Innovative performance and firm size: a Meta-Regression Analysis

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Abstract

The aim of this research is to determine factors related to observed heterogeneity in the empirical literature regarding the relationship between size and innovative performance at firm level. Based on a systematic review of international literature published between 1993 and 2017, a meta-regression analysis is carried out in order to evaluate publication bias in the empirical evidence. The results show a positive relationship between firm size and innovative performance, which is moderated by diverse factors. Among them, methodological choices of the authors prevail, linked to the operationalization of size and innovation. Signs of publication bias are detected, and partially explained by methodological choices.

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1 Introduction

Innovation studies at the firm level have successfully integrated technological change, competition and industrial organization logics within its conceptual framework. Since mid-twentieth century, a considerable amount of empirical and theoretical studies have contributed to this approach. So far, progress has been achieved on understanding complexity of innovation process as theory incorporates critical dimensions not only at the firm level but at sectoral and regional levels as well.

On the other hand, strengthening of this empirical research program on innovation has given birth to National Innovation Surveys since early 90's. These surveys are constantly updated since Frascati Manual (OECD 1963), based on methodological documents such as Oslo (OECD 1992) and Bogotá (Jaramillo, Lugones, & Salazar 2001) Manuals. Thanks to these documents, comparable evidence on industrial innovative activity is available across countries.

Development and abidance on these surveys allows certain academic consensus regarding innovation at the firm level, which are based on empirical evidence. In spite of this, evidence on innovative performance (IP) in industrial firms is still very heterogeneous. Specifically, since Schumpeter's work, hypothesis about firm size encouraging innovation has been exhaustively tested. However, diverse results lead to diverse explanations supporting a positive, negative or non linear relationship between variables. Such heterogeneity on the IP-firm size relationship is widely documented in literature reviews whose aim is to describe it rather than explaining it (Becheikh, Landry, & Amara 2006; Hall & Mairesse 2006; Santos *et al.* 2015). Nevertheless, current academic consensus on this matter endorses a positive relationship (Cohen, 2010).

Meta-Regression Analysis (MRA) is a quantitative method which takes advantage of accumulated empirical evidence in order to synthesize it. Analysis is based upon statistical information within available academic documents. This information is the input that allows explanation of observed variability in empirical evidence through regression techniques. In economics, applied MRA reveal huge potential on public policy design. Lastly, MRA provides statistical tests for assessing publication bias.

Sample in this paper is composed by comparable econometric articles inquiring about firm size as an innovation driver. Published between 1993 and 2017, articles in the sample provide econometric estimations for product and process IP as a function of several explanatory variables, including firm size. Bibliographic search concluded with data covering the last 30 years of empirical research all over the world, though evidence for developed countries prevail. A significant fraction of cases is based on National Innovation Surveys.

Determining which elements are associated with observed heterogeneity in empirical evidence on IP-firm size relationship is the main objective in this research. On the one hand, examination of factors explaining variability across regression coefficients is made. On the other hand, publication bias in the literature is assessed.

Heading results confirm a positive and statistically significant relationship between firm size and IP, despite observed heterogeneity. Such heterogeneity is explained partly by features of enterprises within primary samples and by authors' methodological influences when analysing and modelling data. Among most important methodological influences, operationalization of

IP stands out. While most articles measure IP through obtained results, some of them consider input measures such as research and development (R&D) investment or innovative activities.

The relevance of this kind of studies lays on the impact on policy makers and scientific community that academic findings have (Grazzi & Pietrobelli 2016; Stanley & Jarrell 1989). In social sciences (particularly in economics) empirical evidence may be heterogeneous due to differences in data or analysis techniques. MRA potentially can explain such variability and therefore link empirical findings with articles' features.

The rest of the paper is organized as follows. Section 2 provides the theoretical framework for innovation and derived hypotheses. MRA method as well as sample and variables are detailed in Section 3. Section 4 presents a brief description of data and econometric results. Finally, Section 5 concludes.

2 Theoretical framework

Technological change was early posited as crucial in economic development since classic authors; however studies on industrial organization field have adopted Schumpeter's approach. Firms are the main character within this framework because they drive technological change through **innovation**. By means of new or improved products or productive processes, organizational improvements, market development and new supply sources, firms turn innovation into economic results. Thus, innovation has a clear impact on competitive performance and productivity (Polák 2017; Ugur *et al.* 2015).

There are two different conceptualizations of technological competition along Schumpeter's work. In first place, open and dynamic market structures enable entrepreneurs and small and medium enterprises (SMEs) to introduce outer knowledge via innovation (Langlois 2003; Schumpeter 1935). Technological and organizational improvements may even give SMEs a competitive advantage to displace incumbents. As innovation spreads and technology is available, competitive advantage vanishes. This need for protection lead firms to secure their innovation activities, bringing market structure closer to imperfect competition (Yoguel, Barletta, & Pereira 2013). As a consequence, in second place innovative activities concentrate among few big firms which now lead technological competition (Schumpeter 1942). As knowledge becomes tacit and specific, firm develop internal capabilities to innovate and generate profits. Thus, investment on innovative activities (typically in R&D units) tends to concentrate innovation around bigger firms[1], which become heterogeneous.

Applied studies on firm theory have devoted considerable effort on testing these ideas since Schumpeter's work. Empirical evidence shows a clear relationship between technological progress and economic performance at the firm (Bowen, Rostami, & Steel 2010; Rosenbusch, Brinckmann, & Bausch 2011; Rousseau *et al.* 2016; Santos *et al.* 2015), sectoral (Pavitt 1984) or country level (Lundvall 1992).

[1] Entrepreneurial innovative leadership is described as a "creative destruction" regime while concentrating innovative capacity towards big firms is described as "creative accumulation".

One of the most important relationships is that regarding firm size and innovative performance (IP)[2]. This relationship counts on with heterogeneous evidence: even though usually a direct relationship is reported, numerous studies present a negative or even void correlation (Becheikh *et al.*, 2006; Cohen, 2010). While heterogeneity is widely documented, its sources are not that clear (Hall & Mairesse 2006; Rosenbusch *et al.* 2011).

Current academic consensus for direct relationship is based on an analogous relation between firm size and R&D activities. Theoretical arguments supporting this consensus are: i) bigger firms benefit from capital market imperfections; ii) innovative processes yield scale economies; iii) R&D returns increase with production (specially for process innovation); iv) R&D is more productive when complemented with other activities such as marketing (Cohen 2010:133; Knott & Vieregger 2016; de-Oliveira & Rodil-Marzábal 2019). Nevertheless, excessive bureaucracy and coordination failures in big enterprises reduce IP and thus give a chance to assess a negative relationship. These arguments emphasize organizational flexibility in SMEs and bureaucratic rigidities in big firms (Forés & Camisón 2016; Petruzzelli, Ardito, & Savino 2018). The latter approach contributes to understanding higher innovation rates in SMEs (Knott & Vieregger 2016). Recently, open innovation processes have shown new ways in which innovation takes place where firm size becomes a minor issue (Callejón & García-Quevedo 2011; Teplov, Albats, & Podmetina 2019).

Different approaches in firm theory consider size as a major feature to assess heterogeneity among enterprises. Size is related to transaction costs, available resources, internal capabilities or adaptative abilities in uncertain environments (Nelson & Winter 1982; Penrose 2009; Teece & Pisano 1994; Williamson 1979). These views have a conductive threat since productive activities require resources. Resources may generate complementary capabilities to enable better adjustment to inconstant environments. Regarding innovation, there is a virtuous circle in which invested resources lead to new products or processes that rise profits. This way, successful innovation promotes growth (Crépon, Duguet, & Mairesse 1998; Ugur, Awaworyi, & Solomon 2016).

Systematic disparities in empirical evidence about the relationship between IP and firm size has motivated several meta-analyzes (Table 1) on innovation (Damanpour, 1991; Duran, Kammerlander, van Essen, & Zellweger, 2016; Montoya-Weiss & Calantone, 1994) and particularly on the relationship previously discussed (Camisón *et al.* 2002; Damanpour 1992, 2010). Results endorse a positive correlation and find some sources of heterogeneity. These articles provide a solid background, though they only retrieve evidence mostly for developed countries and do not analyse publication bias.

Table 1: Previous meta-analyses on innovation

Meta-analysis	Research problem	Period	Articles included
Damanpour (1991)	Organizational innovation determinants	1960-1988	46
Damanpour (1992)	Innovation and size	1967-1988	20
Montoya-Wiess & Calantone (1994)	Product innovation determinants	--	47
Camisón *et al.* (2002)	Innovation and size	1970-2001	53

[2] IP is the operationalization for “introducing innovations into the market”.

