Demand, Innovation and Research Intensity Across Sectors

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Abstract: The paper investigates the relationship between demand, innovation and research intensity in different groups of industries. Results reported in the paper indicate that demand exerts a positive and significant impact on innovation, and that this impact is stronger in high-tech industries than in low-tech industries. The paper also provides evidence that demand does not impact on research intensity, despite its impact on innovation. This finding holds both for low-tech and high-tech industries, using both R&D to value added and patents per millions of hours worked as measures of research intensity. This result points out that research intensity is not influenced by demand growth, but most likely depends on each country's capacity to develop a mature National Innovation System.

Keywords: Demand; Innovation; Research Intensity; Demand-pull; Technology-push.

1. Introduction

The Schumpeterian literature on economic growth suggests that research intensity is an important determinant of productivity growth. Following the developments of endogenous growth theory, several studies sought to investigate the empirical relationship between innovative activity and long-term productivity growth. As Jones (1995) has shown, gross innovative activity (measured by R&D expenditure or patent counts) does not have a significant impact on productivity growth. Nonetheless, subsequent studies revealed that research intensity (R&D to output or patents per worker) is normally found to exert a positive and significant impact on long-term productivity growth (e.g. Ha and Howitt, 2007; Madsen, 2008).

The Kaldorian literature on economic growth, however, stresses that demand growth is the main determinant of productivity growth. Kaldor (1966) attributed this impact to both static and dynamic increasing returns to scale (such as learning-by-doing and induced innovation), which result in productivity growth in the long term. After Kaldor's (1966) seminal paper on the relationship between demand growth and productivity growth, empirical investigations using different methods and covering different countries and time periods confirmed that demand growth has indeed a positive and significant effect on productivity growth (e.g. McCombie and Thirlwall, 1994; McCombie, Pugno and Soro, 2002).

More recently, Romero and Britto (2017) showed that although demand growth is crucial for productivity growth, in sectors or countries with higher research intensity, productivity growth presents a stronger response to demand growth. The authors carried out a thorough empirical investigation combining the insights of the Schumpeterian and the Kaldorian macroeconomic approach to long-term growth. Their results indicate that research intensity is not relevant for long-term growth on its own, but that it increases the response of productivity growth to demand growth. Moreover, the authors showed also that this effect is similar both in low-tech and in high-tech industries, while demand growth exerts a stronger independent effect on productivity growth in the high-tech sector.

In Romero and Britto's (2017) paper, research intensity is assumed to be an exogenous variable. According to them, the level of research intensity of each country is determined by the country's capacity to develop a mature National Innovation System (e.g. Nelson, 1993; Lundvall, 1992). They argue that the development of this system is not explained by demand growth.

Nonetheless, a large number of works point out that demand growth influences innovation. According to Schmookler (1966), demand indicates social needs, providing a direction and an incentive for innovation. Moreover, demand growth increases the potential returns to innovative activity. Schmookler (1966) provided the first empirical evidence of the influence of demand upon innovation. Using sector-level data, he found a strong positive relationship between investment in capital goods-using industries and patents granted by capital goods-producer industries. Thus, his results indicate that the direction of causality runs from demand to innovation. After his seminal findings, several other empirical investigations confirmed the importance of demand for innovation (e.g. Geroski and Walters, 1995; Piva and Vivarelli, 2007).

If demand indeed impacts innovation, it is reasonable to suspect that demand might also impact on research intensity. Nonetheless, it is important to note that finding a positive impact of demand growth on innovative activity is not the same as finding that demand has a positive impact on research intensity.

Despite the importance of research intensity in the Schumpeterian growth literature, and notwithstanding the fact that several papers have tested the relationship between demand and innovation, very few studies investigated the relationship between demand and research intensity. One notable exception is León-Ledesma's (2002) paper, which provided some evidence that demand growth has no significant impact on research intensity.

In this context, the objective of this paper is twofold. First, it aims to test the relationship between demand and innovative activity, measured by R&D and patents, taking into account differences between low-tech and high-tech industries. Second, it aims to test if demand impacts on research intensity as well. These relationships were investigated using disaggregate industry-level value added data from EU KLEMS to measure demand growth, R&D data from the ANBERD database, and patent data from USPTO (transposed to industry classification using Lybbert and Zolas' (2014) methodology). The databased used comprises 12 industries, for 18 countries over 1976-2006.

