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Innovation and productivity among heterogeneous firms☆

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ABSTRACT

This paper examines the links between firm innovation and productivity using the largest cross-country panel dataset assembled for this purpose to date. We use harmonized and comparable data on a total of 40,577 small, medium and large firms surveyed in the World Bank Enterprise Surveys (WBES) and provide some support for the reported patterns previously found in the innovation literature. Our results indicate that estimates from studies using cross-section data may be upward biased but nevertheless, innovative firms are significantly and economically more productive in both the manufacturing and services sectors.

1. Introduction

There is a high correlation between survival and improved firm productivity (Syverson, 2011). As such, can productivity be stimulated? Recent research suggests the answer is yes. Several papers point to firm characteristics, input and output demand and elements of the market structure as influencers of productivity growth (Melitz, 2003; Javorcik, 2004; Syverson, 2004, 2011; Aghion et al., 2014; among others). Similarly, a growing literature has shown that innovation and productivity are somehow related (Mulkay et al., 2001; Griffith et al., 2006; Huergo, 2006; Piga and Atzeni, 2007; Hall, 2010, 2011; Alvarez and Crespi, 2015; among others).[1] The vast majority of these studies point out that research and development (R&D) is positively correlated with innovation output which in turn is positively correlated with productivity.

This pass through of innovation to productivity improvement may happen through many channels. Hall (2011) highlights that innovation may increase the efficiency of resource use and leads to the forming of sustainable competitive advantages among innovating firms. Investment in R&D tends to increase absorptive capacity, assimilation of knowledge, and catch up among weaker firms (Crespi and Zuniga, 2012). Furthermore, innovation and application of new ideas could stimulate the formation of new sectors (structural change), changes in production structures, specialization, and a gradual expansion of more knowledge-intensive activities (Alvarez et al., 2015).

Yet, there are three important gaps in the literature which may lead to scepticism of this positive relationship between innovation and productivity. First, there has been a number of firm-level studies that have examined the relationship between firm innovation and productivity, but almost all use cross-section data (Mohnen and Hall, 2013).[2] This is partly due to the nature of innovation surveys, which solicits information on innovation activity up to three years prior and rarely re-sample (Hall, 2010). We know that innovation is risky, firm specific, and a firm's effectiveness in bringing it to fruition is most times inadequately monitored. This makes unobserved heterogeneity a potentially important source of variation among firms (Crowley and

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[1] Mohnen and Hall (2013) points out that innovation can be divided into technological innovations in the form of new products and services and non-technological innovations in the form of organizational or marketing changes.

[2] One notable exception is the study by Chudnovsky et al. (2006) which used a panel dataset for a sample of Argentine firms.

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McCann, 2018). Moreover, unobserved firm heterogeneity has been shown to be highly consequential in other strands of the literature, particularly as it relates to firm performance (Eckel and Near, 2010; Goldberg et al., 2010; De Loecker, 2011; Timoshenko, 2015).

Our first contribution to the literature is to explicitly account for unobserved firm heterogeneity in the innovation process by exploiting the uniquely available panel structure of our dataset. We use harmonized and comparable data on a total of 40,577 small, medium and large firms surveyed at least twice in 2002, 2005, 2006, 2009, 2010 or 2016 in the World Bank Enterprise Surveys (WBES). In so doing, we provide new information to the literature by shedding light on the possible impact that firm heterogeneity has on the link between innovation and performance.

A second gap in the literature is that cross-country analyses are rare, owing largely to the lack of harmonized cross-country innovation surveys (Alvarez et al., 2015). To date, most firm-level studies of the relationship between innovation and productivity have been national-level studies (Mulkay et al., 2001; Huergo, 2006; Piga and Atzeni, 2007; Hall, 2010); among others, with only a few of such studies taking a cross-country approach (Griffith et al., 2006; Alvarez and Crespi, 2015; Alvarez et al., 2015). The empirical evidence from the literature on economic geography suggests that, as it regards innovation, the world is highly uneven, both at an international and also on an intra-national scale (Crowley and McCann, 2018). There is also growing evidence that innovation varies across countries based on income. For instance, (Cirera and Muzi, 2016) point out that innovation in developing economies is likely to be different from innovation in developed countries – more incremental and less radical.[3] Furthermore, there is growing evidence of a spatial dimension to productivity differences (Acemoglu and Dell, 2010).

Our second contribution is in this vein. We build and use the largest cross-country panel dataset available in the literature to assess the relationship between innovation and productivity using a structural model in the mould of the Crepon-Duguet-Mairesse (CDM) framework (Crépon et al., 1998). The geographic coverage of our data is the widest to date for this type of study and spans Central and Eastern Europe (CEE), the Baltics, Asia and Latin America and the Caribbean (LAC).[4]

The final gap in the literature of relevance to this paper is that until recently, innovation in the services sector has been unexplored in terms of its role in productivity growth (Zahler et al., 2014). Recent evidence on innovation in services from developed economies and some (still scarce) from developing countries suggests that the services sector is as innovative as the manufacturing sector (Alvarez et al., 2015). Tether (2005) using information for several European countries finds that services firms in fact do innovate, although the propensity to innovate technologically is lower than manufacturing firms. Building on this literature, our final contribution is to explicitly compare and contrast the relationship between innovation and productivity across the manufacturing and services sectors.

Our findings comprehensively reinforce the traditional patterns in the innovation literature, whereby innovation effort, capital intensity of firms and human capital are important for product and process innovations which in turn significantly and economically improves productivity. Some important differences arise from our study that underscores the importance of tailored and contextualised innovation policies. For instance, we find strong evidence that unobserved firm heterogeneity is a potentially important source of variation among firms. Explicitly accounting for unobserved firm heterogeneity reduces the magnitude of the effect of innovation input on innovation output and of innovation output on productivity, although all maintain a positive significance in our regressions.

Not all business climate reforms are binding constraints to investing in innovation, giving some support to research that suggests that a hierarchy of pertinence can be devised as it regards business climate reforms (see Paunov and Rollo (2015) as an example). We show that firms that paid for security, had better access to short term credit through the use of a line of credit and are audited by an external auditor were more likely to invest in R&D but the functioning of customs is not a binding constraint for innovation related expenditure.

Similarly, the effect of investment in R&D and technology on the likelihood of witnessing an innovation output varies tremendously by sector. Investment in R&D and technology unequivocally increases the likelihood a firm innovates in the manufacturing sector but its effect is smaller and changes sign more frequently in the services sector. In addition, government support has a strong positive effect on all types of innovation in the manufacturing sector but only on process innovation in the services sector. Moreover, whilst process and product innovation are positively related to productivity in both the manufacturing and services sectors, the impact of process innovation is markedly greater in the services sector compared to the manufacturing sector. On the contrary, product innovation seems to have a greater effect on productivity in the manufacturing sector compared to the services sector.

These heterogeneities suggest that effective innovation polices cannot be based on a "one size fits all" approach. Stimulating investment in R&D by providing subsidies for R&D investment as an example, based on our results will have little effect on spurring innovation in the services sector. Whilst some polices make good sense in the aggregate and have very little downside risk (e.g. facilitating access to finance, improving government efficiency and reducing unnecessary bureaucracy and red tape, reducing corruption, etc.), to truly stimulate innovation requires micro-targeting and monitoring of reforms.

The article is organized as follows. Section 2 discusses the links between innovation and productivity. This is followed in Section 3 by a description of the data set and variables to be used in the study. Section 4 outlines the econometric model to be employed in the study, and the results are presented in Section 5. The final section contains a short discussion and some concluding remarks.

2. Innovation and productivity

Innovation has long been identified as critical for economic development (Schumpeter, 1934; Romer, 1990), but the analysis and measurement of the relationship between innovation and productivity is possibly one of the most controversial fields of work in empirical economics (Crespi and Zuniga, 2012). This controversy is due largely to issues related to measurement. Firstly, how is innovation measured? Widely used measures of innovation are R&D expenditures or patent counts but many researchers have argued that while these measures are quantifiable, they are fraught with weaknesses. Griffith et al. (2006) point out that R&D is a measure of inputs, and takes no account of the productivity and effectiveness of effort.

Further, R&D is likely highly correlated with size since only large firms can absorb the sunk costs associated with these investments. At the same time, patents are a crude measure of innovation outputs that captures only some types of invention. Moreover, filing for a patent is driven in large part by the extent to which a firm's management and/or ownership deems it important given the nature of the business, the institutional environment with regards to enforcement and appropriability, among other challenges. Also, is witnessing an innovation output and productivity changes simultaneously occurring events and is the relationship bi-causal?

Some of the earliest attempts at empirically linking innovation and

[3] As of the 2018 fiscal year, 78 countries were classified as high income (developed) countries by the World Bank, having Gross National Income (GNI) per capita of $12,236 or more. Using this classification, 33 of the countries in our sample are developing countries and 10 are developed countries.