Lee & Xia (2006)	ICT innovation and size	2000-2004	21
Damanpour (2010)	Innovation and size	1983-2003	20
Bowen *et al.* (2010)	Innovation and performance	--	55
Ugur *et al.* (2015)	R&D and productivity	1980-2013	65
Ugur *et al.* (2016)	Innovation and employment	1980-2013	35
Rousseau *et al.* (2016)	Innovation and performance	1991-2013	62
Duran *et al.* (2016)	Innovation in family business	1981-2012	108

Source: authors.

So far, theoretical consensus defends a positive relationship between firm size and IP. Therefore:

Hypothesis 1: available empirical literature corroborates a direct link between firm size and IP.

Although researchers agree about a direct link, they are aware of several factors conditioning this link. Hence, single homogeneous pieces of evidence cannot be expected because samples and econometric techniques are heterogeneous themselves. Following common practice in MRA, we name the first group of factors as "sample features" and the second one as "methodological influences". Some of the most important factors are reviewed below.

Sector

Probably the most relevant aspect when studying innovation at the firm level is industrial sector. Technological differences across sectors may condition internal innovative processes (Audretsch & Acs, 1991; Scherer, 1965). In order to understand sectoral innovation patterns, theory focuses on two main concepts: technological opportunities (TO) and appropiability conditions. There are three sources of TO: progress in science and techniques, improvements in other industries which favour inter-industrial developments and intra-industrial progress that lead further advances (Klevorick *et al.* 1995).

This approach is suitable for understanding technological rather than organizational innovations. Therefore, during the 80's TOs are found to be close to science based sectors and external knowledge sources (thought not conclusively) as a driver for high R&D rates (Becheikh *et al.* 2006; Rosenbusch *et al.* 2011). This is the root on which sectoral technological intensity is formalized (Hatzichronoglou 1997). If within "high tech" sectors (nearby scientific frontier) innovation opportunities are handy, firms' features (including size) may contribute in a different way. Nevertheless, TOs are far from being static and thus change along with technological conditions (Marín *et al.* 2015; Marín & Petralia 2018). When a TO is generated within certain sector, improvement paths become more clear and innovation rates increase: a "technological regime" is ongoing (Leiponen & Drejer 2007; Nelson & Winter 1982). Back into Schumpeter's work, creative destruction is identified within sectors which TOs are higher and which appropiability conditions are low. On the other hand, accumulative creation is related to lesser TOs, higher entry barriers and knowledge stock (Breschi, Malerba, & Orsenigo 2000; Castellacci 2007).

Region

Geography and historical course are recognized to influence economic processes, particularly within firms (McCann 2007). Differences in innovation and wealth rates across regions are partly explained by institutional and productive framework (Bosma & Schutjens 2011). Same as with firms, literature has emphasized on regional capabilities that stimulate diversification as well as innovation (Boschma & Capone 2015; Neffke *et al.* 2018).

Regional analysis is old-established with Marshallian industrial districts (Marshall 1922). In this way, seminal work by Sábato and Botana (1968) highlights the value of interactions among productive sector, science and technology infrastructure and national State as systemic issues conditioning aggregate innovative performance. Over time, this tripartite approach would evolve to the notion of "national innovation system" (Lundvall 1992). National innovation systems are composed by interactions among agents and institutions which endeavour knowledge spillovers and technical change (Raspe 2009; Stuetzer *et al.* 2014).

Innovation measures

When reviewing empirical literature, differences upon data structure, analytic strategies, estimation methods and operational definition of variables come across. This differences matter considerably (Stanley 2001). Thus, methodological choices influence empirical results and add sources of heterogeneity. In innovation literature, IP measures are one of the most important methodological issues conditioning results (Audretsch & Acs 1991; Bowen *et al.* 2010; Cohen, Lee, & Walsh forthcoming). Prior meta-analyses show that firm size and IP link is stronger when latter is measured by inputs (innovative activities, R&D investment) rather than results (innovative output, patents, innovative sales) (Camisón *et al.*, 2002; Damanpour, 2010).

Size measures

Another crucial factor is firm size measures. Based on statistical data restrictions, employees number and sales are usually used (Cohen 2010). Both Damanpour (2010) and Lee & Xia (2006) find that size measures influence relationship with IP. Financial measures are closely correlated to IP, mainly on process innovation. This finding fits with arguments highlighting advantages of big firms due to capital market failures. When funding innovative projects, cash flow may be a better solvency trace than employees.

Elements above cited introduce important dimensions of innovation, which can conditionate analysis. These factors account for the complexity of this phenomenon, since they consider sector specificities that companies face, as well as geographical and institutional conditioning which affect innovation possibilities. The fact that both the operationalization of these variables and analysis strategy are not neutral is added to these implications. Therefore:

Hypothesis 2: both sample features and methodological influences are sources of heterogeneity in current empirical evidence.

3 Method

Among meta-analytic techniques, MRA enables systematic summaries based on quantitative (econometric) empirical evidence (Nelson & Kennedy 2009). This method relies on statistical information provided by scientific sources such as papers, books or working papers.

The aim of this methodology is to synthesize statistical relationships (called "effect-sizes") between variables (Rhodes 2012). Following Stanley & Doucouliagos (2012), MRA seeks to answer three questions. ¿Which is the average (or "genuine") effect size[3]? ¿Can we identify sources of heterogeneity beyond sample error in the evidence? ¿Is there publication bias affecting research results?

In this context, the piece of evidence becomes the analysis unit. Thus, the population is composed of every paper presenting one or several econometric models. Common features are necessary for building variables and carrying on the analysis. In order to do this, inclusion criteria must be defined prior to bibliographic search. To achieve a representative sample and avoiding biases, searching must be as wide as possible. If key words are accurate, sample is obtained after filtering papers without the desired effect size (qualitative studies, inverse effect-size). Data frame is completed with information regarding the effect-size (standard error, number of observations) and the paper (region, date, model specification) (Dimos & Pugh 2016; Rousseau *et al.* 2016).

3.1 Meta-Regression Analysis

Meta-analytic techniques allow examination of statistically significant effect sizes as well as their distribution in the population (Nelson & Kennedy 2009; Rhodes 2012). Effect sizes are defined as "measures quantifying association between variables" (Stanley & Doucouliagos 2012:20). There are multiple effect sizes (regression coefficients, elasticities) which may not be comparable. Partial correlation coefficients (PCC) are homogeneous effect sizes that can be obtained from primary regression coefficient estimates. PCCs have no measurement unit but show magnitude and direction in statistical associations (Dimos & Pugh 2016; Stanley & Doucouliagos 2012). PCCs are easily calculated from information usually reported in papers, which gives them a substantial advantage. PCC and its standard error are defined as:

$$PCC = \frac{t}{\sqrt{t^2+df}} \qquad [1]$$

$$s.e.(PCC) = \sqrt{\frac{(1-PCC)^2}{df}} \qquad [2]$$

Where t is the statistic value of the significance test and df are the estimate's degrees of freedom (Aloe & Thompson 2013; Dimos & Pugh 2016). On the one hand, PCC weighs the significance level of each estimate by its degrees of freedom and is bounded between -1 and 1. Higher PCCs imply a higher t/df ratio. On the other hand, *s.e.(PCC)* inversely depends on freedom degrees: as freedom degrees grow (e.g. simple size grows), PCC becomes more precise (standard errors decrease). PCCs are typically assumed to be unbiased and normally distributed with mean β_0 and variance v_i (Viechtbauer 2010). Estimation of the average effect size is given by:

$$PCC_i = \beta_0 + e_i \qquad i=1,\dots,n \qquad [3]$$

Where PCC is the effect size in paper i, β_0 is the average effect size and $e_i \sim N(0; v_i)$ is the error term. In this model every effect size refers to a single population parameter and is called

[3] In this case, the average effect size between firm size and innovative performance.

homogeneous effect model[4]. Equation [3] is clearly heteroscedastic, requiring an error correction through Weighted Least Squares (WLS). MRA uses precision as weighing, which gives more precise effects a major relevance. In this paper we use the inverse of PCC variance (w_i=1/v_i) as weighing (Rice, Higgins, & Lumley 2018; Thompson & Higgins 2002).

Heterogeneity among effect sizes is measured by **Q test.** This is essentially a chi-squared test with the null H_0: $CCP_1=\ldots=CCP_n$ (Viechtbauer 2007). Formally:

$$Q = \sum_{i=1}^{n} w_i \, (PCC_i - \hat{\beta}_0)^2 \quad \sim \chi^2_{n-1}$$

[4]

Where n are the observations, w_i is the weighing and $\hat{\beta}_0$ the estimated average effect. P-value is computed as p = Pr(Q> χ^2_{n-1}). Rejecting the null provides evidence of heterogeneity beyond sample error in literature under examination.