The remainder of the paper is organized as follows. Section two discusses the empirical evidence related to both the relationships between demand and innovation, and between demand and research intensity. Section three analyses the empirical investigation carried out in the paper. Section four presents the concluding remarks.

2. Demand, innovation and research intensity: theory and evidence

In the seminal works of Schmookler (1966) and Myers and Marquis (1969), it is possible to establish two main mechanisms through which the dynamics of demand can impact innovative activity. Fontana and Guerzoni (2008) have called them the *incentive effect* and the *uncertainty effect*.

The incentive effect of demand on innovation results from the increase in rents generated due to the innovation. When a firm innovates, it acquires a temporary monopoly over that innovation. This new monopoly power generates abnormal profits, with the firm's individual demand function becoming less elastic and increasing the mark-up over unit costs. In this scenario, a rise in demand would increase the amount of monopoly rents that can be earned by an innovative firm, creating *incentives* to allocate more resources to innovative activity (Schmookler, 1966; Geroski and Walters, 1995; Fontana and Guerzoni, 2008).

The uncertainty effect of demand on innovation works via reducing uncertainty about the innovations' market performance. The characteristic novelty of an innovation, together with the lack of information about user's capabilities to benefit from it (von Tunzelmann and Wang, 2003), raises doubts about the profitability of investments in innovative activity (Garcia-Quevedo *et al.*, 2016). In a market economy, the interaction between producers and consumers allows for a mutual exchange of information. In this sense, demand is a source of knowledge that helps to diminish the *uncertainty* about the success of new products and services. Hence, a rise in demand increases the flow of information to the firm and fosters innovative activity (Myers and Marquis, 1969; Von Hippel, 1978; Fontana and Guerzoni, 2008).

The importance of demand for innovation is not undisputed, and several critiques have been raised about this relationship. On the one hand, it is argued that the concept of demand used to characterize the uncertainty effect is too broad and vague, making it difficult to measure and study (Mowery and Rosenberg, 1979; Dosi, 1982). On the other hand, some authors discuss the presence of reverse causality in measuring the incentive effect (Kleinknecht and Verspagen, 1990). In fact, this reverse causality is the basis of an alternative hypothesis about the determinants of innovation. Some authors postulate that innovation is based on advances in scientific knowledge and technological resources, which are independent of the dynamics of demand. In other words, innovation is autonomous in relation to demand (Dosi, 1982). Moreover, the introduction of new products, services or processes in the market by an individual firm will lead to an improvement of this firm's economic performance, leading to higher demand (Kleinknecht and Verspagen, 1990).

Since Schmookler's (1966) seminal contribution, however, several studies have re-examined the impact of demand on innovation by improving his original database, changing dependent and independent variables and controlling for firm and sector level specificities (Scherer, 1982; Kleinknecht and Verspagen, 1990; Piva and Vivarelli 2007). The total amount of patents (or the variation in this amount) is certainly the most frequent measure of innovative activity in early studies of the relationship between demand and innovation (Scherer, 1982; Walsh 1984; Geroski and Walters, 1995). Nonetheless, as Kleinknecht and Verspagen (1990) underlined, patents are an innovation outcome. Hence, there is generally a time gap between the actual occurrence of innovative activity and the patent registration. Consequently, to verify that demand lags behind patents does not confirm causality running from demand to innovative activity, since it is not possible to know for certain when this activity occurred. Moreover, there could also be a time gap between innovations and patent applications, once firms may test their inventions in the market before fulfilling an application (Kleinknecht and Verspagen, 1990).

More recently, with the introduction of Community Innovation Surveys (CIS), R&D investment has emerged as a more precise measure of innovative activity for analyzing the demand-innovation nexus. Since R&D is an innovation input, using this variable solves the possible endogeneity problem. A possible positive impact of innovation on demand can only occur after innovation has actually happened. Hence, it is hard to argue that R&D investment itself would raise demand, once it has to take place before the invention (Piva and Vivarelli, 2007).

