as to where to locate which economic activity (Meyer and Peng, 2016). As the institutional environments in offshoring firms (which include their sub-units) are fragmented, diverse, and often lead to conflicting demands on the organization, traditional concepts from neo-institutionalism such as ‘organizational fields’ do not apply (Kostova et al., 2008). To account for the specific characteristics of institutional environments of offshoring firms, we draw on the concept of ‘meta-organizational fields’ (Kostova et al., 2008). In the past few decades, a meta-organizational field has emerged that comprises multinational firms across national borders and industries. These firms engage in practices such as IO, and share values, rules, guidelines and norms about how to do business across borders (Kostova et al., 2008).

Accordingly, a comprehensive understanding of the contingencies of IO as a successful management practice requires consideration of the institutional environments of the firm, its decision makers, and its stakeholders (Lam, 2003; Kostova, 1999). In particular we argue that institutional environments influence two processes that are critical for IO to benefit a firm: first, the ‘reverse’ knowledge transfer and integration of overseas innovations; and, second, the attractiveness of conducting innovation activities abroad.

**Institutions and Reverse Knowledge Transfer**

Whereas conventional knowledge flows originate in the parent company and are received in foreign subunits (Yang et al., 2008), IO usually includes knowledge transfer in both directions: from and to the parent organization (reverse knowledge transfer). Successful IO depends on parent organizations embracing knowledge generated within the global network of the MNE, but outside the home country. The success of this reverse knowledge transfer depends on the cognitive and normative institutions in the home country. For example, organizations with an ethno-centric value system or otherwise affected by a ‘not-invented here’ syndrome (von Zedtwitz and Gassmann, 2002) are unlikely to effectively absorb new ideas generated through IO. In each institutional context, assumptions about the way things are done and should be done manifest in the behaviour of economic actors who strive to enhance their access to resources through enhanced legitimacy (Meyer and Rowan, 1977; Deephouse, 1996). These institutions vary both over time and across geographies.

**Time frame.** The institutional environment influencing the IO–innovation performance relationship, i.e. the meta-organizational field, has been substantially transformed by global trends over the past decades. In consequence, cognitive and normative pressures have generally become more favourable to IO and enhanced its legitimacy. Such favourable institutional conditions can be expected to have a positive influence on the effectiveness and efficiency of IO.

Whereas a general perception used to be that home-grown innovation is critical for economic development, firms have offshored more and more R&D activity in the past decades creating global innovation networks (Cano-Kollmann et al., 2018; Ernst, 2006). As collective mind-sets have become more open to sourcing knowledge-intensive parts of the value chain from abroad (Lewin and Volberda, 2011; Pisani and Ricart, 2016), IO is viewed more widely as a promising management practice benefiting from knowledge diversity. Consequently, IO as a management practice has acquired greater
Enhanced legitimacy encourages greater numbers of firms to mimic early adopters of IO. Such mimetic isomorphism within the meta-organizational field helps attract stakeholder support because stakeholders tend to support standard management practices (Kostova et al., 2008; Surroca et al., 2013). Increased stakeholder support helps with implementing IO as a management practice (Hutzschenreuter et al., 2011) and reduces the likelihood of negative reactions on the part of customers, employees, local government, and other stakeholders (Kshetri, 2007; Funk et al., 2010).

Enhanced legitimacy not only facilitates firms allocating resources to IO projects, but also reduces cognitive barriers to utilizing innovation input, such as the ‘not-invented-here’ syndrome (von Zedtwitz and Gassmann, 2002; Katz and Allen, 1982). As a result, innovation input sourced abroad can be more effectively integrated across borders, resulting in new combinations of diverse ideas, technologies, and other innovation resources. As new combinations of diverse resources can generate increased innovation output (Schumpeter, 1934), shrinking barriers to knowledge sharing, adoption, and integration should increase the effectiveness of IO.

In addition, IO has become easier to implement due to trends of liberalization of trade and foreign direct investment, which have reduced the costs and risks associated with IO while creating more options for access to external resources and spatial mobility (Ernst, 2006). For example, since joining World Trade Organization in 2001, China has pushed reforms that facilitate international trade and investment, while improving its intellectual property regime (Peng et al., 2017; Brander et al., 2017). Other emerging markets are competing as IO locations through initiatives like incentivizing investment in R&D activities or by improving infrastructure. This increased supply of offshore opportunities increases choice between offshore locations and providers and, along with more commoditized services (Lewin and Peeters, 2006), intensifies competition between locations and thus enhances the (potential) cost efficiency of IO. Hence, offshoring firms now have more options for

locating their innovation activities, and they can transfer knowledge more efficiently across borders.

Hence, we posit:

\[ H2: \text{The strength of the positive relationship between IO and innovation performance increases with time.} \]

Confucian Asian cultures. The strength of the IO–innovation performance relationship depends on how effectively and efficiently individuals in different parts of the world learn from each other. In particular, Confucian Asian cultures facilitate such collaborative learning processes (Nguyen et al., 2006). First, Confucian teachings stress the importance of learning for individual development and growth (Young and Corzine, 2004). Second, interpersonal interactions are built on “Confucian ideas which emphasize the importance of relationships and community” (Javidan et al., 2006, p. 83) leading to an increased adoption of collaborative learning processes (Nguyen et al., 2006). Collaborative learning supported by institutional characteristics of Confucian Asian culture can be expected to strengthen the link between IO and innovation performance as combinative capabilities (Kogut and Zander, 1992) in the organization increase. Combinative capabilities help companies to translate knowledge from foreign sources (Mihalache et al., 2012), to integrate that knowledge into the organization, and to effectively adapt it to the institutional context. Combined innovation resources from diverse backgrounds have idiosyncratic characteristics and enable firms to effectively differentiate their innovation output from that of competitors (Kostova et al., 2008; Galunic and Rodan, 1998).