[4] The majority of existing studies on innovation and productivity are limited to a single country or a specific industry (Cirera and Muzi, 2016). Some exceptions have focused on the experience in Latin America, using cross-country analysis (Raffo et al., 2008; Crespi and Zuniga, 2012; Alvarez and Crespi, 2015; Grazzi and Pietrobelli, 2016).

productivity were Griliches (1979) and later Pakes and Griliches (1980). Their approach was to model the determinants of innovation in a knowledge production function, which is then assumed to influence productivity in an output function. Most of this early literature analyses these relationships on aggregated country- or sector-level information (Hall, 2011). Nevertheless, considering the innovation results from the investment decisions made by individual firms, there is much to learn from microeconomic analysis about the correlations found at the macro-level.

2.1. Micro-level evidence

Crépon et al. (1998) was one of the first to use survey data to examine the relationship between innovation and productivity. Using their now well-known CDM model, they found a positive correlation between firm productivity and higher innovation output in France. A positive association between R&D, innovation and productivity was also found in Asian countries such as South Korea (Lee and Kang, 2007), Malaysia (Hegde and Shapira, 2007), Taiwan (Aw et al., 2011), China (Hu et al., 2005) and Latin American countries such as Argentina (Chudnovsky et al., 2006), Brazil and Mexico (Raffo et al., 2008) and Chile, Colombia, Costa Rica, Panama, Uruguay (Crespi and Zuniga, 2012; Alvarez and Crespi, 2015; Grazzi and Pietrobelli, 2016); and Caribbean countries (Crespi et al., 2017).

Nevertheless, this positive association is not universal across countries and types of innovation. For instance, Benavente (2006) finds no evidence that research supports this relationship for Chile. Raffo et al. (2008) found a significant impact of product innovation for Brazil and Mexico but not for Argentina. Chudnovsky et al. (2006) and Benavente (2006) found no significant effect of innovation on firm productivity (measured as sales per employee) in Argentina and Chile respectively.

Hall (2011) surveys 25 research papers using the CDM model and highlight that the positive relationship between innovation and productivity is primarily due to product innovation as the impact of process innovation is more variable, and often negative. This difference in the impact of product and process innovation highlighted above may be because the typical firm enjoys some market power and operates in the inelastic portion of its demand curve so that revenue productivity falls when it becomes more efficient (Mohnen and Hall, 2013). Another possible explanation is that there is so much measurement error in the innovation variable as captured through innovation surveys (Hall, 2011).

To further highlight this measurement issue, the relationship between innovation and productivity shows some variation depending on how innovation is measured. Roper et al. (2008) used both a binary and a continuous measure of product innovation and a binary indicator for process innovation to examine the relationship with productivity in Ireland. They find no significant effect of both innovation measures on productivity when either measure of innovation is binary but a significant negative effect for product innovation when using the continuous measure of innovation success. This negative effect may be because of time lags due to learning (Mohnen and Hall, 2013) or natural product life cycle disruptions (Roper et al., 2008). For instance, it is possible that the introduction of new products to a plant may disrupt production and reduce productivity (diversion of resources). Another possibility is that newly introduced products are initially produced inefficiently with negative productivity consequences before becoming established.

The best way to deal with these potential issues related to measurement errors is to develop and use better instruments of innovation output (Mohnen and Hall, 2013). There are many challenges with finding such instrumental variables however in that they tend to be time, location and context specific and thus, unfortunately, most innovation surveys do not contain such information. A second best strategy to get around some of these potential measurement errors issues is to conduct cross-country analyses and isolate some of the measurement errors by exploiting country variations (Bertrand and Mullainathan, 2001).[5] Griffith et al. (2006) conducted one of the earliest cross-country micro-econometric comparisons across four European countries-France, Germany, Spain and the United Kingdom and find no significance of process innovation on productivity in all other countries but France. They find that product innovation positively influences productivity in all countries but Germany.

Similarly, Crespi and Zuniga (2012) conduct the first cross-country analyses in Latin America and reported that productivity gaps in the manufacturing sector between innovative and non-innovative firms are much higher compared to industrialized countries. In a more recent cross-country study, Crespi et al. (2016) analyse this relationship and use a wide range of innovation indicators to describe the innovation behaviour of manufacturing firms in Latin America using the WBES for 17 Latin American economies. They present evidence confirming the relationship between innovation input and output, and innovation output and productivity. They also show that the effect of product innovation is almost twice the effect of process innovation on firm productivity.

2.2. The services sector

Existing studies have highlighted a number of specific characteristics of services such as their intangibility, simultaneity of production and consumption, and perishability, making innovation a potentially important activity in the sector (Savona and Steinmueller, 2013). Yet, there is limited empirical evidence on the links between innovation and productivity in services, even though in many countries, services are already the largest sector in the economy and an important determinant of overall productivity growth.

Zahler et al. (2014) using firm-level innovation survey for Chile to compare the manufacturing and tradable services sector, finds that even though services firms have on average a much lower propensity to export than manufacturing firms, services exports are less dominated by large firms and tend to be more skill intensive than manufacturing exports. In addition, they show that services firms appear to be as innovative as, and in some cases more innovative than manufacturing firms in terms of both inputs and outputs of technological innovative activity, even though services innovations more often take a non-technological form.

Similarly, Tether (2005) using information for several European countries, finds that services firms in fact do innovate, although the propensity to innovate technologically is lower than manufacturing firms. He finds some differences in the innovation orientation of services firms: they are more likely to innovate in organization change than firms in the manufacturing industry. Furthermore, Alvarez et al. (2015) analyses the relationship between innovation and productivity in the Chilean services sector and find that services firms are as innovative as firms in the manufacturing industry. Leiponen (2012) focuses on the effects of R&D investments in Finland manufacturing and services firms and shows that R&D has a significant effect on innovation for both industries.

3. Data and limitations

We use a purpose built dataset with information on 40,577 small, medium and large firms from the WBES (see Table 1). WBES data is available for over 130,000 firms in 135 countries.[6] We focus on only 43

[5] The intuition, which we admit is not perfect, is that it is unlikely that over-reporting innovation rates survives in any meaningful way across countries and regions.

[6] The World Bank has been conducting these surveys since 2000 for the manufacturing and services sectors in every region of the world. In each country, businesses in the cities or regions of major economic activities are interviewed. The WBES surveys formal (registered) companies with five or more employees, but excludes firms that are wholly government owned. See www.enterprisesurveys.org/ for further information.

Table 1
Distribution of firms by country and year.
Source: WBES.

	2002	2005	2006	2007	2009	2010	2016	Total
Albania	170	204	0	304	54	0	0	732
Argentina	0	0	549	0	0	776	0	1325
Armenia	171	351	0	0	374	0	0	896
Azerbaijan	170	350	0	0	380	0	0	900
Belarus	250	325	0	0	273	0	0	848
Bolivia	0	0	493	0	0	354	0	847
Bosnia	182	200	0	0	361	0	0	743
Bulgaria	250	300	0	1015	288	0	0	1853
Chile	0	0	519	0	0	660	0	1179
Colombia	0	0	597	0	0	605	0	1202
Croatia	187	236	0	633	104	0	0	1160
Czech Republic	268	343	0	0	250	0	0	861
Dominican Republic	0	0	0	0	0	360	359	719
Ecuador	0	0	331	0	0	240	0	571
El Salvador	0	0	573	0	0	222	0	795
Estonia	170	219	0	0	273	0	0	662
FYROM	170	200	0	0	366	0	0	736
Georgia	174	200	0	0	373	0	0	747
Guatemala	0	0	476	0	0	358	0	834
Honduras	0	0	368	0	0	191	0	559
Hungary	250	610	0	0	291	0	0	1151
Kazakhstan	250	585	0	0	544	0	0	1379
Kyrgyz	173	202	0	0	235	0	0	610
Latvia	176	205	0	0	271	0	0	652
Lithuania	200	205	0	0	276	0	0	681
Mexico	0	0	1480	0	0	1012	0	2492
Moldova	174	350	0	0	363	0	0	887
Montenegro	20	18	0	0	116	0	0	154
Nicaragua	0	0	350	0	0	195	0	545
Panama	0	0	182	0	0	222	0	404
Paraguay	0	0	156	0	0	192	0	348
Peru	0	0	181	0	0	681	0	862
Poland	500	975	0	0	455	0	0	1930
Romania	255	600	0	0	541	0	0	1396
Russia	506	601	0	0	1004	0	0	2111
Serbia	230	282	0	0	388	0	0	900
Slovakia	170	220	0	0	275	0	0	665
Slovenia	188	223	0	0	276	0	0	687
Tajikistan	176	200	0	0	360	0	0	736
Ukraine	463	594	0	0	851	0	0	1908
Uruguay	0	0	287	0	0	450	0	737
Uzbekistan	260	300	0	0	366	0	0	926
Venezuela	0	0	152	0	0	95	0	247
Total	6153	9098	6694	1952	9708	6613	359	40,577

of these countries for two reasons. First, for inclusion in our assessment, given our focus, the innovation component of the survey must have been implemented as an integral part of the survey, something not done in all countries covered by WBES.[7] Second, the survey must have been implemented in each country at least twice so that a panel dataset could be established.