However, using R&D to measure innovative activity is not entirely free from problems. As Piva and Vivarelli (2007) point out, smaller firms innovate mainly through acquisition of external technology and may have no R&D investment at all. Thus, using R&D investment as a proxy can lead to an underestimation of total innovative activity.

These caveats notwithstanding, regardless of the variable used to measure innovative activity, several studies have found evidence of the relevance of demand for innovation (e.g. Scherer, 1982; Brouwer and Kleinknetcht, 1999). Furthermore, several studies found evidence that the effects of demand on innovation vary in quality and in magnitude across different groups of firms (Piva and Vivarelli, 2007; Fontana and Guerzoni, 2008; Antonelli and Gehringer, 2015; Garcia-Quevedo et al, 2016). Hence, not accounting for these different effects would lead to an underestimation of the importance of demand in fostering innovation.

Piva and Vivarelli (2007) have traced a series of characteristics that would make a firm's innovation effort more susceptible to demand dynamics. The authors argue that favorable demand prospects increase expected profitability and enhance the capacity to finance innovative activity. In this perspective, the more dependent a firm's financial stability is to demand scenarios, the higher will be the innovation/demand elasticity. Hence, firms exposed to tighter competition and liquidity and credit constraints would be more sensitive to current sales when deciding to invest in R&D. For similar reasons, diversified firms, firms heading a business group and firms benefiting from public subsidy would have lower innovation/demand elasticity (Piva and Vivarelli, 2007; Hall et al, 2016).

Investigating the demand constraint on innovation from a neoclassical perspective, several authors sought to test the cyclicality of R&D investment. The attempt was to incorporate what makes it pro-cyclical, when some theories predicts otherwise (Aghion and Saint-Paul, 1998). In these works, the main strategy was to incorporate firm and industry-level specific characteristics to explain the responses of innovation to output fluctuations. In general, the results present asymmetric responses of innovation to demand shocks. Firms would present a less pro-cyclical R&D behaviour when they have large sales share of R&D expenditure, are not exposed to price competition and are in the high-tech sector (Arvanitis and Woerter, 2013). However, they would present a more pro-cyclical pattern of R&D investment and patenting in industries with faster obsolescence and weaker patent protection (Fabrizio and Tsolmon, 2014), and when firms have more biding liquidity and credit constraints (Ouyang, 2011; Aghion *et. al.*, 2012). Therefore, these results mainly reinforce the ones found in the study of Piva and Vivarelli (2007).

Despite the extensive literature on the effects of demand on innovation, little evidence has been provided for the nexus between demand and research intensity. As mentioned in the introduction, one notable exception is León-Ledesma's (2002) paper. The author built a model inspired in Schumpeterian and Kaldorian insights, and sough to test each relationship of the model using data for a sample of OECD countries. He estimated the impact of different variables on research intensity, and found that demand growth was not significant.

It is important to note, however, that when research intensity is measured by the R&D to output ratio, the estimated elasticity provides information about the relationship between demand and research intensity. As highlighted by Brouwer and Kleinknetcht (1999), a firm's R&D intensity can decline even if there is an increase in innovative activity, because the firm's overall output can grow faster than R&D expenditure (the same would apply to R&D employment, when research intensity is measured as the number of researchers in relation to total employment). In this case, if the long-term demand elasticity of innovation is equal to one, then demand and innovation activity grow at the same rate, with all else constant, which implies that research intensity decreases over time, because the denominator is higher in absolute terms than the numerator. If this is the case, some other factor would be responsible for explaining the stability and the differences in research intensity across countries.

When research intensity is measured by patents per worker (or by hours worked), however, the implications are different. As Kaldor (1966) has shown, the fact that demand growth impacts on productivity growth implies that output growth leads to a less than proportional increase in employment. Hence, if the long-term elasticity between demand and patents is equal to one, this implies that patents and output are growing at the same rate, ceteris paribus. Nonetheless, following the Kaldorian literature, employment should be growing at a lower rate. Hence, research intensity would be increasing.