In social sciences homogeneous effect sizes rarely apply, thus effect sizes differ from a single average. In this case, an unobservable u_i is added to the model (Higgins, Thompson, & Spiegelhalter 2009; Rhodes 2012). Consequently, $PCC_i \sim N(\beta_0; \tau^2+v_i)$ and τ^2 is the variance between papers or heterogeneity level (Viechtbauer 2010). This leads to the heterogeneous effects model[5]:

$$PCC_i = \beta_i + e_i = \beta_0 + u_i + e_i \qquad [5]$$

Where $u_i \sim \boldsymbol{N}(0; \boldsymbol{\tau}^2)$ and $e_i \sim \boldsymbol{N}(0; \boldsymbol{v}_i)$ are the additive error terms with Cov(e_i; u_i) = 0. Total variance is defined as $\boldsymbol{\tau}^2+v_i$. Average effect estimation weighing is now w_i=1/($\boldsymbol{\tau}^2+v_i$).

Equations [3] and [5] are the simplest, univariate models in MRA. However, moderator variables (**Z** matrix) may be added to explain heterogeneity the same way conventional regression analysis does (Stanley & Doucouliagos 2012). Multivariate MRA model is defined as:

$$CCP_i = \beta_0 + \gamma_1 Z_{1i} + \cdots + \gamma_g Z_{gi} + u_i + e_i \qquad g=1,\ldots,G \qquad [6]$$

Where β_0 is the average effect when every explanatory variable is zero. Heterogeneity in [3] is due to sample error, while heterogeneity in [5] is due to simple error and unobservable effects u_i. Heterogeneity in [6] is also due to observable effects. So far, effect sizes have been treated as independent. However, it is a common fact that papers report more than one effect size. In this case $PCCs$ cannot be taken as independent, for they are expected to be correlated within each paper. Data acquires a hierarchical or multilevel structure, where the observed effects are grouped into clusters represented by each paper (J. P. Nelson and Kennedy, 2009; Stanley and Doucouliagos, 2012; Viechtbauer, 2010). Regression models that best reflect this situation allow coefficients to vary randomly between clusters. Although both intercepts and random slopes are possible, most widespread use is limited to random intercepts (J. P. Nelson and Kennedy, 2009). Intra-study correlation leads to the following expression:

[4] This model is referred in the literature as fixed-effect-size (FES). In order to avoid further confusion this paper uses Rhodes' (2012) nomenclature who distinguishes between homogeneous and heterogeneous effect sizes.
[5] This model is referred in the literature as random-effect-size (RES).

$$CCP_{ij} = \beta_0 + \gamma_1 Z_{1ij} + \cdots + \gamma_g Z_{gij} + u_j + e_{ij} \qquad j=1,\dots,J \qquad [7]$$

Where *i* is the *i-th* effect in *j-th* cluster. Random intercept for each paper is given by β_0+u_j. Intra-paper effects are tested through the LM test (Breusch & Pagan 1980). The null is that effect sizes are independent. Full description of the test is available in Baltagi and Li (1990).

Model displayed in [7] is analogous to unbalanced panel data structures, where papers are individuals with several observations and one unobservable component u_i (Stanley & Doucouliagos 2016; Wooldridge 2002). When cov(X_{ij}, u_j) = 0, u_i can be modelled as a random variable without endogeneity problems. If u_i and explanatory variables are correlated, random effects coefficients will be biased and inconsistent. In this case, the unobservable must be extracted from the error term through ussual fixed effects panel estimation. Another option is to add an identification dummy for each cluster or paper (least squares dummy variable - LSDV) in order to capture the unobservable. To decide whether fixed or random effects estimators are accurate, traditional Hausman test can be applied. Full description of the test is given in Wooldridge (2002:10.7.3).

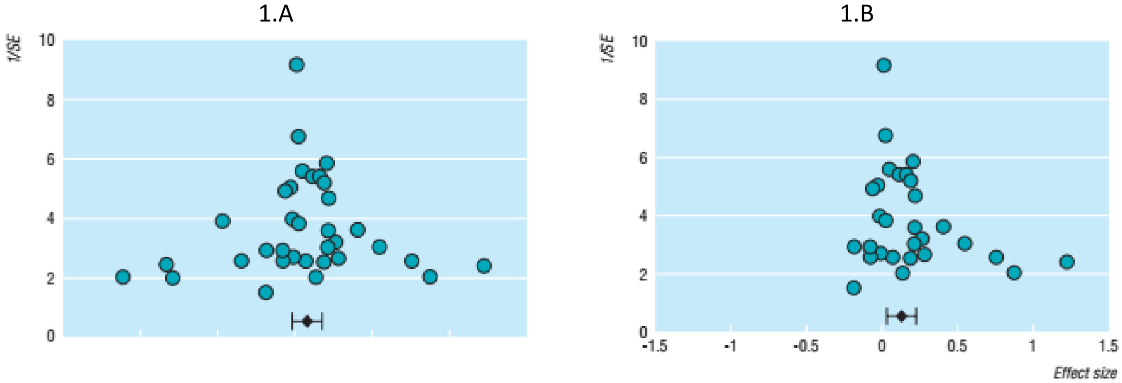
3.2 Publication bias

When researchers force empirical evidence to be sequacious with prior theories or to be statistically significant there is publication bias (Card & Krueger, 1995; Stanley & Doucouliagos, 2012). These biases facilitate access to journals and increase publishing chances. Coercion of empirical results has two implications: on the one hand "right" estimations are overrepresented in the literature. On the other hand, researchers will lose precision after picking the desired model specification or coefficients. When publication bias is absent, effect sizes should vary randomly around the average effect. With publication bias effect sizes and precision (inverse variance) are correlated, that is to say:

$$\mathrm{Cov}(CCP_i, \sqrt{v_i}) \neq 0$$

Visual inspection of data is the first step in detecting publication bias. Funnel plots are scatter diagrams that show effect size precision as a function of its value (Stanley 2005; Stanley & Doucouliagos 2012; Sterne & Egger 2001). Without bias, effect size distribution as a function of precision will resemble to an inverted funnel (Figure 1.A). As Sutton *et al.*(2000) explain the funnel shape shows that imprecise effects have a wider range of values while precise effects gather round the "genuine" effect. Asymmetry in funnel plots may imply publication bias (Figure 1.B).

Figure 1: Funnel plot with and without publication bias



Source: Sutton *et al.* (2000).

Funnel plots are a useful tool, though their interpretation may depend on the analyst own criteria. Formal econometric analysis complete publication bias examination. Starting from original equation [3], correlation between the observed effect and its standard error is added to get:

$$CCP_i = \beta_0 + \beta_1\sqrt{v_i} + e_i \qquad [8]$$

Where β_0 represents the corrected average effect, β_1 measures the bias magnitude and direction and e_i is the error term. Symmetry is posited under the null H_0) β_1=0 (FAT[6] test) while non-significant average effect is posited under the null H_0) β_0=0 (PET[7] test). Again, equation [8] must correct heteroskedasticity through WLS with inverse variance as weighing. Nevertheless, recent studies (Moreno *et al.* 2009) have shown that when significant average effects exists, variance yields more accurate estimation than standard error, which leads to PEESE[8] test:

$$CCP_i = \beta_0 + \beta_1 v_i + e_i \qquad [9]$$

Methodological influences are known as key factors linked to publication bias (Havránková 2015; Liston-Heyes & Heyes 2019; Ugur *et al.* 2016). Econometric issues may be related to effects' variance. Thus, modelling publication bias is similar to heterogeneity modelling by means of moderator variables. Methodological influences make up the **K** variables which by definition are included as interaction effects with variance (Stanley & Doucouliagos 2012):

$$CCP_i = \beta_0 + \beta_1 v_i + \sum_{h=1}^{H} \delta_h K_{hi} v_i + e_i$$

$$h=1,\dots, H \qquad [10]$$

Publication bias is no longer reflected by a single parameter, but in every *K*-variable contributing to that bias. When combining [10] with heterogeneity modelling in [7], full MRA model is obtained:

$$CCP_i = \beta_0 + \beta_1 v_i + \sum_{g=1}^{G} \gamma_g Z_{gi} + \sum_{h=1}^{H} \delta_h K_{hi} v_i + e_i$$

[11]

Where γ_g and δ_h are coefficients for each *g Z*-variable and *h K*-variables respectively. Adding intra-paper clustering leads to the final model:

$$CCP_{ij} = \beta_0 + \beta_1 v_i + \sum_{g=1}^{G} \gamma_g z_{gij} + \sum_{h=1}^{H} \delta_h K_{hij} v_i + u_j + e_{ij}$$

[12]