Confucian values emphasizing learning and the importance of relationships also increase the legitimacy of IO as a management practice. Confucian Asian countries such as China, Japan and South Korea have historically benefited substantially from the integration of foreign knowledge (Ghauri and Fang, 2001), and stakeholders in these cultures are thus less likely to oppose the integration of
knowledge sourced through IO. Increased legitimacy of IO as a management practice encourages stakeholders to support IO, which may enhance innovation adoption and in turn innovation performance. Enhanced legitimacy also encourages firms to allocate resources to support IO. In addition, Confucian values of hierarchy and harmony empower top management to monitor innovation activity and to push the diffusion of innovation throughout the firm (Shane, 1994). Accordingly, Confucian Asian home-country contexts should increase the effectiveness of IO, thus strengthening the relationship between IO and innovation performance.

Furthermore, Confucian values are likely to increase the efficiency of IO by supporting collaborative behaviour (Javidan et al., 2006) in the form of trust-based relationships between economic actors (Wong and Tjosvold, 2006). Trust-based relationships require less control and coordination than more transactional relationships (Gulati and Singh, 1998) and foster the combination of knowledge from different sources and the transformation of individual to organizational knowledge. Lower transaction and coordination costs enhance the efficiency of innovation processes that are spanning borders. Hence, we posit:

\[ H3: \text{The positive relationship between IO and innovation performance is stronger for firms from countries with a Confucian Asian culture than for firms from other countries.} \]

National Innovation Systems and Institutional Arbitrage

The second condition that makes IO potentially beneficial for a firm is the relative efficiency of innovation activities abroad compared to the home country. Countries vary in their national innovations systems (Lundberg, 2010; Nelsen and Rosenberg, 1993), and thus the degree to which they enable firms to conduct R&D activities, and to translate such activities into innovation performance. Where institutions supporting domestic innovation are relatively weak, firms have potentially more to gain from IO.
Recent studies of institutions have identified the phenomenon of ‘institutional arbitrage’: the location of each activity where costs of compliance with local institutions is lowest (Jackson and Deeg, 2008; Li and Zhou, 2017; Surroca et al., 2013). These studies suggest that variations in regulatory institutions can create incentives for firms to locate their activities abroad if institutions at home are relatively unsupportive to that activity. A related line of work talks of ‘institutional escape’ to describe firms that pursue growth abroad rather than in their unfavourable home environment (Boisot and Meyer, 2008; Weng and Peng, 2018; Witt and Lewin 2007). These literatures tend to focus on the impact of institutions such as environmental or labour regulations on the location of environmentally-sensitive or labour-intensive production. However, we can extend this theoretical argument to the case of innovation.

**Institutions supporting innovation.** Innovation depends on several features of the national institutional framework, as highlighted by the national innovation systems literature (Lundvall, 2010; Sharif, 2006). Such institutions include, for example, the governance of universities and research institutes, the work conditions of skilled workers, and financial support for innovation activity (Lewin et al., 2009, Lundvall, 2010). They are essential for local firms to develop innovation capabilities and for foreign multinationals to successfully perform their IO activities (e.g. Chung and Alcacer, 2002; Romijn and Albaladejo, 2002).

Without institutional support, investments in innovation activities are less likely to be effective. Thus, when innovation-related institutions are not very favourable, investments in R&D activities abroad may have a greater potential to generate innovations than R&D at home. In other words, in a form of institutional arbitrage, MNEs from countries with weak innovation-supporting institutions may create more innovation benefits by tapping into innovation clusters abroad than MNEs from countries whose institutions support innovation. For example, for firms in countries with weak institutional
support for innovation, sourcing innovation input in a foreign location with financial support for innovation activity provided by the host government will decrease the cost of innovation and therefore increase its efficiency. Similarly, greater availability of and better working conditions for highly-skilled employees due to high institutional support abroad increase the effectiveness of innovation in foreign locations compared to a home location with weak institutional support for innovation. In other words, firms that are embedded in an environment with weak institutional support for innovation can likely increase innovation performance by offshoring innovation input. Hence, we posit:

**H4:** The positive relationship between IO and innovation performance is weaker for firms from countries with institutions that are more supportive of innovation than for firms from countries characterized by institutions that are less supportive of innovation.

**Rule of law.** Among the institutions influencing innovation activities, of particular importance is the rule of law, as it reflects the effectiveness of the protection of intellectual property rights and the quality of contract enforcement (Brander et al., 2017; Estrin et al., 2016; Kaufmann et al., 2010). The strength of the rule of law is critical for innovation activities because it enables firms investing in R&D activities to earn IPRs, and to protect these against illicit use by other parties, including for example former employees and competitors. In other words, the rule of law can strengthen or weaken firms’ ability to appropriate value created by their innovation activities.

If the rule of law in the home country is weak, firms may be concerned that innovation activities at home may lead to, for example, swift copying by domestic competitors or former employees. Consequently, firms may pursue a form of institutional arbitrage by locating sensitive innovation activities in other countries, where higher levels of protection of intellectual property give them greater control over their innovation inputs. At the same time, a weak rule of law environment can help firms to better integrate innovation from abroad in the parent organisation. To successfully navigate their

In a complex institutional environment under a weak rule of law, firms are likely to develop coping capabilities such as strategic flexibility (Luo and Tung, 2018). Strategic flexibility is also a success factor for innovation as it allows firms to deal with uncertainties inherent in innovation processes (Zhou and Wu, 2010). Thus, strategic flexibility developed to cope with a weak legal environment may also help firms to transfer and integrate foreign innovations in the parent organization, and thus to enhance innovation performance.