3. Empirical investigation

3.1. Data

Demand for the output of different industries was measured by valued added from the EU KLEMS Database. The sample used comprises 18 OECD countries (Australia, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, South Korea, Italy, Japan, Netherlands, Portugal, Spain, Sweden, USA, and the United Kingdom), for which data on value added and number of hours worked by persons engaged in production are consistently available for 12 manufacturing industries over the period 1977-2006 (see O'Mahony and Timmer, 2009). Value added in constant 1995 prices were transformed from national currencies to 1995 US dollars using industry-specific PPPs from the Groningen Growth and Development Centre (GGDC) Productivity Level Database (Inklaar and Timmer, 2008). The fuel industry was dropped from the sample due to the industry's well know measurement problems.

The 12 industries were split into two samples following the OECD technological classification (OECD, 2003). Low-tech industries comprises 5 low-tech industries (Food, Textiles, Wood, Paper and Other Manufactures) plus 3 medium-low-tech industries (Plastics, Minerals and Metals). High-tech industries comprises 3 medium-high industries (Chemicals, Machinery and Transport) plus the high-tech industry (Electrical).

The ratio of patents to the number of millions of hours worked by persons engaged in production was used as a measure of research intensity in each country i, industry j and period t. It is common to use patent data gathered from a single patent office to avoid differences in patent legislations between countries (see Soete, 1981; Nagaoca *et al.*, 2010). USPTO is normally the most common choice, given that the US has the biggest market in the world, so that most high-value patents are registered there. Patents registered at the USPTO were analysed and the first 4 digits of the International Patent Classification (IPC) codes were extracted from each patent registration along with the country of origin of the first author of the patent and the year the patent was granted. Collecting information from each individual patent from the USPTO allowed employing the correspondence table between the IPC 2-digits and the International Standard Industrial Classification (ISIC) (Revision 3) 2-digits developed by Lybbert and Zolas (2014) to find the number of patents from each country in each of the industries of the EU KLEMS Database. The number of hours worked by persons engaged in production (in millions) used to calculate research intensity is from the EU KLEMS Database.

As an alternative measure of research intensity, the ratio of R&D expenditure to value added was calculated using data from the OECD Analytical Business Enterprise Research and Development (ANBERD) Database, for the period 1976-2006. Data from 1987 to 2006 are classified according to ISIC Rev. 3, while data from 1976 to 1986 are according at ISIC Rev. 2. At the level of aggregation used in this paper this does not represent a problem, since it is straightforward to make the data compatible.

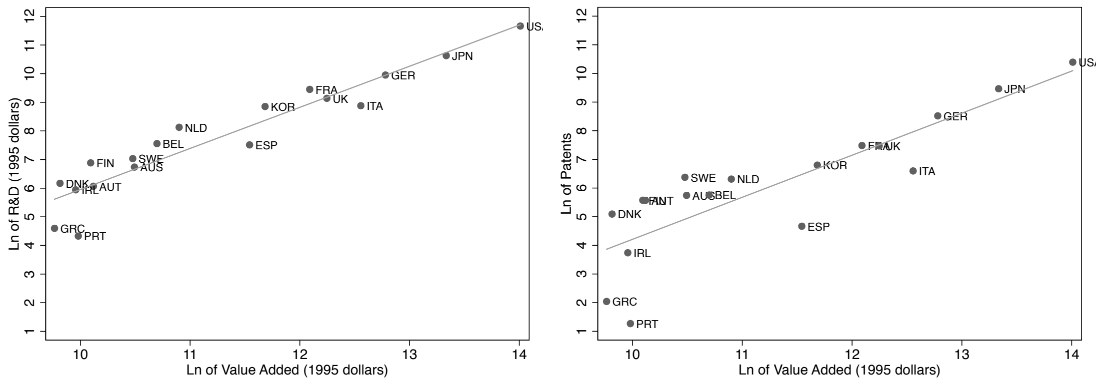
3.2. Descriptive analysis

The aim of this paper is to investigate whether the effect of demand on innovation varies between technological sectors, and whether demand affects research intensity as well.

As found in a number of studies, Figure 1 shows the positive correlation between demand and innovation. This figure highlights that this relationship is quite clear, taking both patents and R&D expenditure as proxy for innovation.