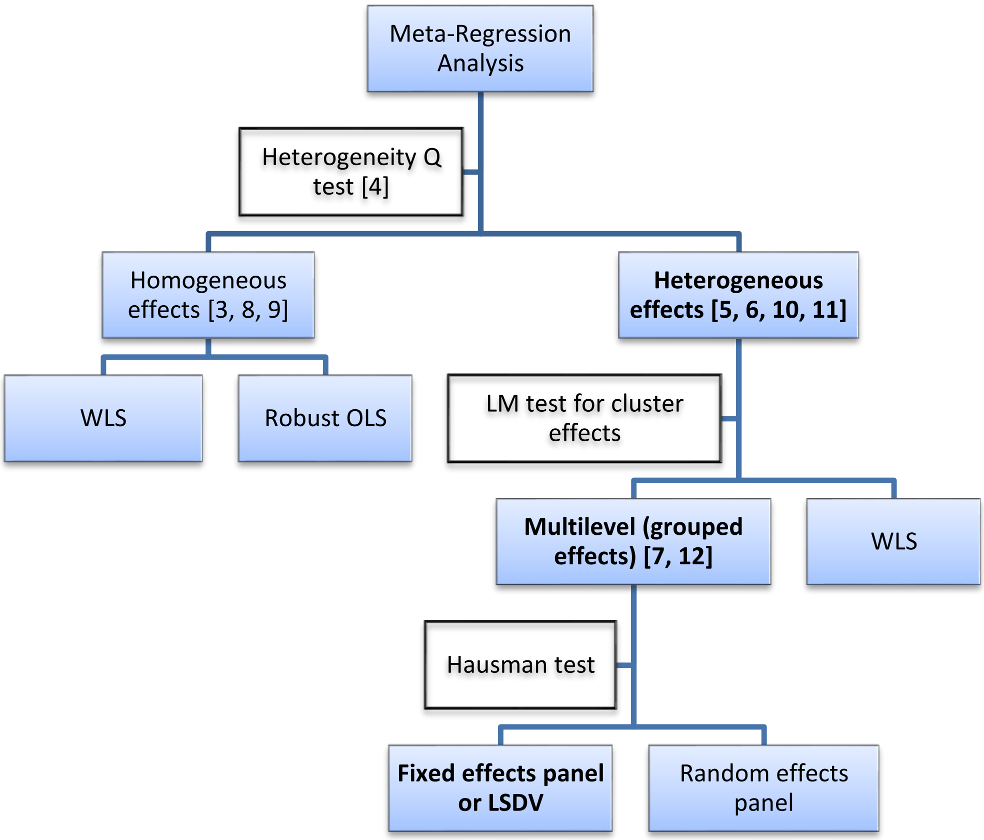
[6] Funnel asymmetry test.
[7] Precision-effect test.
[8] Precision-effect estimate with standard error.

Where:

γ_g = vector of *Z*-variables coefficients
δ_h = vector of *K*-variables coefficients
Z = matrix of *G* variables related to effects' heterogeneity
K = matrix of *H* variables explaining publication bias
$j = 1, 2, \ldots, J$ papers
$i = 1, 2, \ldots, I$ effect sizes
u_j = cluster effect
e_{ij} = error term

To sum up, Figure 2 displays modelling criteria in MRA. Equations and statistical tests for model specification above discussed are referenced. Model specifications used in this paper are marked in bold.

Figure 2: MRA modelling schema



Source: adapted from Feld & Heckemeyer (2011:249).

3.3 Sample and moderator variables

In this research, target population is compound of quantitative academic articles investigating sources of IP at the firm level. Within these sources, firm size must be present. Current sample arises from two different searches. The first one was carried out during July-October of 2017. The second one was a complementary searching between June and July 2018. However, key words and inclusion criteria were built upon Becheikh, Landry & Amara's

(2006) and Cohen's (2010) literature reviews. On this basis, sample contains articles with the following features: i) published between 1993 and 2017[9]; ii) written in English and Spanish; iii) at firm level; iv) manufacturing-sector oriented; v) econometric modelling of IP[10]; vi) IP as dependent variable; vii) regarding technological innovation[11]; viii) continuous operationalization of firm size; ix) journal articles and grey literature.

Empirical articles in the sample come from several sources: American Economic Association database (ECONLIT), Asociación Argentina de Economía Política database (AAEP), JSTOR, SCOPUS, SSRN, SciELO, Bielefeld Academic Search Engine (BASE) and LA Referencia. Specialized journals *Technovation* and *PyMEs, Innovación y Desarrollo* were also inspected. Finally, Scholar Google as well as conferences proceedings were consulted to attend for geographical representativeness, especially in underdeveloped countries. A summary is shown in Table 2.

Table 2: Data sources

Data source	Key words	Possible articles	Selected articles	Source share in sample	Number of estimations
Becheikh *et al.* (2006)	--	101	24	19,2%	159
Cohen (2010)	--	157	10	8,0%	69
ECONLIT	Firm size RyD; "firm level" innovation; innovation survey	310	51	40,8%	320
JSTOR	Innovation "firm size"	93	3	2,4%	13
SciELO	Innovation "firm size"; innovación; tamaño empresa; firma	12	1	0,8%	1
SSRN	Innovation "firm size"; technological regimes	70	10	8,0%	75
Technovation	Innovation "firm size"; empirical	21	2	1,6%	19
Scholar google + PyMEs, Innovación y Desarrollo + AAEP	Innovación; tamaño de la empresa; firma; América Latina; Argentina	36	12	9,6%	125
SCOPUS + BASE + LA Referencia	"technological innovation"; econometric; América Latina;	--	12	9,6%	94

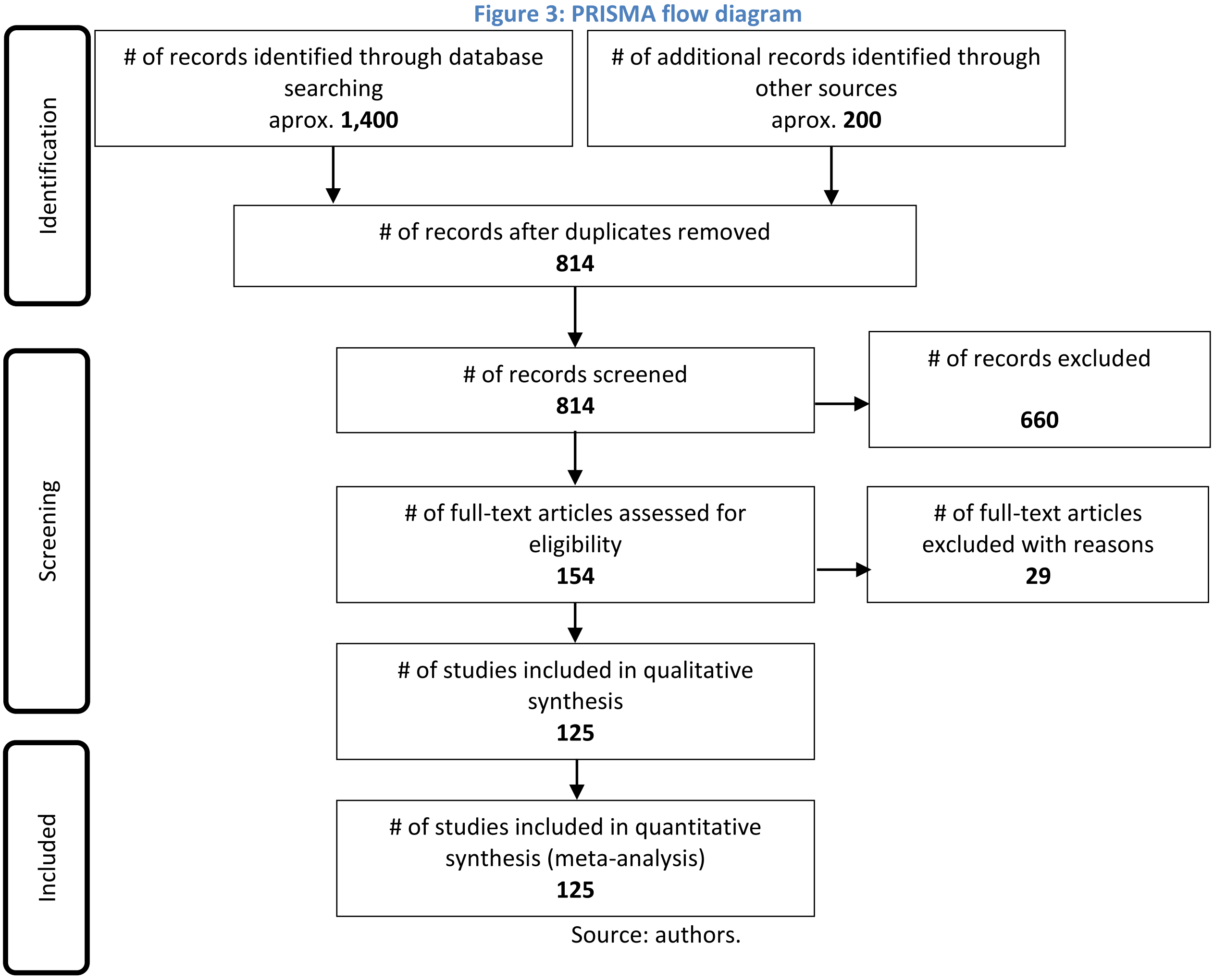
[9] Publication of Oslo Manual (OECD 1992) gives a common framework for collecting empirical evidence through National Innovation Surveys.
[10] We excluded econometric articles lacking minimum information to calculate PCCs.
[11] Product and process innovation.