By contrast, the benefits of locating innovation activity abroad may be less for firms in strong rule of law countries. A strong rule of law supports home country innovation through a higher degree of property rights protection and law enforcement. In addition, firms located in strong rule of law countries may be hindered from integrating innovation from abroad in the parent organization. Countries with a strong rule of law tend to have strict regulations on privacy and data security. Firms from these countries would be obliged to implement these rules on international transfers of data. When offshoring innovation, firms in strong rule of law countries may face requirements that they cannot guarantee in operations in the offshore location (Kshetri, 2007). This may make the reverse knowledge transfer from foreign subunits costlier for firms in strong rule of law countries – for example for forms of IO that involve transferring large amounts of data. In other words, countries with a strong rule of law likely have regulations that make reverse knowledge transfer associated with IO more difficult.

Thus, a weak rule of law in the home country likely makes innovation in host countries more attractive, decreasing the cost of innovation and therefore increasing some of the potential benefits of IO. At the same time, firms in such home country contexts are likely to face less regulatory constraints and more organizational flexibility, which increase the benefits of IO to the parent organization. Therefore, we posit:

**H5: The positive relationship between IO and innovation performance is stronger for firms from countries with a weak rule of law than for firms from countries with a strong rule of law.**
METHODS

Literature Search and Data Collection

The goal of our meta-analytic literature search has been to identify all quantitative studies of the relationship between IO and innovation performance. Hence, we started with a keyword-based search in relevant databases including ProQuest, EBSCOhost, ScienceDirect, and Web of Science. In addition, we searched the reference lists of articles for further studies.

Two authors next coded all studies independently and agreed that 57 studies matched the following inclusion criteria, which are in line with previously conducted meta-analytical studies in innovation research (Damanpour, 1991; Montoya-Weiss and Calantone, 1994; Rosenbusch et al., 2011): First, studies had to examine the relationship between IO and innovation performance. Second, they had to use a measure of IO aligned with our definition of IO to ensure validity of the aggregation, especially because offshoring research suffers from definitional ambiguity (e.g., Mudambi and Venzin, 2010). Similarly, we required studies to use a measure of innovation performance aligned with our definition. Third, the nature of this meta-analysis dictated that eligible studies should have used a quantitative approach. Furthermore, studies had to provide bivariate statistics for the relationship between IO and innovation performance. To address the failure of 17 studies to provide the necessary statistics, we contacted the authors to request further information. Authors of six of those studies provided us with the statistics necessary to have their studies included in our meta-analytical sample. Fourth, we only included studies that were publicly available in academic journals, books, working papers, or dissertations. Last, every sample could be included only once in the meta-analysis so as to avoid overrepresentation of particular firms in the sample. Hence, when several publications were based on the same sample, we excluded the publications with overlapping samples.
Our final meta-analytic database comprises 46 studies analysing 48 independent samples. The Appendix includes a description of the meta-analytical sample.

Coding

As coding of the underlying research is crucial for the quality of a meta-analysis, two authors coded the 48 samples independently. A third author compared the two codings. Interrater agreement was above 93%. In the remaining cases where the two coders did not agree, the author group discussed the codings to reach consensus.

In a first step, we coded the sample size and the effect size(s) for each sample. We coded the number of observations as the sample size. This procedure is in line with previously published meta-analyses which rely on panel and cross-sectional data (e.g., Kysucky and Norden, 2015; Park and Shaw, 2013). In the vast majority of cases, effect sizes are Pearson correlation coefficients ($r$). Whenever other statistics were available that could be converted into $r$, we did so.

Table I shows the coding for the dependent and independent variables. Our dependent variable is innovation performance. In line with previously published research, we distinguish intermediate and final innovation outcomes of the innovation process (Acs et al., 2002). We coded patent quantity and quality, as well as measures of technical strength as intermediate innovation performance. New product and process introductions, sales derived from new products, and aggregate measures of final innovation performance were coded as final innovation performance. The Appendix shows the coding for each sample.

The focal independent variable is IO. We defined IO as the cross-border sourcing of innovation input which leads to knowledge transfer across borders during the innovation process. Accordingly, we
A number of moderator variables could influence the relationship between IO and innovation performance. First, we coded the year of data collection. Whenever data collection occurred over a longer timeframe, we coded the mean year of data collection. For the sub-group analysis, we coded whether the mean year of data collection was before or after the year 2000. That was because cross-country innovation activity increased after 2000 when trade barriers were lifted, information technology facilitated cross-country R&D, and the legitimacy of foreign sourcing increased (cf. Lewin and Volberda, 2011).

Second, we include a number of variables describing the home-country institutional environment. We first coded the country of origin of the offshoring firms in the sample. Subsequently, we coded whether the country was associated with Confucian Asia according to the GLOBE study of culture and leadership (House et al., 2004). To capture the quality of institutions supporting innovation in a country, we adopted the innovation input index (III), which is one of two components\(^1\) of the Global Innovation Index published by jointly Cornell, INSEAD, and the World Intellectual Property Organization (Cornell et al., 2018). Finally, using World Bank records, we coded the rule of law, at the time of data collection (World Bank, 2016; see also Kaufmann et al., 2010). The latter two indices vary over time. We used the rule of law index provided for the mean year of data collection. If it was not available for that year, we used the index for the closest available year. As the method for calculating the Global Innovation Index changed over the time leading to inconsistencies in temporal comparisons we used indices for the first available years 1997 and 1998 for all studies. For the categorization into sub-groups, we split the sample at the mean value. Whenever, a sample was based on data from two home countries, we checked whether both countries belonged to the same sub-group. If they were
categorized in the same sub-group, we used the average of their scores in the meta-analytical regression analysis (MARA).