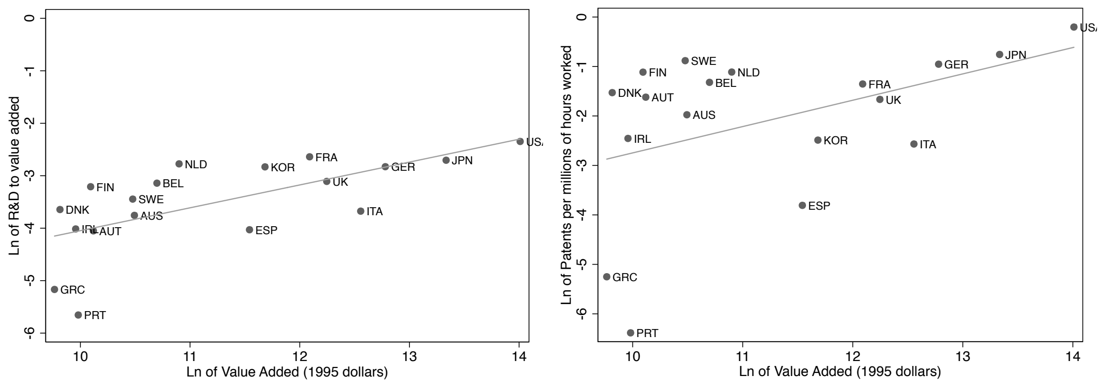
Figure 2 shows that there is also a positive correlation between demand and research intensity, measured by R&D to value added and patents per millions of hours worked. Nonetheless, this relationship seems weaker than the one observed between demand and innovation. The fact that the correlation between demand and research intensity is less clear casts doubt about the validity of this relationship, highlighting the importance of this paper's investigation.

Figure 1: Demand and Innovation



Note: Averages over the period 1977-2006.
Source: Authors' elaboration.

Figure 2: Demand and Research Intensity

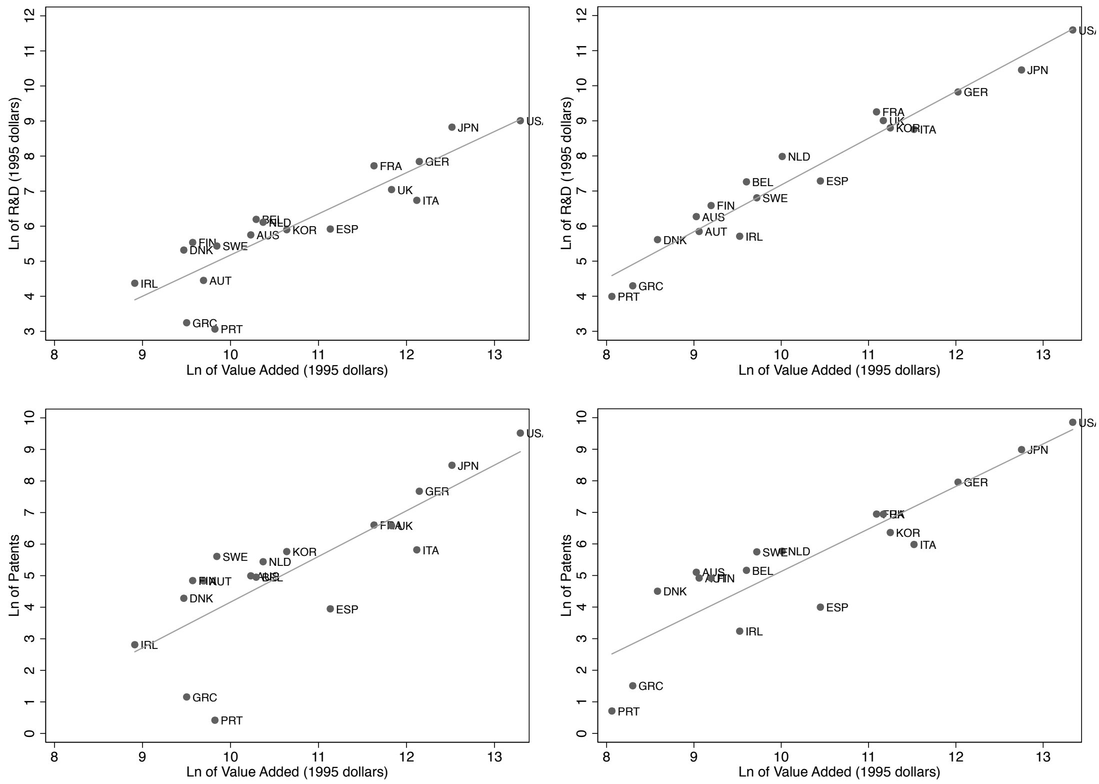


Note: Averages over the period 1976-2006.
Source: Authors' elaboration.