Table 2 shows the key statistics for all the variables used in this analysis. In terms of innovation, the survey questions require that managers respond to questions on whether the firm has implemented product or process innovation activities as well as their R&D and technological involvement in the last three fiscal years. The specific questions are, *"Over the last three fiscal years: (i) Did this establishment introduce onto the market any new or significantly improved products?; (ii) Has this establishment introduced any new or significantly improved production processes including methods of supplying services and ways of delivering products?; (iii) Has the firm invested in R&D over the last three fiscal years and if yes, how much?; (iv) What is this firms annual expenditure on purchases of information technology?"*

Overall, 55% of the firms in our dataset declare to be innovators (introduced either a process or product innovation). Regarding process and product innovation complementarity, only 30% of our sample firms introduced the two types of technological innovation in the same three-year time period. This is of interest because as pointed out by Mothe et al. (2015), some empirical studies have acknowledged the existence of synergistic effects that may arise due to complementary/substitution effects for product/process innovation but results from these studies are inconclusive. Including this extension to our analysis is intended to shed some light on this issue. In particular, we build two aggregate innovation measures to capture if the firm undertook both types of innovation together, or at least in quick succession of each other (Innovation 2) or independently (Innovation 1). About 15% of the firms in the sample reported investing in R&D with a R&D intensity (R&D investment per worker) of 7.33.

Throughout the literature, various drivers of innovations have been identified. For instance, innovation is associated with investments in machinery and equipment (Romer, 1990), investments in R&D (Crépon et al., 1998; Mairesse et al., 2005; Crespi et al., 2016), investments in human capital (Romer, 1990; Crespi et al., 2016) and expenditures on training (Crespi et al., 2016) designed to enhance the absorptive capacity of the workforce (Alvarez et al., 2015). In terms of firm size, the broad consensus is that small and very large firms have the highest innovation propensities (Hall, 2011), although the sector (Cainelli et al., 2005) and the ownership structure of the business also matters (Zahler et al., 2014). We follow this literature and include a wide battery of control variables as highlighted in Table 2.

3.1. Limitations

Notwithstanding the benefits of the WBES, there are at least four limitations to consider. First, the WBES does not cover informal firms. If the proportion of firms in the informal sector is small, this would be innocuous but as pointed out by Crespi et al. (2016), in countries like Paraguay and Nicaragua, the informal sector accounts for an estimated 70% of total GDP. As such, we urge some caution with the interpretation of our findings since unintentionally they condition on formality.

Second, earlier WBES solicited financial data at the national currency level. We follow the World Bank methodology and use the market exchange rates to convert all financial variables to US dollars and subsequently deflate these numbers to the reference year (2010) using the CPI from the Penn World Tables. An alternative would be to use a measure of purchasing power parity (PPP) or the rate at which the currency of one country would have to be converted into that of another country to buy the same number of goods and services in each country.[8] Throughout the empirical implementation we always use country fixed effects if firm fixed effects are not used. The use of country fixed effects partly mitigates any issues caused by any persistent discrepancies between purchasing power parity and exchange rates.

Third, although largely consistent and harmonious across all countries, there are some important distinctions between the implementation strategy across regions and time. For instance, in Latin America in 2010, the innovation module of the WBES excluded the service sector and so analysis using 2010 data from Latin America are conditioned on the manufacturing sector. Although we use industry fixed effects throughout the analysis in appropriate places, we present results having split the sample according to the survey implementation strategy (BEEPS versus LACES) to highlight any heterogeneity arising from this implementation strategy.

Fourth, our measure of innovation is based on self-reported recall activity in a survey that covers many other areas of the firm's activity.

[7] As an example, Brazil was surveyed in 2009 but the relevant questions on R&D could not be identified and so this country is not included in our analysis.

[8] See Crespi et al. (2016) for a very persuasive argument why this would not be a good idea in this case.

Table 2
Descriptive statistics.
Source: WBES. The number of observations for all variables (except R&D intensity) was 40,577 (6412). All monetary values are converted to real US$ by using the consumer price index (CPI) from the World Development Indicators and annual averaged exchange rate from the Penn World Tables version 8.

	Definition	Mean	Std. dev.	Min	Max
Labour Productivity	Log sales per worker (US$)	13.0	4.2	1	27
Product Innovation	(0/1) if firm introduced a process innovation	0.4	0.5	0	1
Process Innovation	(0/1) if firm introduced a product innovation	0.5	0.5	0	1
Innovation 1	(0/1) if firm introduced product or process innovation	0.6	0.5	0	1
Innovation 2	(0/1) if firm introduced product and process innovation	0.3	0.5	0	1
R&D intensity	R&D expenditure per worker (US$)	7.3	2.9	0	20
Invested in R&D	(0/1) if firm invested in R&D	0.2	0.4	0	1
Subsidiary	(0/1) if the firm is a part of a larger firm	0.1	0.3	0	1
FDI	(0/1) if firm has 10% or more of foreign ownership	0.1	0.3	0	1
Size 1	(0/1) if the firm has less than 20 employees	0.4	0.5	0	1
Size 2	(0/1) if the firm has between 20 and 99 employees	0.3	0.5	0	1
Size 3	(0/1) if the firm has 100 or more employees	0.2	0.4	0	1
Skill	Proportion of skilled full time workers (%)	1.8	4.1	0	63
Human capital	Fraction of workers with bachelor degree (%)	26.4	24.1	0	100
Government support	(0/1) if the firm received government support for innovation in the last three years	0.1	0.3	0	1
Foreign technology	(0/1) if the firm uses foreign technology	0.1	0.2	0	1
Broadband	(0/1) if the firm has a broadband internet connection	0.4	0.5	0	1
Fixed Asset	(0/1) if the firm invested in fixed assets in the last three years	0.5	0.5	0	1
Age	Age of firm (years)	18.4	18.3	1	310
Importer	(0/1) if the firm uses imported inputs	0.7	0.5	0	1
Exports	Fraction of sales exported (%)	10.5	24.9	0	100
Managerial Experience	Managerial experience (years)	17.8	9.2	0	70
Diversification	Fraction of sales from the firm's main product/service	82.8	20.8	1	100
Competition 1	(0/1) 1 competitor	0.0	0.1	0	1
Competition 2	(0/1) 2 competitors	0.0	0.1	0	1
Competition 3	(0/1) 3 competitors	0.1	0.3	0	1
Competition 4	(0/1) 4 competitors	0.1	0.3	0	1
Competition 5	(0/1) more than 5 competitors	0.1	0.3	0	1
Email	(0/1) if the firm uses email to communicate with customers	0.7	0.4	0	1
Website	(0/1) if the firm has its own website	0.6	0.5	0	1
Certification	(0/1) if the firm has an internationally-recognized quality certification	0.2	0.4	0	1
Capital	Log total book value of fixed assets (US$)	6.7	3.3	−8.5	21
Material	Log total material inputs (US$)	13.1	3.4	−1.3	22
Capacity Utilization	Capacity utilization (%) in last fiscal year	76.8	17.7	0	100
Line of Credit	(0/1) if the firm has an active line of credit	0.3	0.5	0	1
Customs	(0/1) if customs administration is a constraint for the firm	0.3	0.5	0	1
Delivery	Proportion of inputs paid for on delivery (%)	44.1	39.5	0	100
Overdraft	(0/1) if the firm has an active overdraft facility	0.3	0.5	0	1
Security	(0/1) if the firm paid for security in the last three years	0.6	0.5	0	1

Cirera and Muzi (2016) present the results of an experiment that compares self-reported innovation rates in short questionnaires like the WBES and more specific innovation surveys with follow-up innovation related questions depending on answers given. They show that a small set of questions included in a multi-topic, firm-level survey like WBES tends to overestimate innovation rates.

Furthermore, the information on process and product innovation that we use is based on dummy variables instead of a continuous measure like the innovative sales share. Bertrand and Mullainathan (2001) show the likely bias when analysing subjective data given their likely correlation with context variables. The authors conclude that while subjective variables can be carefully used as explanatory variables or to explain behavioural differences between individual agents, models that use subjective data as dependent variables are likely to produce biased estimates.

The best remedy to these limitations is to use both subjective and objective measures of innovation and contrast empirical findings. Unfortunately, this is not possible for our analysis as no comparable objective data was sought across the sample countries in the innovation module of WBES. As such, we exploit: (i) the wide regional variation to minimize the scale of measurement errors issues; and (ii) the panel structure of the dataset to account for firm heterogeneity.