We also included several control variables. First, we coded whether studies were published in peer-reviewed journals to account for publication bias (cf. Mueller et al., 2013). Second, we distinguished intermediate innovation output such as patents, and final innovation output measures such as new product introductions (cf. Acs et al., 2002). Third, we distinguished high-tech and low-tech industries to account for potential industry effects (cf. Rousseau et al., 2016). High-tech industries include high-tech manufacturing industries such as the semiconductor and pharmaceutical sectors and high-tech services such as software.

**Method of Analysis**

In line with previous research (e.g. Rosenbusch et al., 2013; Klier et al., 2017; Schommer et al., in press), we used a combination of sub-group analysis and MARA. The sub-group analysis allows us to interpret the direction and magnitude of effects in sub-groups. A MARA takes account of interdependencies between moderators and control variables. For both analyses we used the Comprehensive Meta-Analysis software package that is based on the methods suggested by Hedges and Olkin (2014).

The effect size is the Pearson product-moment correlation $r$. To calculate the average correlation in the overall sample and within different sub-samples, $r$ is weighted with the inverse of its variance. As we can assume that the studies in our sample were drawn from different populations because methods, settings, research objects etc. differ between studies, we relied on random and mixed effects models rather than fixed effects models in the sub-group analyses as well as the MARA. In random effects models, the variance includes a component capturing the between-study variance in addition to within-study variance (Borenstein et al., 2007). Hence, random effects models produce more
conservative and more reliable estimates (Hedges and Vevea, 1998). In addition to the average effect size, we calculated the corresponding 95%-confidence intervals and $Z$ values that indicate the significance of the effect in the overall sample and within the sub-groups. The $Q_{between}$ statistics indicate whether the effect sizes vary significantly between sub-groups, and hence this value signals the presence of a moderator effect.

In the MARA, the dependent variable is the effect size involving the relationship between IO and innovation performance. The moderators serve as independent variables. Model 1 includes only the control variables. Model 2 adds the year of data collection. Models 3 to 5 add different variables describing the home-country institutional environment: its cultural characteristics, innovation-supporting institutions, and strength of the rule of law. A common issue in meta-analyses is the correlation between environmental variables potentially leading to multicollinearity, and the relatively small number of research objects (primary studies) leading to a statistical power problem if the number of independent variables in the regression is too high. For that reason and in line with prior meta-analytical work (cf. Mueller et al., 2013), we include the variables assessing the institutional environment of offshoring firms separately in Models 3 to 5.

RESULTS

Main Results

The results of the sub-group analysis and the MARA are presented in Tables II and III. Our first hypothesis concerns the overall relationship between IO and innovation performance, and is supported by the data. The average effect size based on 48 independent samples stemming from 46 studies and including 113,111 observations was $r_{ave}=.15$. The 95% confidence interval does not include zero, indicating that the effect is significantly positive. The $I^2$ statistic points to inconsistencies in results...
across studies due to heterogeneity ($I^2 = 94.50$). This suggests the presence of moderators of the relationship between IO and innovation performance, which we explore next.

The first contextual moderator hypothesis relates to the timeframe when the data collection took place. Hypothesis 2 predicted that firms have benefited more from IO in more recent years, but it is not supported by the data. On the contrary, the sub-group analysis shows that the benefits derived from IO were greater ($Q_{between} = 6.60, p = .01$) in the years leading up to the turn of the millennium ($r = .20$) when compared to later timeframes ($r = .11$). The regression shows the same result ($B = -.01, p = .01$). We offer our interpretation of this unexpected finding below.

Hypotheses 3 to 5 deal with the moderating influence of the offshoring firms’ home-country institutional environment on the IO–innovation performance relationship. To test Hypothesis 3, we grouped the studies into research samples from Confucian Asian cultures and those from other cultures. Both the regression analysis ($B = .21, p = .01$) and the sub-group analysis confirmed our hypothesis that offshoring firms from Confucian Asian cultures ($r = .23$) benefit more ($Q_{between} = 5.81, p = .02$) from IO than firms headquartered in other cultures ($r = .12$).

Hypothesis 4 suggests that offshoring firms from countries with weak institutional support for innovation benefit more from IO than firms that are embedded in contexts with strong institutional support for innovation. Our sub-group analysis shows that the benefits derived from IO are greater ($Q_{between} = 12.50, p = .00$) in markets with low values of innovation institutions ($r = .22$) than in markets with high values of innovation supporting institutions ($r = .10$). The regression confirms this result ($B = -.22, p = .00$), in line with Hypothesis 4.
Similarly, we find that offshoring firms from countries with a weak rule of law ($r=.23$) benefit significantly more from IO ($Q_{between}=9.97, p=.00$) than firms embedded in an institutional environment characterized by a stronger legal environment ($r=.11$), a finding that lends support for Hypothesis 5. Again, the result is supported by the regression analysis ($B=-.13, p=.00$).

Finally, we tested for the influence of methodological and context-related control variables. First, our analysis revealed that publication status was a methodological moderator that affected the size of reported relationships ($Q_{between}=3.53, p=.06$). However, contrary to the file-drawer argument, unpublished studies reported even higher effect sizes ($r=.27$) than published studies ($r=.13$). Further, we distinguished between different operationalizations of innovation performance: intermediate innovation performance ($r=.14$) and final innovation performance ($r=.16$). Again, we did not find evidence for a moderator effect ($Q_{between}=0.17, p=.68$) in the sub-group analyses. However, some of the regression analyses show a significant coefficient for this control variable. Last, we addressed potential context-related moderators and tested whether the link between IO and innovation performance is stronger in high-tech than in low-tech industries. However, firms in high-tech ($r=.15$) and low-tech industries ($r=.14$) do not differ significantly when it comes to IO–innovation performance relationship ($Q_{between}=0.07, p=.79$).