Figure 3 shows the correlations between demand and innovation in the low-tech and in the high-tech sectors. This figure indicates that this relationship seems to be valid for both sectors. Nonetheless, visually, it is not distinguishable if it is higher for one of them. The only clear difference is in terms of the intercept.

Figure 3: Demand and Innovation by Technological Sector

A. Low-Tech B. High-Tech



Note: Averages over the period 1976-2006.
Source: Authors' elaboration.

3.3. Estimation strategy

The regressions reported in this paper were estimated using panel data estimators for industries *i* in countries *j* at time *t*. The estimated regressions were:

$$\ln\mathrm{Inov}_{ijt} = \beta_0 + \beta_1 \ln\mathrm{Inov}_{ijt-1} + \beta_2 \ln Y_{ijt} - \beta_3 \ln Y_{ijt-1} + u_{ijt} \quad (1)$$

$$\ln\mathrm{RI}_{ijt} = \beta_0 + \beta_1 \ln\mathrm{RI}_{ijt-1} - \beta_2 \ln Y_{ijt} + \beta_3 \ln Y_{ijt-1} + u_{ijt} \quad (2)$$

where *Inov* denotes innovation, which is measured either by the number of patents or the real expenditure on *R&D* in each industry. *Y* is the real value added, and *RI* is research intensity, measured either by R&D to value added or by patents per millions of hours worked.

There are two econometric issues involved in estimating these equations. First, it is necessary to control for unobserved fixed effects (FE). Second, it is necessary to deal with endogeneity between the dependent variable and: (i) its first lag, which is introduced as an explanatory variable; and (ii) the logarithm of value added, due to reverse causality.

In the tests reported in this paper, these problems were addressed employing the System Generalised Method of Moments (SYS-GMM) estimator (Blundell and Bond, 2000). This method employs a system of equations in levels and in differences to estimate the parameters, using as instruments the lags of the variables in differences and in levels, respectively (see Roodman, 2009: 114). This is a Two-Step Feasible Efficient System GMM estimator, which controls for fixed effects via first differences. The two-step approach is used to obtain a feasible efficient GMM estimator, given that GMM is inefficient in the presence of heteroskedasticity. In the first step a Two-Stage Least Square (2SLS) is regressed. The residuals from the first stage are then employed to form the weighting matrix that is used to eliminate heteroskedasticity, while in the second step the parameters are estimated satisfying the orthogonality conditions of the instruments, i.e. minimising the L moment conditions $E[Z_{\mathrm{ijt}} u_{\mathrm{ijt}}] = 0$, where Z is the matrix that contains the L included and excluded instruments. The identification of the parameters using System GMM requires overidentification, tested using Hansen's J Test, and no autocorrelation, tested using Arellano and Bond's (1991) Autoregressive (AR) Test.

The database used in this paper comprises data for 12 industries, in 18 countries, during 30 years. Since the panel is for industries in each country, it has 216 units and 30 years. To make this panel compatible with the small panel data assumption of the System GMM, 3-year averages were calculated, so that the final panel presents 216 units and 10 time periods. It is important to note, however, that some years of R&D data are missing for Austria, Belgium, Denmark, Greece, South Korea, Portugal, Sweden, and the United Kingdom. Consequently, the results using R&D are reported for a robustness check, but the main analysis of the paper will be focused on the results found using patent data to measure innovation and research intensity.

3.3. Results: all industries

The results reported in Table 1 indicate that output has a positive and significant impact on innovation, both when using patents and R&D to measure innovation. Table 1 presents the estimates of equation (1) for the whole sample, i.e. considering all industries. The lag of output has a negative and significant coefficient in all regressions but the one where FE is used and innovation is measured by patents. The results using System GMM are very similar to the ones found using a simple Fixed Effects estimator. In both System GMM regressions the Arellano-Bond AR test and the Hansen J test suggest that the instruments used are valid. The main difference is that the estimated coefficients increase when System GMM is employed.