4. Methodology

Our analysis is very closely related to all previous studies using the CDM model to estimate the relationship between innovation and productivity. It is most closely related to Crespi et al. (2016) in that we employ a similar dataset but we contribute to the literature in three important ways. First, we expand the battery of countries to provide a more complete global view of the relationship between innovation and productivity. Second, we explicitly account for firm heterogeneity in the production of knowledge by exploiting the panel structure of our dataset. Third, we include data for the services sector and compare and contrast the associations with the manufacturing sector.

The CDM model is based on a multi-equation framework that takes into account the whole process of innovation thereby considering the decisions of the firms to engage in innovation activities, the results of these efforts, and their impact on productivity. The three stages can therefore be summarized in reverse order algebraically as follows:

$$P_{\mathrm{it}} = \beta_1 K_{\mathrm{it}} + \beta_2 X_{\mathrm{it}} + \psi_i + \eta_{\mathrm{it}} \tag{1}$$

$$K_{\mathrm{it}} = \gamma S^*_{\mathrm{it}} + \delta W_{\mathrm{it}} + \rho_i + \xi_{\mathrm{it}} \tag{2}$$

where P_{it} is the log of real sales per worker (labour productivity), ψ_i and ρ_i are firm fixed effects and X_{it} and W_{it} are matrices of control variables, and η_{it} and ξ_{it} are normally distributed error terms. K_{it} deserves a more detailed explanation because it is this link to productivity that creates the empirical challenge.

K_{it} is knowledge outputs, the introduction of a new product or process (technological innovation) at the firm level. To generate these knowledge outputs, firms must exert some innovation effort (S^*_{it}).

Unfortunately, these efforts are poorly monitored, measured and reported. To highlight how this may happen, consider a manager that decides one day to reorganize the layout of his/her manufacturing plant. Undertaking this reorganization, no matter how trivial it is viewed at the time, is an attempt at innovating. Deciding to reorganize is one part of the innovation input decision, another decision is often made about how much effort (money, time, energy, etc.) should be exerted on this particular activity vis a vis other production related activities. Neither of these decisions would likely be recorded accurately, if recorded at all.

It is this lack of recording/reporting on efforts of this nature that make innovation effort a latent variable. As such, S_{it}^* is unobserved (a latent variable). Algebraically this situation can be formalized as follows:

$$S_{\mathrm{it}}^* = Z_{\mathrm{it}}'\beta + u_{\mathrm{it}} \tag{3}$$

where Z_{it} is a vector of determinants of innovation effort so that β is a vector of parameters, and u_{it} is an error term with the usual properties. As done in the literature, we proxy a firms innovative effort using the natural log of expenditures on R&D and technology per worker. But, as highlighted by Griffith et al. (2006), it is widely observed in the data that many firms report witnessing an innovation output but do not report investing in innovation. One simple explanation for this is reporting error but as convincingly argued by Hall (2011), this is unlikely given the fact that this occurrence is witnessed in so many different countries. A more plausible explanation is selection bias due to the fact that a firm's manager may not report innovation expenditure if it falls below an unknown minimum threshold c.

To address this selection issue, we assume the following selection equation describing whether the firm decides to do (and/or report) innovation investment or not:

$$G_{\mathrm{it}} = \begin{cases} 1 & \text{if} \quad G_{\mathrm{it}}^* = r_{\mathrm{it}}'\theta + e_{\mathrm{it}} > c \\ 0 & \text{if} \quad G_{\mathrm{it}}^* = r_{\mathrm{it}}'\theta + e_{\mathrm{it}} \le c \end{cases} \tag{4}$$

where G_{it} is a binary endogenous variable for innovation decision that is equal to zero for firms that do not invest in innovation and one otherwise. G_{it}^* is a corresponding latent variable such that firms decide to do (and/or report) innovation investment if it is above a certain threshold level c, and where r_{it} is a vector of variables explaining the innovation investment decision such that θ is the parameter of interest, and e_{it} is an error term. Conditional on a firm doing innovation activities, we can observe the amount of resources invested in innovation as:

$$S_{\mathrm{it}} = \begin{cases} S_{\mathrm{it}}^* = Z_{\mathrm{it}}'\beta + u_{\mathrm{it}} & \text{if} \quad G_{\mathrm{it}} = 1 \\ 0 & \text{if} \quad G_{\mathrm{it}} = 0 \end{cases} \tag{5}$$

Assuming u_{it} and e_{it} in Eqs. (4) and (5) are bivariate normal with zero mean, variances of unity and correlation ρ_{ue}, we estimate these equations using a generalized Tobit model.

As suggested by Griffith et al. (2006) all these equations are estimated as a three stage recursive model that does not allow for feedback effects between equations. Eqs. (4) and (5) are estimated as a Tobit model and the residuals saved. These residuals are then used to estimate Eq. (2) using a linear probability model so that we can include a firm fixed effect and the residuals again saved. These residuals are then used as an instrument for knowledge output in Eq. (1) which is estimated using two stage least squares.

4.1. Identification

As done by most of the papers estimating the CDM model, we use size as a parameter shifter (exclusion restriction) in the three stages of our estimation. That is, size enters explicitly in all equations except Eq. (5), because R&D and technological expenditure investment intensity is implicitly scaled for size. Van de Vrande et al. (2009) argue that small and medium sized firms are hampered by lack of financial resources, scant opportunities to recruit specialized workers, and a narrow innovation portfolio which curtails the spreading of the high risks associated with innovation.

Considering that the majority of the firms in our sample are small and medium sized, we also include managerial perceptions of the institutional environment that the firm operates in. Despite the shortfalls of managerial perceptions as control variables (Ayyagari et al., 2012), they have the advantage that these perceptions vary tremendously across firms. Further, they are likely to impact only on the decision to invest since small and medium sized firms do not have the resources to spread risk relative to large firm (Beck et al., 2008). For these reasons we deem managerial perceptions of the institutional environment to be valid exclusion restriction in our study.

To be precise, we include a dummy variable for the accessibility of formal short term financing among firms (line of credit with a financial institution); a dummy variable for the relative effect of customs as a constraint for the operations of the firm; and a dummy variable reflecting if the firm's financial records are audited by an external auditor. We also include a dummy variable equal to one if the firm pays for external security services which is intended as a proxy for the impact of crime and violence on firms and indicates one possible substitute for innovation investments. Overall, these variables were selected because they were found to be the most restrictive for the operations of the firms in developing countries (see Morris, 2017 and Grazzi and Pietrobelli, 2016 as examples).

Whilst the Tobit model addresses issues related to selection bias, it does not completely address the fact that innovation effort is not completely modelled by R&D and technological expenses. In this regard, Hall (2011) notes that a sizeable portion of these efforts are firm specific and never monitored. Further, firms are heterogeneous in terms of managerial ability, management effort, and entrepreneurial orientation (Bernard et al., 2007). These are features of a firm which may affect both innovation effort and outcomes, generating endogeneity in cross-section estimates, even after the adoption of sector and industry fixed effects. As such, we explicitly account for unobserved firm heterogeneity in the innovation process by exploiting the uniquely available panel structure of our dataset. We include firm fixed effects in the estimation of Eq. (2), something that, to the best of our knowledge, has not been done in the literature. Other exclusion restrictions included in the transition from Eq. (2) to Eq. (1) are: (i) a dummy variable if firms have a formal mechanism for appropriating intellectual property; (ii) a dummy for being a subsidiary of a larger firm; (iii) age; (iv) a dummy variable for being an exporter; (v) managerial experience; (vi) a dummy variable for having an internationally recognized quality certification; and (v) the proportion of the firm owned domestically.

The three most important hypothesis we test based on this empirical strategy are: (i) innovation effort positively influences innovation output which positively influences productivity; (ii) firm heterogeneity exerts an upward bias on the generation of knowledge; and (iii) the effect of innovation on productivity is stronger in manufacturing compared to services but with a varied effect of process and product innovation in each sector.

5. Results

To make our results easy to follow we separate the three stages of the innovation process described earlier according to the estimation of the key equations. The next three sub-sections reflect these stages.

5.1. Innovation investment and intensity

The main results on the decision to invest are presented in Table 3. The table shows marginal effects evaluated at the sample mean for whether a firm invests in innovation and how much it invests. We show pooled results which combine firms in the manufacturing and services sectors and then disaggregate these sectors to compare and contrast

Table 3
Innovation investment and innovation intensity.