**Robustness Checks**

The first test of robustness was to seek outliers in effect sizes but the distribution of effect sizes did not indicate that any are present, as none of the effect sizes are more than two standard deviations above or below the mean effect size. However, as large sample sizes can create influential cases that have a considerable impact on outcomes, we also calculated sample-adjusted meta-analytic deviancy (SAMD) statistics as suggested by Huffcutt and Arthur (1995) and Geyskens and colleagues (2009).
Based on the SAMD statistic we identified five potential outliers. Running the MARA without these studies did not change our findings.

Furthermore, we tested for differences between smaller, i.e. with less than 500 employees ($r=.16$), and larger organizations ($r=.15$), but did not find a significant difference ($Q_{between}=0.05, p=.83$).

In addition, we tested whether organizational forms of innovation offshoring produced different results. The test involved differentiating between captive offshoring, where firms establish subsidiaries abroad which perform innovation activities, and non-captive offshoring, which is organized externally, for example through alliencing or licensing agreements. This test showed a non-significant ($Q_{between}=0.75, p=.39$) difference in the correlations of innovation performance with captive offshoring and non-captive offshoring respectively. As neither of these variables revealed any significant differences in the sub-group analyses and they reduced the number of cases in the regression analyses to an extent where multicollinearity became an issue, we chose to omit them from the MARA.

To ensure that our results regarding the home-country institutional environment are not driven by the stage of economic development we also ran regressions with GDP per capita as a control variable. All of our results were confirmed in these regressions. In addition, we checked whether there is a China effect, i.e. whether our results are driven by differences between China and other home countries. Running MARA based on a sub-sample of studies which excludes studies based on Chinese samples did not lead to different results.

Finally, we checked whether the results held if we used the number of research objects instead of the number of observations as the sample size. Again, our results proved robust.

DISCUSSION

Research on the IO–innovation performance relationship is extensive, and yet its findings about the direction, strength, and the context-dependency of the relationship have been inconclusive. Our
aggregation of empirical evidence regarding this relationship was motivated by an aspiration to understand how and to what extent the IO–innovation performance relationship is influenced by institutions that differ across offshoring firms’ home-country contexts and over time.

Our findings show that IO is generally positively related to firms’ innovation performance. The effect size ($r_e = .15$) is within the usual range of other meta-analyses in the internationalization and innovation literature (see e.g., Bausch and Krist, 2007; Rosenbusch et al., 2011; van Wijk et al., 2008). Thus, our findings are sufficiently strong to support the argument that IO is an effective management practice that tends to enhance the innovation performance of offshoring firms. Specifically, according to the received literature, IO enables firms to increase knowledge depth by accessing specialized knowledge in new geographic knowledge clusters, and to enhance knowledge breadth by diversifying knowledge sources. Thus, IO helps firms to combine innovation inputs from diverse sources worldwide, make better use of knowledge spillovers, increase flexibility, and avoid technology lock-in in the innovation process – all of which are associated with superior innovation outcomes.

The finding that IO on average enhances firms’ innovation performance is highly relevant for theory and practice. In the following we will discuss the theoretical and practical implications of our results. We start with an illustrative case, Lenovo.

**Case Illustration: Lenovo**

Chinese MNEs have in recent years accelerated their outward investments, and many of their investments have been undertaken specifically with the aim to access innovation inputs overseas, and to enhance the capabilities of the parent firm (Luo and Tung, 2018). While many of these firms struggle to realize the aspired innovation benefits, among other reasons due to weak human capital and absorptive capacity at home (Meyer and Xin, 2018), some companies appear to have been very successful, including carmaker Geely and computer maker Lenovo.
Lenovo was one of the first Chinese firms to acquire major strategic assets abroad. In 2004, Lenovo acquired IBM’s PC division and established innovation laboratories in the USA. The firm went on to expand its innovation laboratories to include India (2006), Brazil (2014), Israel (2015) and Germany (2015), among other locations. Its offshoring of innovation activities enabled Lenovo to access specialized knowledge from diverse foreign sources and diffuse it within its organization while maintaining the operational efficiency that had been its strength in the past. Lenovo has grown to be an innovative industry leader, due in part to the diversity of specialized innovation inputs sourced from its worldwide innovation laboratories (Quelch and Knoop, 2006).

The evolution of the meta-organizational field and its impact can be illustrated with the case of Lenovo. Originating from a country with an Asian Confucian culture, Lenovo was an early mover in seeking innovation overseas. It stayed ahead of domestic and international competition in terms of innovation performance by accessing even more specialized and geographically diverse knowledge sources via its far-shoring operations. Arguably, at least in the initial years, the move to overseas innovation represented an institutional escape from a home-country context that was traditionally focused on the efficient exploitation of labour but not on innovation (Rui and Yip, 2008). Limitations to, for example, domestic R&D support and weak legal protection of IPR, encouraged Lenovo to jump over those barriers and source diverse specialized knowledge from offshore providers. In so doing, Lenovo gained a reputation of being a leading innovator at home and worldwide (The Economist, 2014).

**Theoretical Implications**

The main focus of this research is on the institutional contingencies that influence the direction and strength of the relationship between IO and innovation performance. In general, our findings highlight the need to incorporate the home country in international business and innovation research.

(e.g., Bausch and Krist, 2007; Marano et al., 2016; Meyer and Peng, 2016), and especially to consider differences in institutional environments when examining the association of IO with innovation performance. Specifically, we find that the strength of the IO–innovation performance relationship varies with differences in the institutional environment at home and over time.

While empirical findings that confirm theory-based expectations enhance the robustness of what has come to be regarded as ‘common knowledge’, findings that challenge current wisdom can potentially break new ground. Thus, our most interesting finding may be that, contrary to our expectations, more recent studies find less positive effects of IO for firms. This appears to challenge, for example, Marano and colleagues’ (2016) meta-analytical findings indicating that studies using more recent samples elicit a stronger internationalization–performance relationship. Why may the benefit of IO be diminishing?