Most importantly, the estimated parameters using System GMM indicate that the long-run elasticity between demand and innovation slightly above one. This result does not allow to clearly state whether research intensity will tend to increase, decrease or remain stable as demand grows.

The estimated parameters using System GMM when research intensity is measured by patents per millions of hours worked, however, indicate that demand has a long-run impact on research intensity. The results once again show that the long-term elasticity of the relationship between demand and innovation slightly above one and the constant is not significant. Nonetheless, in this case, since employment tends to grow more slowly than value added, this elasticity implies that demand and innovation grow at the same rate, which is higher than that of employment. This means that the relationship between demand and research intensity is positive in the long run.

Hence, using R&D to value added and patents per millions of hours worked generates contrasting results. In the first case, demand has no clear impact on research intensity. In the second case, demand seems to have a positive long-run impact on research intensity. These results highlight the importance of estimating equation (2) in order to obtain further information of whether demand has indeed no effect on research intensity in the long-term.

Table 1: Demand and innovation - All Industries

Dependent Variable Estimator Model	Ln of R&D FE (i)	Ln of R&D Sys-GMM (ii)	Ln of Patents FE (iii)	Ln of Patents Sys-GMM (iv)
Ln of R&D (Lag)	0.536***	0.829***		
	(0.0648)	(0.0946)		
Ln of Demand	0.612***	1.613***	0.181***	1.813**
	(0.0982)	(0.444)	(0.0673)	(0.702)
Ln of Demand (Lag)	-0.261***	-1.425***	-0.0245	-1.908**
	(0.0957)	(0.355)	(0.0561)	(0.820)
Ln of Patents (Lag)			0.768***	1.083***
			(0.0282)	(0.131)
Constant	-1.101*	-0.739	-0.715***	0.342
	(0.588)	(0.583)	(0.254)	(0.695)
Long-term effect:	0.76	1.10	0.78	1.14
Observations:	1585	1585	1937	1937
R-squared	0.652		0.857	
Instruments/lags:		18/2-4		14/3
A.-B. AR Test:		0.167		0.804
Hansen J Test:		0.135		0.346

Note: All regressions include time dummies. Robust standard errors between brackets.
Significance: ***=1%; **=5%; *=10%.
Source: Authors' elaboration

Table 2: Demand and research intensity - All Industries

Dependent Variable Estimator Model	Ln of R&D/VA FE (i)	Ln of R&D/VA Sys-GMM (ii)	Ln of Pat./L FE (iii)	Ln of Pat./L Sys-GMM (iv)
Ln of R&D/VA (Lag)	0.538***	0.815***		
	(0.0634)	(0.0876)		
Ln of Demand	-0.375***	0.479	-0.162**	0.244
	(0.0978)	(0.368)	(0.0731)	(0.265)
Ln of Demand (Lag)	0.261***	-0.460	0.223***	-0.166
	(0.0982)	(0.355)	(0.0609)	(0.271)
Ln of Pat./L (Lag)			0.775***	0.721***
			(0.0293)	(0.0725)
Constant	-1.085*	-0.781	-1.165***	-1.168***
	(0.586)	(0.537)	(0.313)	(0.361)
Long-term effect:	-0.25	0.00	0.27	0.00
Observations:	1585	1585	1937	1937
R-squared	0.487		0.861	
Instruments/lags:		22/2-6		22/2-6
A.-B. AR Test:		0.200		0.448
Hansen J Test:		0.120		0.004

Note: All regressions include time dummies. Robust standard errors between brackets.
Significance: ***=1%; **=5%; *=10%.
Source: Authors' elaboration

The estimates of equation (2), reported in Table 2, suggest that current and past demand have no significant impact on research intensity in the long-term. Interestingly, the fixed effects regressions indicate that demand has a negative effect on research intensity, while its lag has a positive effect. Nonetheless, when simultaneity is controlled for using System GMM, current and past demand are no longer significant. Most importantly, this result holds for both measures of research intensity. The Arellano-Bond

AR test and the Hansen J test indicate the validity of the instruments when R&D to value added is used to proxy research intensity. In the case of patents to millions of hours worked, however, the Hansen J test indicates that the instruments are not valid.