	Pooled sample		Manufacturing		Services	
	Intensity	R&D	Intensity	R&D	Intensity	R&D
Age	−0.003***	0.002***	−0.002*	0.002***	−0.006**	0.004***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.003)	(0.001)
Subsidiary	−0.049	−0.064*	−0.066	−0.155***	0.217	−0.725***
	(0.076)	(0.037)	(0.077)	(0.037)	(0.866)	(0.179)
Experience	0.004	0.005***	0.007***	0.005***	−0.028	−0.004
	(0.002)	(0.001)	(0.002)	(0.001)	(0.048)	(0.004)
FDI	0.097	−0.035	0.097	0.043	0.279**	0.265***
	(0.059)	(0.028)	(0.069)	(0.032)	(0.140)	(0.046)
Human capital	0.010***	−0.000	0.013***	0.001	0.010***	0.003***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)
Diversification	0.001	−0.002***	0.000	−0.001***	−0.017**	−0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.001)
Foreign technology	0.202**	0.453***	0.150*	0.319***	0.354	−0.026
	(0.080)	(0.036)	(0.076)	(0.035)	(0.691)	(0.224)
Broadband	−0.122	−0.251***	−0.030	0.137***	0.934	0.498***
	(0.108)	(0.038)	(0.062)	(0.027)	(0.736)	(0.079)
Email	0.153	0.416***	0.190*	0.189***	−0.065	−0.070
	(0.109)	(0.036)	(0.111)	(0.039)	(0.171)	(0.059)
Website	0.164**	0.285***	0.177**	0.228***	−0.770	−0.218***
	(0.076)	(0.029)	(0.074)	(0.028)	(0.731)	(0.082)
Certification	0.173***	0.296***	0.192***	0.300***	0.201	0.258***
	(0.060)	(0.024)	(0.067)	(0.026)	(0.130)	(0.047)
Competition 2	0.345**	0.169**	0.573***	0.271***	−0.368	1.729***
	(0.156)	(0.074)	(0.161)	(0.073)	(1.560)	(0.660)
Competition 3	0.137**	0.320***	0.385***	0.474***	1.715**	1.182***
	(0.067)	(0.030)	(0.083)	(0.030)	(0.772)	(0.261)
Competition 4			0.476***	0.426***		
			(0.080)	(0.030)		
Size		0.000***		0.000***		0.000***
		(0.000)		(0.000)		(0.000)
Security		0.242***		0.280***		0.217***
		(0.021)		(0.025)		(0.035)
Customs		0.160***		0.227***		0.188***
		(0.020)		(0.023)		(0.035)
Line of Credit		0.255***		0.086***		−1.173***
		(0.027)		(0.025)		(0.118)
Audit		0.190***		0.201***		0.273***
		(0.021)		(0.024)		(0.035)
Mills Lambda		0.607***		0.417***		0.748***
		(0.144)		(0.156)		(0.261)
N		37,298		20,753		16,545

Notes: The numbers are marginal effects (at the sample mean) for the probability of investing in innovation and for the expected value of innovation investment intensity conditional on a firm investing in innovation, respectively. All regressions include industry, country and time fixed effects. The pooled sample covers all the firm in our dataset and the two sub-samples are for Latin America and the other developing economies separated.
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

investment in innovation by sector. As discussed earlier, we consider that all firms invest in innovation but only some report doing so because there is a minimum threshold under which firms tend not to report or even record these investments.

The results confirm the validity of the choice of a sample selection model with correlated disturbances. In particular, the correlation coefficient between the disturbances (Rho) from the two equations is positive and significant at normal levels of testing. In some sense, this is a validation that in fact there is selection bias associated with the strict use of firms that report to be investing in innovation as there is a fraction of firms that do not report because these investments are below a certain threshold.

To highlight the relative validity of our parameter shifters, overall, the decision to invest in R&D is strongly correlated with the size of the firm. Large firms from both the manufacturing and services sectors are more likely to invest in innovation, although the coefficient on size as shown in the table is relatively small, indicating its effect may not be that great. Firms that paid for security, had better access to short term credit through the use of a line of credit and are audited by an external auditor were more likely to invest in R&D. Interestingly, firms whose managers reported that dealing with customs was a constraint for their operations were also more likely to invest in R&D, suggesting that although the functioning of customs is a key business climate variable, it is not a binding constraint for innovation related expenditure.

Older firms are more likely to invest in R&D but do so less intensively. Access to external knowledge is positively related to the decision to invest in innovation. Specifically, firms that had an internationally recognized quality certification, used foreign technology, had broadband and used email to communicate with customers and suppliers are positively related to investment in R&D. Similarly, increasing the proportion of workers with at least a bachelors degree is positively correlated with the decision to invest in innovation and also the intensity with which they invest in innovation. Firms make the decision to invest in innovation as a way of dealing with competition intensity. On the contrary, firms that are subsidiaries of a larger firm, and those that are less diversified in its product/service offerings are less likely to invest in innovation and do so less intensively.

Some interesting differences arise between the manufacturing and

Table 4
The impact of R&D intensity on innovation output (knowledge production).

	Process	Product	Innovation 1	Innovation 2
Cross section	0.282***	0.345***	0.294***	0.334***
	(0.014)	(0.015)	(0.014)	(0.015)
Panel	0.164***	0.215***	0.181***	0.198***
	(0.050)	(0.050)	(0.050)	(0.048)
BEEPS	0.059*	0.114***	0.041	0.132***
	(0.034)	(0.035)	(0.032)	(0.034)
LACES	0.228***	0.265***	0.296***	0.197***
	(0.037)	(0.038)	(0.038)	(0.034)
Manufacturing	0.249***	0.316***	0.337***	0.228***
	(0.049)	(0.048)	(0.048)	(0.047)
Services	0.164**	−0.012	0.053	0.099*
	(0.075)	(0.063)	(0.081)	(0.056)

Notes: These results are from estimating the determinants of undertaking technological innovation where our main variable of interest is R&D intensity shown in this table. Each column shows a different regression using OLS. The panel data estimates include firm and time fixed effects while the cross section data estimates include country, industry and time fixed effects. Standard errors in parentheses are clustered at the firm level.
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

services sector as it regards the decision to invest innovation. Experience is positively correlated with the decision to invest in R&D among manufacturing firms but we find no evidence that it significantly influences this decision in the services sector. This is also true for firms that use foreign technology but contrarily firms that have at least 10% foreign ownership are more likely to invest in R&D in the services sector but not so in the manufacturing sector.

These deviations also extend to the intensity with which firms invest in innovation. Many of the variables which significantly impact innovation investment intensity in the manufacturing sector do not impact this decision in the services sector. For instance, managerial experience, use of foreign technology, use of basic information communication technology such as email and websites to communicate with customers and suppliers and having an internationally recognized quality certification all significantly impact the decision to innovate among manufacturing firms but have a neutral effect on this decision in the services sector. This provides some supporting evidence that the drivers of innovation are very different for firms in the manufacturing and services sector and suggests that innovation policy should be tailored to account for this heterogeneity.

5.2. Knowledge production

As highlighted earlier, we consider four different types of innovation outputs for all our results. These are product innovation, process innovation and two aggregated measures of innovation that capture the relationship between these two technological innovation output, Innovation 1 (product or process) and Innovation 2 (product and process). Given our research questions, we also consider several dimensions of heterogeneity. These include variation due to firm heterogeneity (results using cross-section versus panel data); variation across geographic region (BEEPS versus LACES); and variation across sector (manufacturing versus services firms). All these results are summarized in Table 4 after estimating the knowledge production function as described in Eq. (2).[9]

As shown in Table 4, there is a positive and significant correlation between R&D intensity (investment in R&D per worker) and the likelihood a firm will innovate. In fact, from our baseline model a 10% increase in R&D intensity translates to a 1.64% increase in the probability that a firm will undertake process innovation and 2.15% increase for the probability a firm undertakes a product innovation. Regarding the impact of firm heterogeneity, there is strong evidence of an upward bias in the cross-section estimates. As expected, throughout our analysis, explicitly accounting for unobserved firm heterogeneity using firm fixed effects reduces the coefficients on the key variables covered in Table 4. Moreover, we split the sample by geographic region, separating the countries that participated in the BEEPS from those that were surveyed under the LACES. These results show no significant difference compared to our baseline model and underscore the underlying intuition of a positive association between R&D investment and the probability of witnessing a technological innovation.

The effect of R&D intensity on the likelihood a firm innovates in the manufacturing sector is always positive in our results. A 10% increase in R&D investment translates to a 2.49% increase in the probability that a firm will undertake process innovation and 3.16% increase in product innovation. Similarly, R&D investment positively drive innovation in the services sector but its effect is smaller and is more "noisy" compared to the manufacturing sector. This, we suggest may be due to the fact that R&D may not be a typical innovation investment for services firms (see Mohnen and Hall, 2013 for more on this).