One possibility is that in recent years firms increasingly pursue symbolic benefits from IO as a growing number of firms started to mimic offshoring practices of leading competitors (Flier et al., 2003). The growth in popularity of IO is particularly visible since the turn of the millennium when regulatory barriers noticeably eroded (Lewin et al., 2009). Once offshoring was perceived to be a legitimate management practice, mimetic isomorphism may have accelerated the spread of IO. As bandwagon pressures increased, IO may have become more value-infused, tempting firms to follow the offshoring path to avoid risking the loss of stakeholder support (Lewin and Volberda, 2011). However, such mimetic pressures may have reduced firms’ potential to generate substantive innovation advantages through IO. Moreover, some recent studies suggest that the marginal benefits of increasing innovation performance are diminishing, or even turn negative, at high levels of IO (Mihalache et al., 2012; Steinberg et al., 2017). Thus, it is possible that the increasing legitimacy of IO have moved some firms beyond the optimal degree of IO. This may explain why over the full sample, we observe a weaker IO–innovation performance relationship for the more recent time period.
Our other results concerning the home-country institutional contexts are more in line with expectations, specifically the institutional theory-motivated arguments that IO is most beneficial when home-country institutions support learning from abroad and when home-country institutions open opportunities for institutional arbitrage. First, our results support the prediction that firms embedded in contexts with Confucian values (i.e. Confucian Asian cultures) are more likely to reap innovation benefits from IO. Confucian ideas such as harmony and hierarchy, the emphasis on relationships, community, and life-long learning, as well as a tradition of mutual trust and cooperation seem to make IO more effective and efficient for firms from countries with a Confucian Asian culture.

Second, our results confirm that stronger national innovation systems, especially innovation-supporting institutions and a strong rule of law, reduce the positive IO–innovation performance relationship. In line with prior research (e.g., Guillen and Garcia-Canal, 2009; Luo and Tung, 2018), our findings suggest that a weak rule of law in the home country provides firms with more opportunities (Arregle et al., 2013) and more flexibility (Marano et al., 2016) to efficiently and effectively translate offshored innovation activity into capabilities valuable to the parent firm (see also Luo and Tung, 2018). This insight contributes to recent theorizing regarding institutional arbitrage (Jackson and Deeg, 2008; Li and Zhou, 2017) and institutional escape (Witt and Lewin, 2007). The prior literature has focused on regulatory restrictions arising from environmental and labour standards. However, the logic of these arguments also extends to national innovation systems, including for example the training and working conditions of skilled workers and the rule of law.

**Practical Implications**

Our findings are also relevant to management practice. Firms are encouraged to implement IO practices because they are positively related to innovation performance. However, we recommend managers consider how the institutional context of their company’s home country influences the
innovation-related outcomes of IO. Firms in countries with Confucian Asian cultures or weak national innovation systems face larger potential benefits of IO. Furthermore, managers would be wise to keep abreast of changes in the institutional context over time. While IO remains a valuable management practice, the strength of its innovation performance-enhancing effect appears to have diminished over time. An alert offshoring firm might compensate for some of the downside risks of ‘bandwagon effects’ by sourcing innovation inputs from more geographically distant and specialized knowledge clusters to create meaningful differentiation advantages from IO.

Our results can also benefit policymakers as they imply that firms undertaking IO can enhance their innovation performance even when domestic innovation-supporting institutions are weak. Many developing and emerging economies fit these criteria, including African economies known as lions on the move. To spur the growth of their domestic businesses, policymakers might support IO and foster knowledge transfer between domestic and foreign businesses. Such policy instruments have been utilized successfully in China to improve the innovativeness of its firms (Kotabe et al., 2011). The resulting increases in innovation performance strengthen the local economy because more firms acquire a stronger competitive position in global markets.

**Limitations and Future Research Avenues**

The results of our meta-analysis are subject to limitations that suggest avenues for future research on IO. First, the variation on key parameters in the data is constrained by the range of studies incorporated in the meta-analytical database. In our study, limits in the variation of time and geographies constrain the potential to investigate some emergent questions in greater depth. In particular, our finding that the relationship between IO and innovation performance has become weaker over time merits further research. While this finding implies that time-related effects need to be more carefully considered in research on the outcomes of firm strategies (e.g., Hough, 2006), we cannot

identify the exact mechanisms behind these temporal effects. Future research is needed to disentangle the complex global changes that occurred over the period of the primary research underlying this meta-analysis (1973-2014). Empirically, we recommend that future research uses multilevel growth modelling to capture systematic patterns of change in the IO–innovation performance relationship over time (see also Marano et al., 2016).

Second, we have shown that several home-country institutions moderate the IO–innovation performance relationship. These results imply that home-country variables should be a focus of future theoretical frameworks and methodological designs rather than remaining a simple control variable (cf. Marano et al., 2016). The R² values in the MARA indicate that in addition to the three home-country institutions studied here, there may be others that affect the IO–innovation performance relationship. Qualitative research could be particularly useful to identify lesser-known facets of the home-country institutional environment that contribute to firms’ ability to translate IO practices into innovation advantages, including the role of legitimacy, conformity, and/or institutional fit. In this regard, fuzzy-set analysis might be employed to identify specific configurations of home-country institutions that affect the IO–innovation performance link.