	“innovación tecnológica”				
Total	--	**800**	**125**	**100,0%**	**880**

Source: authors.

PRISMA flow diagram (showing database setting) is presented in Figure 3. For identification phase, inclusion criteria and data sources were defined by two authors (FB and NL) and lately validated by a third author (FG). Screening and first exclusion step was carried out by FB, while last discarding and final sample was carried out jointly (FB and NL).

Figure 3: PRISMA flow diagram



Source: authors.

From roughly 1,600 pieces of evidence, we end up with 125 articles reporting a total of 880 estimations[12]. As detailed next, this sample covers diverse regions, sectors and econometric models. These features are the moderator variables to carry out the multivariate MRA. Typically, moderators refer to geographical data origin, publication year and econometric issues, among many others (Stanley *et al.* 2013; Stanley & Doucouliagos 2012). Table 3 displays the variables explaining heterogeneity in current MRA.

[12] The list of articles together with key features is presented in the Appendix.

Table 3: Moderator variables

Variable	Description	Scale	Operational definition
sector (*Z*)	Industrial sectors grouped by technological intensity to which firms in samples belong	Categorical	Manufacturing (base category including every industrial sector), high, medium & low technology[13].
region (*Z*)	Continent or geographical regions to which data belongs	Categorical	Europe (base), Africa, Latin America and the Caribbean, Asia, USA, USA and Europe, International, Oceania.
cross section (*Z*)	Data structure	Binary	1 if cross sectional, 0 if panel.
innovative firms (*Z*)	Indicates if firms have innovative activities prior to analysis	Binary	1 if firms are exclusively innovative , 0 c.c.
innovation measure (*Z*)	Innovation metric employed	Categorical	Results (base), innovative activities, invested resources.
model (*K*)	Type of econometric model	Categorical	Linear models (base), GLM, GMM, COX.
main model (*Z*)	Denotes if estimation belongs to the article´s main model	Binary	1 if it is within the main model, 0 c.c.
sales (*K*)	Indicates whether firm size is measured by sales or employees	Binary	1 for sales, 0 for employees.
published (*K*)	Denotes whether article is published or grey literature	Binary	1 if published, 0 c.c.
control (*K*)	Distinguishes firm size as control or independent variable in estimation	Binary	1 for control, 0 c.c.
v_i	PCC_i variance	Continuous	--
IDarticle	Article identifier for clustering	*j=1,…,125*	--

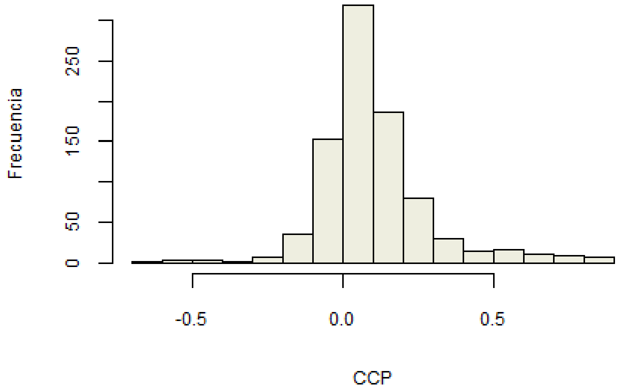
Source: authors.

4 Findings

A brief description of data is presented next. In first place, PCC distribution (Figure 4) looks symmetrical although it does not fit within a normal distribution (p-value for Shapiro-Wilk test < 0,001). Positive and negative effect sizes are to be found. However, positive effects are notably more frequent, representing roughly 77% of the sample.

[13] Classification corresponds to Hatzichronoglou (1997).

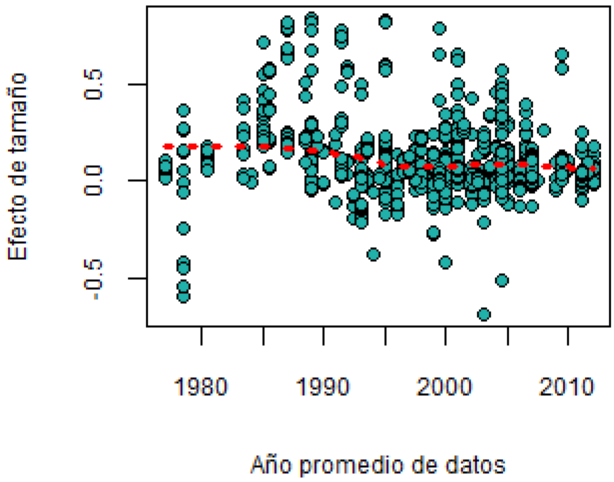
Figure 4: Histogram of PCC



Source: authors.

Distribution of PCC over time is shown in Figure 5. Average year of data in each primary model is taken as reference. Figure does not reveal a clear trend but effect sizes prior to 1995 are higher than more recent ones. Thus, a stroger relationhip is observed until mid 90's, when the business model focuses on global networks, whose organizative structures are more flexible (Castells 2017). A linear decreasing trend can be estimated, but it cannot account for more than 3% of total variance.

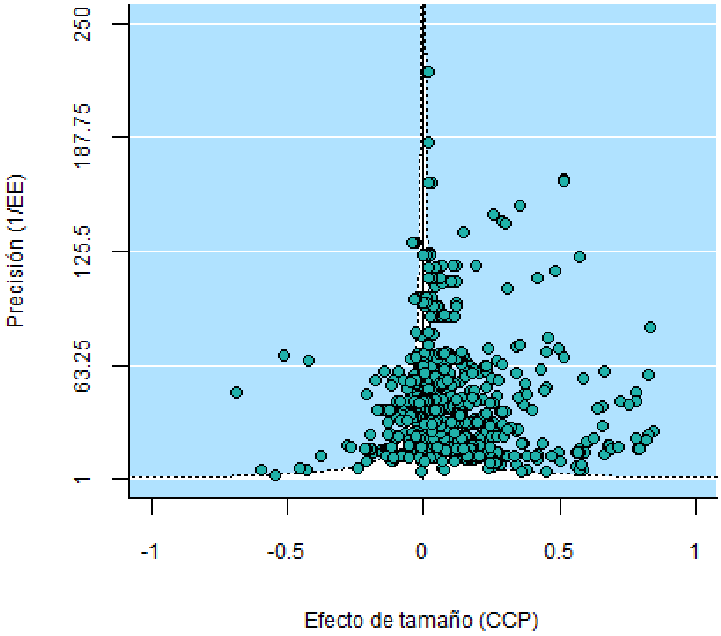
Figure 5: PCC distribution over time



Source: authors.

Figure 6 introduces a funnel plot, which exhibits a relatively symmetrical distribution. Again, positive effects prevail within an heterogeneous grouping. As effects become more precise they cluster around a positive value. In addition, negative effect are less precise (*i.e.* more variable) than positive ones.

Figure 6: Funnel plot of PCC



Source: authors.

In a complementary way, Table 4 presents PCCs' sign and significance level. Corrected residuals corroborate an association between positive and significant estimations[14].

Table 4: estimations' significance level and sign

Sign	P-value of coefficient		Total
	Significant	Non significant	
Positive	71,7% (8,1)	28,3% (-8,1)	100%
Negative	40,6% (-8,1)	59,4% (8,1)	100%

Corrected residuals in brackets.

Source: authors.

4.1 Univariate MRA estimation

In line with previous meta-analyses, univariate MRA throws a clear result (Table 5): average "genuine" effect on firm size and IP is positive (Camisón, 2002; Damanpour, 2010). Accurate PCC gather round a 0.13 value. In addition, there is evidence of heterogeneity beyond sample error (p-value of Q test < 0.01). Table 5 presents estimations for homogeneous (model 1) and heterogeneous effects within random (model 2) and fixed clusters (model 3)[15]. Homogeneity hypothesis is rejected by Q test en each model. Additionally, LM test suggests cluster effects within papers, which are correlated with variance (according to Hausman test). Thus, conclusions are based on model 3 (LSDV). Although LSDV model accounts for 72% of observed variability, R^2 is not a good comparison between LSDV and random effects. As stated by Verbeek (2004), fixed effects models or LSDV have usually high R^2 due to dummy variables inclusion.

[14] P-value of χ^2 test<0,001.

[15] Using software R with metafor package (Viechtbauer, 2010).