5.3. Output production

Finally, we present summarized results having estimated the output production function as described in Eq. (1) in Table 5. The standard errors in parentheses are clustered at the firm level and all regressions are from IV regressions. The first stage regression results all have significant *F*-statistics and are large enough not to cause any concerns that the instruments are under-performing.[10] We estimate the effect of innovation on three measures of productivity, labour productivity (log sales per worker) and total factor productivity (TFP) using both the Olley and Pakes method and the Levinsohn and Petrin method.[11]

Our results indicate that innovation has a strong and economically significant effect on productivity, even when controlling for intermediate inputs and capital stock per worker, employment, and human capital. From our baseline results, firms are 13% (30%) more productive compared to other firms if they undertook a process innovation (product innovation) in the last three years. The implication of this result is that, consistent with Crespi et al. (2016), product innovation is over twice as beneficial for firms in our sample.

Similar to above, we examine heterogeneity across the broad geographic groupings of countries in the dataset by separating firms surveyed using the LACES from other countries surveyed using BEEPS. At this stage our main concern is the possibility that bias may arise in our results as a result of cross-region shocks. For instance, Gruss (2014) show that Latin America is highly dependent on commodities and has greatly benefited from the recent commodities boom between 2000 and 2011. Although we do not consider commodities firms directly, their connection to the regional economy and as a result pass through of economic fortunes from this boom could present one avenue through which a cross region shocks may influence our results. This impact we believe is adequately managed since we use interactions of country, industry, and time fixed effects. Nevertheless, we show these results for comparison. These results are also presented in Table 5. The coefficients in countries surveyed under LACES version of WBES are all higher than those for firms surveyed under BEEPS version, for all variations of

[9] The corresponding detailed results tables are presented as Tables A1–A3 in the Appendix.

[10] Detailed out put tables are presented in Tables A4–A7. The first stage IV results can be made available upon request.

[11] For both of these methods, we use the log of sales as the dependent variable; size, proportion of skilled workers in the firm as free variables; capital as the state variable; and estimates of realized material cost as the proxy variable.

Table 5
The impact of innovation on productivity.

	Labour productivity	TFP_OP	TFP_LP	Labour productivity	TFP_OP	TFP_LP
	Process innovation			Product innovation		
Cross section	0.168**	0.486**	0.470**	0.284***	0.483**	0.456**
	(0.067)	(0.237)	(0.220)	(0.073)	(0.231)	(0.215)
Panel	0.134*	0.108	0.116*	0.304***	0.324**	0.301**
	(0.070)	(0.077)	(0.069)	(0.074)	(0.149)	(0.137)
BEEPS	0.219***	0.071	0.023	0.164*	0.243***	0.212**
	(0.072)	(0.123)	(0.118)	(0.090)	(0.093)	(0.089)
LAC	0.698**	0.081	0.084	0.683***	0.438*	0.340*
	(0.335)	(0.112)	(0.086)	(0.256)	(0.225)	(0.180)
Manufacturing	0.152**	−0.016	−0.025	0.292***	0.204**	0.181**
	(0.070)	(0.058)	(0.050)	(0.075)	(0.082)	(0.075)
Services	0.787***	0.107**	0.063*	0.927***	0.172**	0.093
	(0.254)	(0.042)	(0.036)	(0.292)	(0.071)	(0.061)
	Innovation 1			Innovation 2		
Cross section	0.270***	0.420**	0.399**	0.166**	0.582**	0.558**
	(0.062)	(0.186)	(0.173)	(0.080)	(0.296)	(0.275)
Panel	0.257***	0.217**	0.200**	0.161*	0.275*	0.270**
	(0.064)	(0.103)	(0.093)	(0.082)	(0.143)	(0.131)
BEEPS	0.229***	0.248*	0.217	0.125	0.157*	0.116
	(0.069)	(0.140)	(0.138)	(0.093)	(0.094)	(0.092)
LAC	0.662**	0.144	0.113	0.728**	0.487*	0.395*
	(0.280)	(0.104)	(0.079)	(0.302)	(0.270)	(0.217)
Manufacturing	0.288***	−0.007	−0.013	0.120	0.179*	0.152
	(0.063)	(0.063)	(0.054)	(0.083)	(0.107)	(0.097)
Services	0.576**	0.167***	0.118***	1.560***	0.098	0.007
	(0.269)	(0.052)	(0.042)	(0.303)	(0.070)	(0.066)

Notes: These results are from estimating the determinants of undertaking technological innovation where our main variable of interest is R&D intensity. Each column shows a different regression using OLS. TFP_OP refers to estimating TFP using the Olley and Pakes method while TFP_LP is TFP using the Levinsohn and Petrin method. The panel data estimates include firm and time fixed effects while the cross section data estimates include country, industry and time fixed effects. Standard errors in parentheses are clustered at the firm level.

* Significant at 10% level.

** Significant at 5% level.

*** Significant at 1% level.

productivity used in our analysis. This suggests that innovation may have a higher pay-off in LAC compared to other economies.

Further, there is some variation in the impact of innovation on productivity in the manufacturing and services sectors. Whilst both types of technological innovation are positively related to productivity, the impact of process innovation is markedly greater in the services sector. On the contrary, product innovation seems to have a greater effect on productivity in the manufacturing sector compared to the services sector, except for when labour productivity is used.

6. Discussion and conclusion

A key objective of this article was to analyse the effect of innovation on productivity across manufacturing and services firms globally. We conduct the largest cross-country assessment of this relationship by using harmonized and comparable data on firms in 43 countries using data from the WBES. Our findings comprehensively reinforce the traditional patterns in the innovation literature, whereby innovation effort, capital intensity of firms and human capital are important for product and process innovations which in turn significantly and economically improves productivity. Some important differences arise from our study that suggest that "one size fits all" innovation polices may be ineffective.

To underscore this, our results suggest that not all business climate reforms are binding constraints to investing in innovation, giving some support to research that suggests that a hierarchy of pertinence can be devised as it regards business climate reforms. For instance, we showed that firms that paid for security, had better access to short term credit through the use of a line of credit and are audited by an external auditor were more likely to invest in R&D but the functioning of customs is not a binding constraint for innovation related expenditure. Therefore, innovation policy development should be attuned to variations in the impact of business climate reforms on innovation. To further stress the need for tailored innovation supporting policy development, some interesting differences arise between the manufacturing and services sectors as it regards the decision to invest in innovation. Experience is positively correlated with the decision to invest in R&D among manufacturing firms but we find no evidence that it significantly influences this decision in the services sector. This is also true for firms that use foreign technology. Interestingly, firms that benefit from FDI are more likely to invest in R&D in the services sector but not so in the manufacturing sector. These sectoral differences also extend to the intensity with which firms invest in innovation. Many of the variables which significantly impact innovation investment intensity in the manufacturing sector do not impact this decision in the services sector. For instance, managerial experience, use of foreign technology, use of basic information communication technology such as email and websites to communicate with customers and suppliers and having an internationally recognized quality certification all significantly impact the decision to innovate among manufacturing firms but have a neutral effect on this decision in the services sector.

Even more, the effect of investment in R&D and technology on the likelihood of witnessing an innovation output varies tremendously by sector. Investment in R&D and technology unequivocally increases the likelihood a firm innovates in the manufacturing sector but its effect is smaller and is more varied in the services sector. In addition, government support has a strong positive effect on all types of innovation in the manufacturing sector but only on process innovation in the services sector. One reason for this may be related to the measurement and evaluation indicators for most of these programs, which (Crespi et al., 2016) argues are mostly focussed on physical asset acquisitions.

Whilst both types of technological innovations are positively related to productivity in both the manufacturing and services sectors, the impact of process innovation is markedly greater in the services sector compared to the manufacturing sector. On the contrary, product innovation seems to have a greater effect on productivity in the manufacturing sector compared to the services sector.

Regarding the impact of firm heterogeneity, there is strong evidence of an upward bias in the cross-section estimates. Throughout our analysis, explicitly accounting for unobserved firm heterogeneity using firm fixed effects reduces the coefficients on the key variables. This finding suggests that future research could benefit from having better longitudinal data to get beyond a two period analysis of firms' innovative activities and more sophisticated (objective) measures of innovation outcomes.

In conclusion, this paper shows that innovation and productivity are positively related but the flow of the process is very complex and heterogeneous. The main takeaway therefore is that innovation policy should be tailored differently for the manufacturing and services sectors and more accommodating to varying risk taking innovative behaviour among firms. While it is relatively easy to develop public sector policies such as providing R&D related subsidies or tax breaks for all firms, in most cases with aggregated measurement indicators (like the World Bank Doing Business Indicators or the Global Competitiveness Report Index), our results suggest these may be sub-optimal. Innovation policies, from our results should be micro-targeted, focusing more so on horizontal reforms as opposed to vertical reforms, with disaggregated measurement indicators that consider a wide battery of heterogeneity among firms.