Third, while we focused solely on the home-country environment, international business scholars tend to consider also the host-country environment and the institutional distance between home and host country (Kostova and Zaheer, 1999). Previous research has sought to explain how the host-country context and the distance between home and host country are related to IO. For example, Doh and colleagues (2009) found that locational factors such as wage differentials affect location choice in IO decisions. Furthermore, multinationals employ different organizational control mechanisms depending on differences in informal institutions between home- and host-country markets (Sartor and Beamish, 2014). Kotabe and colleagues (2011) show that political ties to host-country institutions support access to foreign knowledge. Thus, future research may incorporate host-country institutions
Fourth, with the rise of the meta-organizational field of internationally active firms, a multi-level perspective needs to be adopted when applying institutional theory to international business research (Kostova et al., 2008). Future studies should develop methodologies to capture not only national institutional contexts, but also institutions at the meta-level spanning across national contexts. Future research could investigate whether firms gain legitimacy and better access to resources when conforming to supranational meta-organizational fields rather than to their narrower domestic contexts. Such multi-level studies will expand our understanding of the mechanisms underlying the relationships identified in this meta-analysis.

Fifth and related to point four, multinational organizations seem to be moving away from the one-headquarter model. “Disaggregated and dispersed headquarter systems” (Nell et al., 2017, p. 1121) may lead to different IO practices affecting knowledge transfer between locations and knowledge integration throughout the multinational organization (Nell et al. 2017). Primary empirical research could examine how moving the location of headquarters, a move from a single headquarter to a dispersed headquarter system, or further disaggregation of a headquarter system affect knowledge transfer and integration processes in IO. Schotter and colleagues (2017), for example, have linked the choice of headquarter system to information processing. Innovation processing in turn is crucial for IO practices and may therefore influence the IO–innovation performance link.

Sixth, prior literature makes an important distinction between captive and outsourced IO, and some studies point to performance differences between these different organizational forms (e.g. Grimpe and Kaiser, 2010; Nieto and Rodriguez, 2011; Steinberg et al., 2017). We have tested for such a difference in our robustness checks (see above), and did not find any significant effect. This however...

Ought not to be the last word on this matter. Future research should revisit the question under which institutional conditions captive or outsourced organizational forms of IO are more beneficial to a firm’s innovation performance. As a starting point, researchers could examine the performance effects of different types of alliances that aim at outsourcing knowledge processes as proposed by Mudambi and Tallman (2010). More specifically, the effectiveness of different partner types, their variety, and their relevance (Hagedoorn et al., 2018) could depend on the institutional environment.

CONCLUSION

IO has become a widely adopted management practice over the last three decades. Nevertheless, the extent to which the outcomes of IO are context-dependent remains an under-researched topic, especially in relation to the influence of home-country institutions and differences in the institutional environment that occur over time. Our research shows that, overall, IO produces innovation benefits by enabling firms to combine knowledge from highly specialised and diverse sources, to increase flexibility in the innovation process, and to reduce the risk of technology lock-in.

While IO is beneficial overall, the strength of the relationship between IO and innovation performance depends on the context. Our results show that home-country institutions and time affect the strength of the positive IO–innovation performance relationship. Specifically, firms embedded in societal institutions imbued with Confucian Asian values and/or a weak national innovation system in the home country, tend to derive greater benefits from IO.

1 The other component is the Innovation Output Index.
REFERENCES


World Bank (2016). Worldwide Governance Indicators.


Table I: Coding of the independent and dependent variables

<table>
<thead>
<tr>
<th>Innovation offshoring</th>
<th>Intermediate innovation performance</th>
<th>Final innovation performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coding</td>
<td>Frequency</td>
<td>Coding</td>
</tr>
<tr>
<td>Extent of foreign R&amp;D</td>
<td>22</td>
<td>Patent quantity</td>
</tr>
<tr>
<td>Coordination of international R&amp;D</td>
<td>14</td>
<td>Patent quality</td>
</tr>
<tr>
<td>R&amp;D cooperation with foreign partners</td>
<td>10</td>
<td>Aggregated measures of technical strength</td>
</tr>
<tr>
<td>Geographic dispersion of R&amp;D</td>
<td>6</td>
<td>Aggregated measures of innovation performance</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sales derived from new products</td>
</tr>
<tr>
<td></td>
<td></td>
<td>New product introductions</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Process innovation</td>
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Table II: Results of the Overall and Sub-Group Analyses