Table 5: univariate MRA

	Model 1	Model 2	Model 3
	Homogeneous effects	Heterogeneous (random effects, robust errors)	**Heterogeneous effects (LSDV)**
Intercept	0,15 (0,03)***	0,14 (0,02)***	0,13 (0,08)*
Variance	-14,43 (1,63)***	-12,61 (14,05)	-4,83 (2,45)**
Observations	874	874	874
R^2	--	0,02	0,72
Q test for residual heterogeneity	QE(gl = 749) = 69226,3 P-val **< ,001**	QE(gl = 872) = 91251,2 P-val **< ,001**	QE(gl = 749) = 25866,4 P-val **< ,0001**
Asymmetry test	Z= -8,86 P-val < **0,001**	Z= -0,89 P-val = **0,37**	Z= -1,97 P-val= **0,048**
LM test (cluster)	--	χ2 = 820,66 gl = 1, p-val<**0,001**	χ2 = 39,86 gl = 1, p-val<**0,001**
Hausman test	χ2 = 5,54 gl = 1, p-val = **0,018**		

Notes: models 1 and 3 include an article identification dummy variable and model 2 includes random effects for the unobservable term (not shown). For LM test, H_0) No cluster effects; for Hausman test, H_0) Random effects estimators are efficient and consistent. Signification code: '***' 0.01, '**' 0.05, '*' 0.1. Source: authors.

Likewise, there is evidence of publication bias: negative and non significant effects are absent, which may be due to researchers themselves or rejected for publication. Asymmetry test derived from variance coefficient implies that effect sizes do not distribute as a funnel, that is, symmetrically. Since average effect size is positive, positive and significant estimations are reasonable to find. The lack of negative and positive PCCs among less precise ones is a sign of publication bias. It is virtually impossible to realize about the cause of such absence. It may be due to rejection by journal referees, due to academic consensus or because they are just not estimated.

4.2 Multivariate MRA estimation

Multivariate MRA results for LSDV and WLS[16] models are shown in Table 6. Similar to univariate MRA, average or "genuine" effect is still positive. In tune with previous meta-analyses, methodological influences rather than firms' features are key sources of heterogeneity (Camisón *et al.* 2002; Damanpour 1992, 2010). Negative correlation between PCC and its variance is again accounted for. Thus unpublished results are precisely the less accurate ones, generally negative or non significant. Nevertheless, this matches the idea that results against academic consensus will not be published in the same proportion than (in this case) positive effects.

Table 6: Multivariate MRA.

		Heterogeneous effects (LSDV)	Unbalanced panel (MCP)
Intercept		0,47 (0,15) ***	0,46 (0,15)***
	Low tech	0,02 (0,02)	0,02 (0,02)
sector	Medium tech	0 (0,08)	0 (0,08)
	High tech	0,02 (0,03)	0,02 (0,02)
region	Africa	0,08 (0,06)	0,08 (0,06)

[16] Using software R with plm package (Croissant & Millo 2008).

	LA and Caribbean	0 (0,11)	0 (0,11)
	Asia	-0,32 (0,14)**	-0,32 (0,14)**
	USA	-0,24 (0,14)	-0,24 (0,14)
	USA and Europe	0,12 (0,07)*	0,124 (0,07)*
	International	-0,24 (0,16)	-0,24 (0,16)
	Oceania	0 (0,05)	0 (0,05)
Cross section		-0,09 (0,04)**	-0,09 (0,04)**
Innovative firms		-0,1 (0,02)***	-0,1 (0,02)***
Innovation measure	Innovative activities	0,07 (0,01)***	0,07 (0,01)***
	Invested resources	0,06 (0,02)***	0,06 (0,02)***
Main model		-0,02 (0,01)**	-0,02 (0,01)**
Sales		0,09 (0,03) ***	0,09 (0,02)***
Published		-0,37 (0,11)***	-0,37 (0,11)***
control		-0,02 (0,09)	-0,02 (0,09)
v_i		-94,76 (53,96)*	-94,71 (53,58)*
sales*v_i		-12,09 (6,28)*	-12,09 (6,23)*
published*v_i		102,49 (53,64)*	102,44 (53,25)*
control*v_i		-16,91 (7,8)**	-16,9 (7,74)**
Observations		874	874
R^2		0,72	0,75
LM test (paper effects)		χ2 = 39,82, df = 1, p-val <0,001	
Hausman test		χ2 = 1457,3 df = 12, p-val <0,001	

Notes: models include an article identification dummy variable (not shown). For LM test, H_0) No cluster effects; for Hausman test, H_0) Random effects estimators are efficient and consistent. Signification code: '***' 0.01, '**' 0.05, '*' 0.1.
Source: authors.

Regression output points out **sectors** are not a source of heterogeneity. That is to say, *ceteris paribus*, effect size is the same across technologically different sectors and samples containing several sectors. Contrary to theoretical discussion, technological regimes are not reflected here.

Even though **region** is a significant variable, compared to Europe only Asian and American plus European effects are statistically different. Thus, geographical origin of data is not an important source of observed variability (Damanpour 2010). Region is a theoretically critical dimension, but results in other economic MRA applications follow the same path (Feld & Heckemeyer 2011; Galindo *et al.* 2015; Havranek, Irsova, & Janda 2012). In current research, severe limitations regarding data do not allow deepening analysis (Camisón *et al.* 2002; Damanpour 2010). A possible cause may be found on heterogeneity within regions (Rose & Stanley 2005).

Cross sectional effects are smaller compared to panel data. Panel data structures account for unobservable effects at the firm level, as well as cumulative effect over time (Baltagi 2005; Dimos & Pugh 2016). This in an important source of heterogeneity in several MRA applications (Feld & Heckemeyer 2011; Galindo *et al.* 2015; Havránková 2015). Besides, panel data estimations in our sample rely on more observations that cross sectional effects. Thus, formers are on average more precise and higher effects.

Negative sign for **innovative firms** reveals a weaker effect when there are previous innovative efforts. Thus, prior trajectory moderates this relationship because persistence in innovative processes leads to technological capabilities related to IP (Buesa *et al.* 2002; Malerba, Orsenigo, & Peretto 1997). This results back up the notion of the innovation-profits-innovation virtuous circle (Bowen *et al.* 2010; Knott & Vieregger 2016). Once innovative routines are incorporated, firm size loses influence on IP (Malerba *et al.* 1997; Ugur *et al.* 2015).

Another key feature is **innovation measure**. Effect sizes are higher when measuring innovation through inputs rather than innovation attainments[17]. Arguments regarding big firms' financial advantages are built on this basis (Camisón *et al.* 2002; Cohen 2010). Instead, weaker effects when modelling innovative output show that other kind of capabilities (like organizational ones) are also important (Nelson 1991). This is what we see for innovative firms (above): once innovative process is ongoing, size is not that relevant (Damanpour 2010).

Main models present a weaker effect size. These are estimations on which researches base their conclusions. Therefore, this group of models are more complete that "non main models". The latter may include misspecified models and robustness checks where firm size captures a higher proportion of IP variability. Adding explanatory variables may reduce effect size by eliminating omitted variable bias (Krassoi Peach & Stanley 2009).

Methodological influences (**sales**, **published** and **control**) enter the model as main effects and interaction effects. These three variables explain partly correlation between PCC value and its variance, and hence are related to publication bias affecting probability of publication. In this context, variable "published" is included to assess its impact on precision of effect sizes (Dimos & Pugh 2016; Doucouliagos & Stanley 2009). Similar to univariate MRA, negative coefficient of variance shows that smaller PCCs associate with higher rates of error.

With respect to **sales** as principal effect, a positive coefficient entails a stronger link between IP and firms size when financial measures are used. This kind of measures picks up more accurately firms' economic constrictions and therefore financial advantages of big enterprises. On the other hand, as an interaction term **sales*$\mathbf{v}_i$** implies more precise effects. That is, cash flow leads to better approximation for financial capabilities related to process innovation in big firms (Damanpour 2010).

On the one hand, **published** (in journals) estimations are in average lower that non published ones. On the other hand, published estimations follow an opposite pattern compared to univariate model: the higher the variance, the higher the effect size (**published*$\mathbf{v}_i$**). This is known as publication bias, given that non journal published estimations are included in our sample (Card & Krueger 1995; Stanley & Doucouliagos 2012). However, such results may be carefully interpreted since they are statistically significant at the 10% level.

[17] Although this variable is defined as part of *K*, robustness checks show that measures are not related to precision. Thus, we only evaluate it as a source of heterogeneity.

Lastly, firm size as control is not a source of heterogeneity. Nevertheless, negative coefficient for **control*v_i** implies that among estimations including size as control, stronger effects are more precise. A possible explanation is that this group of models is related to panel data, whose size effect is greater and dispose larger samples.