There is a need for further research in several areas. For instance, given the heterogeneities highlighted earlier between the manufacturing and services sectors, more research is needed to understand if these heterogeneities extend to industries as well. For example, does the reported relationships between innovation input and innovation output and innovation output and productivity hold for industries in the same sector (manufacturing or services). We know that productivity varies tremendously among narrowly defined industries (Syverson, 2011), so is this true also for the impact of innovation on productivity? Furthermore, we still know very little about the timing effect of the flow from innovation investment to innovation output and innovation output to productivity. In this regard, better longitudinal innovation data is needed globally. Moreover, there is a need to identify better instruments for product and process innovation outputs so as to improve our understanding of the innovation process.

Appendix A

Table A1
Knowledge production function.

	Cross-section				Panel			
	Process	Product	Innovation 1	Innovation 2	Process	Product	Innovation 1	Innovation 2
R&D intensity	0.282***	0.345***	0.294***	0.334***	0.164***	0.215***	0.181***	0.198***
	(0.014)	(0.015)	(0.014)	(0.015)	(0.050)	(0.050)	(0.050)	(0.048)
Subsidiary	−0.007	0.021***	0.000	0.015*	−0.021	0.042*	0.010	0.011
	(0.007)	(0.008)	(0.007)	(0.008)	(0.024)	(0.025)	(0.026)	(0.022)
FDI	−0.033***	−0.034***	−0.035***	−0.032***	−0.129***	−0.093***	−0.113***	−0.110***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.028)	(0.028)	(0.029)	(0.027)
Employment	0.000***	0.000**	0.000	0.000***	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Skill	−0.003***	−0.003***	−0.003***	−0.002***	−0.002**	−0.001	−0.002	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Human capital	−0.003***	−0.003***	−0.003***	−0.003***	−0.002***	−0.002***	−0.002***	−0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Government support	0.059***	0.056***	0.056***	0.059***	0.068**	0.087***	0.071***	0.084***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.028)	(0.028)	(0.026)	(0.028)
Foreign tech	0.024**	0.011	0.034***	0.001	0.114**	0.148***	0.146***	0.116**
	(0.010)	(0.011)	(0.009)	(0.011)	(0.054)	(0.049)	(0.051)	(0.050)
Broadband	0.079***	0.063***	0.083***	0.058***	0.031*	0.025	0.048***	0.008
	(0.006)	(0.006)	(0.006)	(0.005)	(0.017)	(0.017)	(0.017)	(0.016)
Fixed Asset	0.112***	0.100***	0.106***	0.106***	0.045***	0.024*	0.033**	0.035***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.013)	(0.013)	(0.013)	(0.012)
Age	0.001***	0.001***	0.001***	0.001***	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Importer	0.071***	0.079***	0.072***	0.078***	0.036*	−0.002	0.017	0.017
	(0.006)	(0.006)	(0.006)	(0.005)	(0.021)	(0.020)	(0.020)	(0.019)
Exports	0.000***	0.000	0.000***	0.000**	0.001**	0.002***	0.002***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Experience	0.001**	0.001***	0.001***	0.000*	0.002**	0.001	0.002*	0.002*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Product diversity	−0.001***	−0.002***	−0.001***	−0.002***	−0.001	−0.002***	−0.001***	−0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
R-sq	0.293	0.220	0.316	0.209	0.079	0.085	0.097	0.074
N	40173	40173	40173	40173	40173	40173	40173	40173

Notes: These results are from estimating the determinants of undertaking technological innovation where our main variable of interest is R&D intensity. Each column shows a different regression using OLS. The panel data estimates include firm and time fixed effects while the cross section data estimates include country, industry and time fixed effects. Standard errors in parentheses are clustered at the firm level.

* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

Table A2
Knowledge production function.

	BEEPS				LACES			
	Process	Product	Innovation 1	Innovation 2	Process	Product	Innovation 1	Innovation 2
R&D intensity	0.059*	0.114***	0.041	0.132***	0.228***	0.265***	0.296***	0.197***
	(0.034)	(0.035)	(0.032)	(0.034)	(0.037)	(0.038)	(0.038)	(0.034)
Subsidiary	0.057	0.071	0.052	0.077	−0.005	0.083**	0.061*	0.018
	(0.044)	(0.048)	(0.042)	(0.049)	(0.035)	(0.034)	(0.036)	(0.032)
FDI	−0.055*	−0.008	−0.032	−0.031	−0.172***	−0.126**	−0.139**	−0.159***
	(0.032)	(0.032)	(0.029)	(0.033)	(0.052)	(0.055)	(0.055)	(0.050)
Employment	0.000	−0.000	0.000	−0.000	−0.000*	−0.000	−0.000**	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Skill	−0.001	0.001	−0.000	0.000	−0.009**	−0.008**	−0.008**	−0.008**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)	(0.003)
Human capital	−0.001	−0.000	−0.001	−0.000	−0.003***	−0.004***	−0.005***	−0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Government support	0.090***	0.073**	0.078**	0.085**	0.098*	0.180***	0.131**	0.147***
	(0.034)	(0.035)	(0.032)	(0.035)	(0.057)	(0.054)	(0.051)	(0.056)
Foreign tech	−0.066	0.020	−0.018	−0.029	0.241***	0.245***	0.242***	0.244***
	(0.042)	(0.049)	(0.037)	(0.048)	(0.081)	(0.077)	(0.078)	(0.077)
Broadband	0.012	−0.006	0.050**	−0.044*	−0.061*	−0.109***	−0.092**	−0.077**
	(0.026)	(0.027)	(0.025)	(0.027)	(0.034)	(0.037)	(0.038)	(0.031)
Age	−0.000	0.001	0.001	0.000	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Importer	0.079***	0.019	0.063***	0.035*	−0.062	−0.026	−0.089	0.001
	(0.021)	(0.020)	(0.020)	(0.019)	(0.057)	(0.055)	(0.060)	(0.047)
Exports	0.000	0.001**	0.000	0.002***	0.001	0.002**	0.003***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience	−0.000	0.000	−0.000	−0.000	0.003**	0.002	0.003**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Product diversity	−0.001	−0.002***	−0.001*	−0.002***	−0.001	−0.001*	−0.002**	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-sq	0.058	0.052	0.057	0.059	0.231	0.263	0.309	0.204
N	26670	26670	26670	26670	11326	11326	11326	11326

Notes: These results are from estimating the determinants of undertaking technological innovation where our main variable of interest is R&D intensity. Each column shows a different regression using OLS. All estimates in this table include firm and time fixed effects. Standard errors in parentheses are clustered at the firm level.
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

Table A3
Knowledge production function.

	Manufacturing				Services			
	Process	Product	Innovation 1	Innovation 2	Process	Product	Innovation 1	Innovation 2
R&D intensity	0.249***	0.316***	0.337***	0.228***	0.164**	−0.012	0.053	0.099*
	(0.049)	(0.048)	(0.048)	(0.047)	(0.075)	(0.063)	(0.081)	(0.056)
Subsidiary	−0.006	0.056**	0.029	0.021	−0.036	0.157**	0.112	0.009
	(0.025)	(0.025)	(0.025)	(0.024)	(0.066)	(0.073)	(0.081)	(0.060)
FDI	−0.150***	−0.097***	−0.128***	−0.119***	−0.046	−0.038	−0.045	−0.039
	(0.035)	(0.035)	(0.035)	(0.034)	(0.042)	(0.043)	(0.041)	(0.041)
Employment	−0.000	−0.000	−0.000*	−0.000	−0.000	0.000	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Skill	−0.005***	−0.005***	−0.006***	−0.005**	−0.002	0.001	−0.000	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Human capital	−0.003***	−0.003***	−0.004***	−0.002***	−0.002**	−0.000	−0.001	−0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Government support	0.072**	0.119***	0.071**	0.120***	0.078*	0.041	0.087**	0.032
	(0.033)	(0.033)	(0.031)	(0.034)	(0.046)	(0.047)	(0.044)	(0.046)
Foreign tech	0.120**	0.130***	0.118**	0.132***	−0.070	0.207	0.117	0.020
	(0.052)	(0.047)	(0.046)	(0.051)	(0.109)	(0.129)	(0.104)	(0.119)
Broadband	−0.062***	−0.082***	−0.065***	−0.079***	0.038	0.018	0.038	0.017
	(0.021)	(0.021)	(0.021)	(0.020)	(0.029)	(0.028)	(0.030)	(0.026)
Age	−0.000	−0.000	−0.000	−0.000	0.001	0.002	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Importer	0.010	0.034	−0.002	0.047	0.062**	−0.023	0.038	0.001
	(0.034)	(0.031)	(0.032)	(0.030)	(0.025)	(0.025)	(0.026)	(0.023)
Exports	0.001**	0.002***	0.002***	0.001**	−0.000	0.001	−0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

(*continued on next page*)

Table A3 (*continued*)

	Manufacturing				Services			
	Process	Product	Innovation 1	Innovation 2	Process	Product	Innovation 1	Innovation 2
Experience	0.002**	0.001	0.001	0.002*	0.008**	0.001	0.005	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)	(0.003)
Product diversity	−0.000	−0.001**	−0.001**	−0.000	0.001	−0.003***	−0.001	−0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-sq	0.124	0.153	0.189	0.113	0.072	0.064	0.076	0.061
N	22192	22192	22192	22192	16812	16812	16812	16812

Notes: These results are from estimating the determinants of undertaking technological innovation where our main variable of interest is R&D intensity. Each column shows a different regression using OLS. All estimates in this table include firm and time fixed effects. Standard errors in parentheses are clustered at the firm level.
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

Table A4
Output production function by data type.