<table>
<thead>
<tr>
<th>Moderators / Subgroups</th>
<th>$k$</th>
<th>$N$</th>
<th>$r$</th>
<th>95%-confidence interval</th>
<th>$Z$</th>
<th>$p$</th>
<th>$Q_{between}$</th>
<th>$p (Q)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1: Overall effect</td>
<td>48</td>
<td>113,111</td>
<td>0.148</td>
<td>0.117 : 0.178</td>
<td>9.272</td>
<td>0.000</td>
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<td></td>
</tr>
<tr>
<td>H2: Time frame</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Before 2000</td>
<td>22</td>
<td>48,463</td>
<td>0.195</td>
<td>0.146 : 0.243</td>
<td>7.631</td>
<td>0.000</td>
<td>6.598</td>
<td>0.010</td>
</tr>
<tr>
<td>2000 and after</td>
<td>21</td>
<td>64,068</td>
<td>0.106</td>
<td>0.059 : 0.153</td>
<td>4.377</td>
<td>0.000</td>
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<td></td>
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<tr>
<td>H3: Culture</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other cultures</td>
<td>30</td>
<td>97,767</td>
<td>0.116</td>
<td>0.080 : 0.151</td>
<td>6.370</td>
<td>0.000</td>
<td>5.813</td>
<td>0.016</td>
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<td>Confucian Asian cultures</td>
<td>8</td>
<td>7,676</td>
<td>0.234</td>
<td>0.145 : 0.319</td>
<td>5.065</td>
<td>0.000</td>
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<td></td>
</tr>
<tr>
<td>H4: Institutional support for innovation</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weak</td>
<td>12</td>
<td>44,265</td>
<td>0.221</td>
<td>0.174 : 0.266</td>
<td>9.056</td>
<td>0.000</td>
<td>12.503</td>
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<tr>
<td>Strong</td>
<td>22</td>
<td>47,803</td>
<td>0.103</td>
<td>0.057 : 0.148</td>
<td>4.389</td>
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<td></td>
<td></td>
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<tr>
<td>H5: Rule of law</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weak</td>
<td>10</td>
<td>39,878</td>
<td>0.226</td>
<td>0.170 : 0.280</td>
<td>7.730</td>
<td>0.000</td>
<td>9.973</td>
<td>0.002</td>
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<td>Strong</td>
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<td>52,025</td>
<td>0.110</td>
<td>0.065 : 0.155</td>
<td>4.733</td>
<td>0.000</td>
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<td>Controls</td>
<td></td>
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<td></td>
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<td></td>
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<td></td>
</tr>
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<td>Publication Bias</td>
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<tr>
<td>Unpublished</td>
<td>8</td>
<td>1,821</td>
<td>0.273</td>
<td>0.127 : 0.407</td>
<td>3.597</td>
<td>0.000</td>
<td>3.527</td>
<td>0.060</td>
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<tr>
<td>Published</td>
<td>40</td>
<td>111,290</td>
<td>0.130</td>
<td>0.098 : 0.161</td>
<td>7.949</td>
<td>0.000</td>
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<td></td>
</tr>
<tr>
<td>Innovation performance</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate outcomes</td>
<td>25</td>
<td>55,193</td>
<td>0.144</td>
<td>0.098 : 0.19</td>
<td>6.078</td>
<td>0.000</td>
<td>0.174</td>
<td>0.677</td>
</tr>
<tr>
<td>Final outcomes</td>
<td>20</td>
<td>45,042</td>
<td>0.161</td>
<td>0.100 : 0.220</td>
<td>5.144</td>
<td>0.000</td>
<td></td>
<td></td>
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<tr>
<td>Industry</td>
<td></td>
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<td></td>
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<tr>
<td>Low-tech</td>
<td>7</td>
<td>45,326</td>
<td>0.137</td>
<td>0.076 : 0.198</td>
<td>4.345</td>
<td>0.000</td>
<td>0.070</td>
<td>0.791</td>
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<td>High-tech</td>
<td>31</td>
<td>51,436</td>
<td>0.148</td>
<td>0.100 : 0.195</td>
<td>6.007</td>
<td>0.000</td>
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Table III: Results of the Meta-Analytical Regression Analyses (MARA)

<table>
<thead>
<tr>
<th>Moderator</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
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<tbody>
<tr>
<td></td>
<td>B</td>
<td>SE</td>
<td>B</td>
<td>SE</td>
<td>B</td>
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<tr>
<td>Intercept</td>
<td>0.363</td>
<td>**</td>
<td>0.115</td>
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<td>23.463</td>
</tr>
<tr>
<td>Published</td>
<td>-0.178</td>
<td>**</td>
<td>0.076</td>
<td></td>
<td>-0.154</td>
</tr>
<tr>
<td>Output vs. intermediate output</td>
<td>-0.060</td>
<td></td>
<td>0.062</td>
<td></td>
<td>0.075</td>
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<tr>
<td>High tech</td>
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<td></td>
<td>0.081</td>
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<td>-0.031</td>
</tr>
<tr>
<td>Time of data collection</td>
<td>-0.012</td>
<td>**</td>
<td>0.004</td>
<td></td>
<td>0.210</td>
</tr>
<tr>
<td>Confucian Asia</td>
<td>0.210</td>
<td>***</td>
<td>0.078</td>
<td></td>
<td>0.210</td>
</tr>
<tr>
<td>Institutional support for innovation</td>
<td>-0.218</td>
<td>**</td>
<td>0.052</td>
<td></td>
<td>-0.218</td>
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<tr>
<td>Rule of law</td>
<td>-0.135</td>
<td>***</td>
<td>0.047</td>
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<td>-0.135</td>
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<tr>
<td>Q</td>
<td>5.71</td>
<td></td>
<td>15.50</td>
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<td>10.05</td>
</tr>
<tr>
<td>df</td>
<td>3</td>
<td></td>
<td>4</td>
<td></td>
<td>4</td>
</tr>
<tr>
<td>k</td>
<td>36</td>
<td></td>
<td>34</td>
<td></td>
<td>28</td>
</tr>
<tr>
<td>p</td>
<td>0.13</td>
<td></td>
<td>0.00</td>
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<td>0.04</td>
</tr>
<tr>
<td>R² (analog)</td>
<td>0.15</td>
<td></td>
<td>0.38</td>
<td></td>
<td>0.32</td>
</tr>
</tbody>
</table>

*** <.01, ** <.05, *<.10
# Appendix I: List of Studies Included in the Meta-Analysis

<table>
<thead>
<tr>
<th>Authors, year</th>
<th>Outlet</th>
<th>N</th>
<th>r</th>
<th>Tech intensity</th>
<th>Home country</th>
<th>Innovation offshoring</th>
<th>Inter-med. IP</th>
<th>Final IP</th>
<th>Confucian Asia</th>
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COOR = Coordination of international R&D; COOP = R&D cooperation with foreign partners; DISP = Geographic dispersion of R&D; EXT = Extent of foreign R&D; Final IP = Final innovation performance; Intermed. IP = Intermediate innovation performance; NPI = New product introductions; PERF = Aggregated measures of innovation performance; PQUAL = Patent quality; PQUAN = Patent quantity; PROC = Process innovation; SALES = Sales derived from new products; TECH = Aggregated measures of technical strength.

* Values for two countries that were ranked in the same subgroups of culture, innovation input index, and rule of law, were averaged.