Two main results are extracted from multivariate MRA. First, existence of a positive average size effect is confirmed, supporting **H1)**. Such an effect emerges from a distribution whose heterogeneity is beyond sample error. Altogether, econometric estimation seems to indicate that average effect is based upon direct relationship between size and innovative efforts. Bigger firms rely on larger resources (in a wide sense according to resources-based view) to invest which gives them more opportunities to innovate successfully *a priori*. Nevertheless, there is a gap between technological improvements and their introduction into the market, which defines a successful innovation. Once improvement is attained, it is necessary to have organizational and commercial capabilities to turn it into profits. These capabilities are achieved partly when transiting an innovative path that allows embodying innovative routines.

Secondly, heterogeneity is partly explained by contextual features and methodological influences, supporting **H2)**. Apparently, methodological influences such as measuring lead to correlation between estimations and error in a publication bias context.

5 Concluding remarks

This research consists of a systematic review of empirical literature on firm size and IP relationship. Starting from a bibliographic search, sample is composed by 880 estimations within 125 quantitative articles published between 1993 and 2017. A Meta-Regression Analysis is carried out in order to detect sources of heterogeneity and assessing publication bias.

Two main findings arise from econometric analyses. On the one hand, effect sizes are heterogeneous beyond sample error due to methodological influences mostly. On the other hand, there is evidence of publication bias. However, corrected average "genuine" effect size is still positive. Thus, academic consensus of a direct relationship between firm size and IP is confirmed on an empirical basis. Features of firms within primary samples (contextual differences in **Z**) do not play a key role explaining observed heterogeneity. Sectoral and regional differences are non significant or do not show stable coefficients.

Among factors explaining heterogeneity, operationalization of IP is maybe the most important. Although innovation is hard to measure, IP measurements in the literature exhibit somewhat agreement. IP measures include innovative input (innovative activities and R&D budget) and output (sales and patents, among some others). Input measures-based estimations present a stronger effect size compared to output measures. The link between organizational size and innovative financial capacity is at the base of current theoretical consensus of a direct relationship regarding firm size and innovation. However, a weaker effect in output measures implies that other capabilities (*e.g.* organizational and commercial) are needed in order to introduce innovations successfully into the market. This may be the case of innovative firms, whose effect size is weaker that non innovative ones. The former count on other kind of capabilities than the latter, whose learning path is mostly untraveled and thus must rely on their tangible resources. Once innovative path is opened, new routines can be embodied into firms' regular operations.

Firm size operationalization is important as well. In this regard, financial measures yield higher effect sizes. This is consistent with results for IP measures discussed above. Firm size metres like sales reflect more accurately financial constrains when engaging innovative projects. Moreover, these estimations are on average more precise.

Turning to publication bias, the correlation between effect sizes and its variance shows that higher effects are systematically more precise. Higher effects are less variable, which allows thinking about an effort to find positive and statistically significant effects. What is more, evidence extracted from grey literature is less precise, related to negative and non significant effects. This may be a sign of segregation of evidence against current consensus.

Our results support both research hypotheses. In line with prior meta-analyses, this investigation endorses heterogeneity in empirical evidence, which is partly explained by methodological influences. However, data limitations do not allow deepening in econometric analysis. Future enlargement of data frame may possibly shed light on this regard.

To sum up, two limitations are to be accounted for. First, our sample represents a fundamental fraction of empirical evidence but not all of it. Inclusion criteria force the dismissing of a considerable amount of articles. Thus, qualitative or historical approaches are excluded from the beginning. The second limitation is related to the scarcity of evidence for underdeveloped countries. These pieces of evidence could be relevant in order to carry out better regional comparisons.

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Appendix

Table 7: Included studies in MRA

Reference	Number of estimations	Country	Period	Sample size	Innovation measurement	Size measure	Main size effect
Aboal & Garda (2016)	10	Uruguay	2004-2009	1328	IA; Obtained Results	Employees	Positive
Ahuja (2000)	11	International	1982-1992	996	Obtained Results	Employees	Positive
Ahuja & Katila (2001)	6	International	1980-1991	598	Obtained Results	Employees	Positive
Allred & Park (2007)	5	Developed economies	1990-2000	1081	Invested resources	Sales	Positive
Almeida *et al.* (2011)	10	USA and Europe	1990-2003	971	Obtained Results	Employees	Positive
Aristizábal-Ramírez *et al.* (2017)	20	Underdeveloped economies	2006-2013	9101	Obtained Results	Employees	Positive
Arvanitis (2008)	2	Switzerland	1997-1999	595	Obtained Results	Employees	Positive
Aschhoff & Schmidt (2008)	8	Germany	2001-2004	699	Obtained Results	Employees	Null
Audretsch (1995)	7	United States	1975-1982	374	Obtained Results	Sales	Negative; Null
Bachmann *et al.* (2016)	3	Argentina	2002-2004	1241	Obtained Results	Employees	Negative
Baptista & Swann (1998)	11	United Kingdom	1975-1982	1984	Obtained Results	Sales	Positive
Barasa *et al.* (2017)	11	Kenya, Tanzania and Uganda	2010-2012	1541	Obtained Results	Employees	Null
Barge-Gil (2013)	6	Spain	2004-2008	16906	Obtained Results	Employees	Negative
Bartoloni & Baussola (2001)	1	Italy	1990-1992	13334	Obtained Results	Employees	Positive
Battisti *et al.* (2015)	16	Europe	2002-2004	173	Obtained Results	Employees	Positive; Null
Becheikh (2013)	1	Egypt	2009	2132	Obtained Results	Employees	Positive
Belderbos (2001)	2	Japan	1990-1993	194	Obtained Results	Sales	Positive
Benavente (2006)	15	Chile	1997-1998	197	IA; Invested resources; Obtained Results	Employees	Null
Beugelsdijk & Cornet (2002)	6	Germany	1996	1510	Obtained Results	Employees	Negative
Bishop & Wiseman	3	United Kingdom	1996	320	IA; Obtained	Employees	Positive

(1999)					Results		
Blundell *et al.* (1999)	9	United Kingdom	1972-1982	2943	Obtained Results	Sales	Positive
Bond *et al.* (1999)	2	Germany and United Kingdom	1985-1994	218	IA	Sales	Positive
Bratti & Felice (2012)	7	Italy	2001-2003	1635	Obtained Results	Employees	Null
Cabral & Traill (2001)	4	Brazil	1994-1996	202	Obtained Results	Employees	Positive
Capron & Cincera (2004)	4	Belgium	1998	1204	Obtained Results	Employees	Positive
Cassiman & Veugelers (2002)	9	Belgium	1993	316	Obtained Results	Employees	Negative
Cassiman & Veugelers (2006)	15	Belgium	1993	269	IA; Obtained Results	Sales	Various
Cefis (2010)	13	Germany	1998-2002	4604	IA	Employees	Negative; Null
Cefis & Marsili (2015)	8	Netherlands	1994-2002	513	Obtained Results	Employees	Null
Classen *et al.* (2014)	4	Germany	2006	1067	IA; Invested resources; Obtained Results	Employees	Positive
Clausen (2009)	8	Norway	1999-2001	1019	Invested resources	Employees	Positive; Null
Clausen & Pohjola (2013)	6	Norway	1998-2006	1644	Obtained Results	Employees	Various
Cockburn & Henderson (1994)	3	USA and Europe	1993	171	Invested resources	Sales	Null
Conte & Vivarelli (2014)	13	Italy	2002	2247	Invested resources; Obtained Results	Employees	Various
Corsino *et al.* (2011)	4	International	1999-2004	564	Obtained Results	Employees	Positive
Crèpon *et al.* (1998)	8	France	1990	4164	IA; Obtained Results	Employees	Null
Crespi *et al.* (2016)	21	Argentina	1998-2004	2083	Invested resources	Sales	Positive
Czarnitzki & Kraft (2005)	6	Germany	1992-1995	1915	Invested resources	Employees	Positive
Damijan *et al.* (2011)	3	Slovenia	1996-2002	4947	IA; Invested resources; Obtained Results	Employees	Positive
De Propris	1	United Kingdom	1994-	270	Obtained	Employees	Null