	Cross section				Panel			
	Process	Product	Innovation 1	Innovation 2	Process	Product	Innovation 1	Innovation 2
Process	0.168**				0.134*			
	(0.067)				(0.070)			
Product		0.284***				0.304***		
		(0.073)				(0.074)		
Innovation 1			0.270***				0.257***	
			(0.062)				(0.064)	
Innovation 2				0.166**				0.161*
				(0.080)				(0.082)
Capital	0.262***	0.264***	0.263***	0.263***	0.262***	0.264***	0.263***	0.263***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Material	0.605***	0.600***	0.602***	0.604***	0.605***	0.599***	0.602***	0.604***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Skill	0.024	0.029	0.028	0.023	0.023	0.029	0.028	0.023
	(0.047)	(0.049)	(0.049)	(0.047)	(0.047)	(0.050)	(0.049)	(0.047)
Human capital	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Size1	−0.849***	−0.833***	−0.834***	−0.850***	−0.854***	−0.830***	−0.836***	−0.850***
	(0.079)	(0.078)	(0.078)	(0.079)	(0.080)	(0.078)	(0.079)	(0.079)
Size2	−0.498***	−0.490***	−0.493***	−0.497***	−0.499***	−0.490***	−0.493***	−0.497***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
R-sq	0.643	0.642	0.643	0.642	0.643	0.641	0.643	0.642
N	8906	8906	8906	8906	8906	8906	8906	8906

Notes: These results are from estimating the effect of technological innovation on labour productivity. Each column shows a different regression using IV with country, industry and time fixed effects. Standard errors in parentheses are clustered at the firm level.
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

Table A5
Output production function by region.

	Cross section				Panel			
	Process	Product	Innovation 1	Innovation 2	Process	Product	Innovation 1	Innovation 2
Process	0.219***				0.698**			
	(0.072)				(0.335)			
Product		0.164*				0.683***		
		(0.090)				(0.256)		
Innovation 1			0.229***				0.662**	
			(0.069)				(0.280)	
Innovation 2				0.125				0.728**
				(0.093)				(0.302)
Capital	0.244***	0.244***	0.243***	0.244***	0.256***	0.276***	0.266***	0.267***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.029)	(0.030)	(0.029)	(0.029)
Material	0.516***	0.514***	0.517***	0.513***	0.648***	0.635***	0.638***	0.646***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.031)	(0.033)	(0.032)	(0.032)

(*continued on next page*)

Table A5 (*continued*)

	Cross section				Panel			
	Process	Product	Innovation 1	Innovation 2	Process	Product	Innovation 1	Innovation 2
Skill	0.030	0.029	0.031	0.029	0.037	0.039	0.021	0.057
	(0.052)	(0.052)	(0.052)	(0.052)	(0.134)	(0.130)	(0.130)	(0.133)
Human capital	0.006***	0.006***	0.006***	0.006***	−0.002	−0.001	−0.001	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Size1	−0.737***	−0.739***	−0.733***	−0.747***	−1.063***	−1.077***	−1.057***	−1.084***
	(0.128)	(0.129)	(0.128)	(0.129)	(0.170)	(0.168)	(0.170)	(0.167)
Size2	−0.411***	−0.408***	−0.409***	−0.411***	−0.657***	−0.680***	−0.654***	−0.685***
	(0.095)	(0.096)	(0.095)	(0.096)	(0.119)	(0.119)	(0.118)	(0.118)
R-sq	0.394	0.391	0.393	0.392	0.754	0.757	0.757	0.756
N	3096	3096	3096	3096	4831	4831	4831	4831

Notes: These results are from estimating the effect of technological innovation on labour productivity. Each column shows a different regression using IV with country, industry and time fixed effects. Standard errors in parentheses are clustered at the firm level.

* Significant at 10% level.

** Significant at 5% level.

*** Significant at 1% level.

Table A6

Output production function by sector.

	Manufacturing				Services			
	Process	Product	Innovation 1	Innovation 2	Process	Product	Innovation 1	Innovation 2
Process	0.152**				0.787***			
	(0.070)				(0.254)			
Product		0.292***				0.927***		
		(0.075)				(0.292)		
Innovation 1			0.288***				0.576**	
			(0.063)				(0.269)	
Innovation 2				0.120				1.560***
				(0.083)				(0.303)
Capital	0.263***	0.265***	0.264***	0.263***	−0.218	−0.201	−0.219	−0.187
	(0.015)	(0.015)	(0.015)	(0.015)	(0.170)	(0.171)	(0.171)	(0.170)
Material	0.605***	0.599***	0.602***	0.604***	1.094***	1.091***	1.092***	1.094***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.014)	(0.014)	(0.014)	(0.014)
Skill	0.024	0.029	0.030	0.023	−0.084***	−0.084***	−0.084***	−0.083***
	(0.047)	(0.050)	(0.049)	(0.047)	(0.008)	(0.008)	(0.008)	(0.008)
Human capital	0.003**	0.003**	0.003**	0.003**	0.002**	0.002	0.003**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Size1	−0.857***	−0.839***	−0.838***	−0.863***	−1.759***	−1.746***	−1.786***	−1.669***
	(0.080)	(0.079)	(0.079)	(0.080)	(0.086)	(0.087)	(0.086)	(0.089)
Size2	−0.511***	−0.503***	−0.505***	−0.511***	−1.277***	−1.263***	−1.284***	−1.236***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.076)	(0.076)	(0.076)	(0.078)
R-sq	0.645	0.644	0.645	0.645	0.255	0.258	0.260	0.242
N	8816	8816	8816	8816	16810	16810	16810	16810

Notes: These results are from estimating the effect of technological innovation on labour productivity. Each column shows a different regression using IV with country, industry and time fixed effects. Standard errors in parentheses are clustered at the firm level.

* Significant at 10%.

** Significant at 5% level.

*** Significant at 1% level.

Table A7

Output production function using TFP.

	Olley and Pakes				Levinsohn and Petrin			
	Process	Product	Innovation 1	Innovation 2	Process	Product	Innovation 1	Innovation 2
Process	0.108				0.116*			
	(0.077)				(0.069)			
Product		0.324**				0.301**		
		(0.149)				(0.137)		
Innovation 1			0.217**				0.200**	
			(0.103)				(0.093)	
Innovation 2				0.275*				0.270**

(*continued on next page*)

Table A7 (*continued*)

	Olley and Pakes				Levinsohn and Petrin			
	Process	Product	Innovation 1	Innovation 2	Process	Product	Innovation 1	Innovation 2
				(0.143)				(0.131)
Capital	0.451***	0.458***	0.453***	0.454***	0.438***	0.444***	0.440***	0.441***
	(0.012)	(0.009)	(0.011)	(0.010)	(0.011)	(0.008)	(0.010)	(0.009)
Material	0.041**	0.034**	0.038**	0.037**	0.038**	0.032**	0.035**	0.035**
	(0.018)	(0.015)	(0.017)	(0.016)	(0.017)	(0.014)	(0.016)	(0.015)
Skill	−0.032***	−0.029**	−0.030**	−0.030**	−0.038***	−0.036***	−0.037***	−0.036***
	(0.011)	(0.013)	(0.012)	(0.013)	(0.009)	(0.011)	(0.010)	(0.011)
Human capital	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Size1	−0.467***	−0.455***	−0.459***	−0.456***	−0.396***	−0.386***	−0.390***	−0.386***
	(0.027)	(0.027)	(0.026)	(0.027)	(0.022)	(0.022)	(0.021)	(0.022)
Size2	−0.497***	−0.501***	−0.497***	−0.500***	−0.432***	−0.436***	−0.432***	−0.435***
	(0.038)	(0.040)	(0.038)	(0.039)	(0.034)	(0.036)	(0.034)	(0.035)
R-sq	0.790	0.783	0.788	0.786	0.811	0.805	0.809	0.807
N	8908	8908	8908	8908	8908	8908	8908	8908

Notes: These results are from estimating the effect of technological innovation on labour productivity. Each column shows a different regression using IV with country, industry and time fixed effects. Standard errors in parentheses are clustered at the firm level.

* Significant at 10% level.

** Significant at 5% level.

*** Significant at 1% level.

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