(2000)			1996		Results		
Dhingra (2013)	8	Thailand	2003-2006	413	Obtained Results	ambos	Null
Doran & Jordan (2016)	9	Ireland	2004-2006	591	Obtained Results	Employees	Positive
Doran & O'Leary (2016)	4	Ireland	2006-2008	522	Obtained Results	Employees	Null
Elshamy (2015)	1	Egypt	2010-2012	70	Obtained Results	Employees	Positive
Eriksson *et al.* (2014)	8	China	2011	564	IA; Obtained Results	Employees	Positive
Fassio (2015)	3	Germany, Spain and Italy	2002-2004	2126	Invested resources	Sales	Negative
Fitjar *et al.* (2013)	4	Norway	2010	1602	Obtained Results	Employees	Positive
Fitjar & Rodríguez-Pose (2015)	8	Norway	2010	1602	Obtained Results	Employees	Positive
Fontana & Gueronzi (2008)	1	Europe	2000	486	Obtained Results	Employees	Positive
Foster *et al.* (2016)	10	United States	2005-2010	7223000	IA; Invested resources	Employees	Positive
Francois *et al.* (2002)	4	France	1990-1996	3906	Obtained Results	Employees	Positive
Freel (2003)	8	United Kingdom	2001	90	Obtained Results	Employees	Positive
Fritsch & Meschede (2001)	5	Germany	1995	627	Invested resources	Employees	Null
Fu *et al.* (2018)	5	Ghana	2010-2013	501	Obtained Results	Employees	Null
Ganau & Di María (2014)	24	Italy	2004-2006	4367	Obtained Results	Employees	Positive
Ganotakis & Love (2011)	2	United Kingdom	2004	314	Obtained Results	Employees	Positive
Ganter & Hecker (2013)	8	Germany	2002-2008	984	Obtained Results	Employees	Null
Gelabert *et al.* (2009)	7	Spain	2000-2005	4008	Invested resources	Employees	Null
Goedhuys & Veugelers (2012)	4	Brazil	2000-2002	1563	Obtained Results	Employees	Null
González *et al.* (2016)	2	Spain	2001-2011	9462	Obtained Results	Employees	Null
Greve (2003)	8	Japan	1971-1996	147	Invested resources; Obtained Results	Employees	Positive

Gussoni & Mangani (2012)	8	Germany and Spain	1998-2000	1703	Invested resources	Employees	Null
Hall *et al.* (2001)	6	Japan, France and USA	1978-1989	2652	Invested resources	Sales	Positive
Hall & Ziedonis (2001)	6	United States	1979-1995	164	Obtained Results	Employees	Positive
Hao & Jaffe (1993)	13	International	1973-1988	321	Invested resources	Sales	Positive
Harris *et al.* (2003)	4	Australia	1995-1998	11271	Obtained Results	Employees	Positive
Herstad *et al.* (2015)	15	Norway	2006-2008	1230	IA; Obtained Results	Employees	Null
Herstad & Sandven (2014)	4	Norway	2008-2010	616	Obtained Results	Employees	Null
Himmelberg & Peterson (1994)	13	International	1983-1987	368	Invested resources	Sales	Positive
Hitt *et al.* (1997)	2	International	1988-1990	293	Invested resources	Sales	Positive
Hoelz Pinto Ambrozio & Lage de Sousa BID (2015)	24	Caribbean	2010-2014	3644	IA; Invested resources; Obtained Results	Employees	Null
Honig-Haftel & Martin (1993)	8	United States	1983-1988	28	Obtained Results	Employees	Positive
Janz *et al.* (2003)	11	Sweden and Germany	1998-2000	206	Invested resources; Obtained Results	Employees	Negative; Null
Kampik & Dachs (2011)	4	Europe	2002-2004	1718	Invested resources; Obtained Results	Employees	Positive
Kang & Kang (2010)	3	South Korea	2005	1353	Obtained Results	Employees	Positive
Keupp & Gassmann (2013)	4	Switzerland	1990-2008	1476	Obtained Results	Employees	Null
Knott & Vieregger (2016)	2	United States	2008-2011	2030	Invested resources	ambos	Positive
Kochhar & David (1996)	4	NASDAQ	1989	99	Obtained Results	Sales	Positive
Leiblein & madsen (2009)	5	International	1990-1999	2599	Obtained Results	Sales	Null
Lerner & Wulf (2007)	4	International	1987-1997	177	Obtained Results	Sales	Positive
Liu & Buck	3	China	1997-	126	Obtained	Employees	Positive

(2007)			2002		Results		
López & Orlicki (2006)	4	Argentina	1992-2000	1286	Obtained Results	Employees	Null
Losada-Otálora & Zuluaga (2013)	1	Colombia	2004	4780	Obtained Results	Employees	Positive
Love *et al.* (1996)	4	Scotland	1992	318	IA; Obtained Results	Employees	Null
Love & Ashcroft (1999)	3	Scotland	1993	304	Obtained Results	Employees	Positive
Love & Roper (1999)	4	United Kingdom	1995	576	Obtained Results	Employees	Positive
Love & Roper (2002)	4	United Kingdom, Ireland and Germany	1991-1994	684	Obtained Results	Employees	Negative; Null
Machikita *et al.* (2009)	1	Indonesia, Vietnam, Thailand and Philippines	2008	128	Obtained Results	Employees	Positive
MacPherson (1998)	1	United States	1989-1993	129	Obtained Results	Employees	Null
Malerba *et al.* (1997)	2	European Union	1984	164	Obtained Results	Employees	Null
Maré *et al.* (2014)	5	New Zealand	2000-2008	13722	Obtained Results	Employees	Positive
Marín *et al.* (2017)	10	Argentina	2002-2004	1245	Obtained Results	Employees	Negative
Marín & Petralia (2018)	12	Argentina and Brazil	1998-2003	4787	Obtained Results	Employees	Null
Martínez Ros (1999)	7	Spain	1990-1993	8000	Obtained Results	Employees	Positive
Morris BID (2015)	16	Caribbean	2008-2014	2460	Obtained Results	Employees	Null
Mothe *et al.* (2015a)	3	Luxembourg	2004-2006	568	Obtained Results	Employees	Null
Mothe *et al.* (2015b)	3	France	2006-2008	2673	Obtained Results	Employees	Negative
Negassi (2004)	7	France	1990-1996	1234	Obtained Results	Sales	Positive
Nieto *et al.* (2015)	3	Spain	1998-2007	15173	Invested resources; Obtained Results	Employees	Null
Nooteboom *et al.* (2007)	8	International	1986-1997	762	Obtained Results	Sales	Positive
Pradhan (2003)	2	India	1989-2001	1998	Invested resources	Sales	Positive
Raymond *et al.* (2010)	8	Netherlands	1994-2000	1764	Obtained Results	Employees	Positive
Reichstein *et al.* (2008)	12	United Kingdom	1998-2000	376	Obtained Results	Employees	Null

Reichstein & Salter (2006)	4	United Kingdom	2001	2885	Obtained Results	Employees	Positive
Roper & Hewitt-Dundas (2015)	15	Ireland	1991-2008	2040	Obtained Results	Employees	Positive; Null
Rouvinen (2004)	2	Finland	1994-1996	1000	Obtained Results	Employees	Null
Sadowski & Sadowski-Rasters (2006)	2	Netherlands	1994-1996	3427	Obtained Results	Employees	Positive
Sakakibara & Branstetter (1999)	6	Japan	1983-1994	3423	Invested resources; Obtained Results	Sales	Positive
Salomon & Shaver (2005)	24	Spain	1990-1997	3471	Obtained Results	Employees	Null
Segarra Blasco *et al.* (2008)	2	Catalonia	2002-2004	1332	IA	Employees	Positive
Sharma (2007)	20	International	2003-2006	1127	IA; Invested resources	Sales	Positive
Shefer & Frenkel (2005)	2	Israel	1994	179	Invested resources	Sales	Negative; Null
Sorensen & Stuart (2000)	36	Asia, Japan, EU and USA	1986-1992	3349	Obtained Results	ambos	Various
Srholec (2010)	6	Czech Republic	1999-2001	1809	Obtained Results	Employees	Positive
Stuart (1999)	10	International	1986-1992	2685	Invested resources; Obtained Results	Sales	Positive
Tavassoli & Karlsson (2015)	6	Sweden	2002-2012	1722	Obtained Results	Employees	Positive; Null
Tello (2015)	18	Peru	2002-2007	294	IA; Obtained Results	Employees	Positive
Tether & Bascavusoglu-Moreau (2012)	3	United Kingdom	2002-2006	2206	Obtained Results	Employees	Positive
van Beers & Sadowski (2003)	5	Netherlands	1994-1996	1459	Obtained Results	Employees	Positive
van Beveren & Vandenbussche (2010)	3	Belgium	1998-2004	189	Obtained Results	Employees	Null
van Leeuwen & Klomp	8	Netherlands	1994-1996	1926	IA; Invested	Employees	Negative

(2006)					resources; Obtained Results		
Veugelers & Cassiman (2005)	1	Belgium	1990-1992	504	Obtained Results	Employees	Positive
Worter (2007)	1	Switzerland	1999-2005	2777	IA	Employees	Negative
Zoghi *et al.* (2010)	3	Canada	1999-2003	15433	Obtained Results	Employees	Positive
Zuluaga Jiménez *et al.* (2012)	5	Colombia	2003-2004	4819	Obtained Results	Employees	Positive

Note: last column tries to summarise main results in each article. Significantly positive and negative effects are labelled as “positive” and “negative” respectively, while non significant are “null”; extremely heterogeneous evidence is classified as “various”.
Source: authors.

Further description of data and full references of included articles can be found at:

https://drive.google.com/drive/folders/1v33MBjqyTXZdKJu8BZjPZMkpmBEx1Ckf?usp=sharing