3.4. Results: low-tech and high-tech sectors

In this section, the discussion presented in the previous one is repeated, but now dividing the sample of industries into low-tech and high-tech industries. The objective of this division is to analyse whether these different groups of industries present different dynamics in terms of the relationship between demand, innovation and research intensity.

The results for the relationship between demand and innovation in low-tech industries, presented in Table 3, are mixed. When R&D is used, results indicate that demand exerts a positive and significant impact on innovation. The System GMM estimates indicate once again that the long-term relationship is close to one, so that research intensity would be negatively affected by demand. The test statistics indicate that the instruments used are valid. When patents are used to measure innovation, however, the Hansen J test rejects once again the validity of the instruments, while current and past demand are not significant.

Table 3: Demand and innovation - Low-tech industries

Dependent Variable Estimator Model	Ln of R&D FE (i)	Ln of R&D Sys-GMM (ii)	Ln of Patents FE (iii)	Ln of Patents Sys-GMM (iv)
Ln of R&D (Lag)	0.519*** (0.0735)	0.779*** (0.0962)		
Ln of Demand	0.596*** (0.167)	1.040** (0.466)	0.0621 (0.0983)	-0.259 (0.520)
Ln of Demand (Lag)	-0.175 (0.184)	-0.808* (0.460)	0.0759 (0.0882)	0.429 (0.590)
Ln of Patents (Lag)			0.796*** (0.0284)	0.838*** (0.0878)
Constant	-2.009* (1.137)	-0.996* (0.578)	-0.706 (0.439)	-1.034* (0.537)
Long-term effect:	1.24	1.05	0.00	0.00
Observations:	1052	1052	1289	1289
R-squared	0.574		0.859	
Instruments/lags:		20/2-5		20/2-5
A.-B. AR Test:		0.466		0.762
Hansen J Test:		0.070		0.001

Note: All regressions include time dummies. Robust standard errors between brackets.
Significance: ***=1%; **=5%; *=10%.
Source: Authors' elaboration

The results for the high-tech industries indicate that demand has a significant impact on innovation. Test statistics reported in Table 4 indicate that the instruments are valid in the System GMM regressions. When R&D is used to measure innovation, the long-term effect of demand on innovation is 0.7 using fixed effects, and jumps to 1.4 using System GMM. When patents are used as the dependent variable, the long-term effect is 1.06 and 1.05, respectfully. Hence, in the case of the high-tech sector, the results suggest that demand has a significant effect on research intensity in the long run using both measures of research intensity.

Table 4: Demand and innovation - High-tech industries

Dependent Variable	Ln of R&D	Ln of R&D	Ln of Patents	Ln of Patents
Estimator	FE	Sys-GMM	FE	Sys-GMM
Model	(i)	(ii)	(iii)	(iv)
Ln of R&D (Lag)	0.652***	1.100***		
	(0.0784)	(0.108)		
Ln of Demand	0.589***	0.578**	0.329***	0.915***
	(0.0918)	(0.278)	(0.0979)	(0.251)
Ln of Demand (Lag)	-0.353***	-0.719***	-0.0747	-0.671**
	(0.0968)	(0.236)	(0.0664)	(0.295)
Ln of Patents (Lag)			0.689***	0.767***
			(0.0585)	(0.0955)
Constant	0.0147	0.773	-1.098**	-1.258**
	(0.370)	(0.497)	(0.419)	(0.609)
Long-term effect:	0.68	1.41	1.06	1.05
Observations:	533	533	648	648
R-squared	0.848		0.861	
Instruments/lags:		14/2		22/3-7
A.-B. AR Test:		0.081		0.280
Hansen J Test:		0.438		0.152

Note: All regressions include time dummies. Robust standard errors between brackets.
Significance: ***=1%; **=5%; *=10%.
Source: Authors' elaboration

Table 5: Demand and research intensity - Low-tech industries

Dependent Variable	Ln of R&D/VA	Ln of R&D/VA	Ln of Pat./L	Ln of Pat./L
Estimator	FE	Sys-GMM	FE	Sys-GMM
Model	(i)	(ii)	(iii)	(iv)
Ln of R&D/VA (Lag)	0.522***	0.717***		
	(0.0719)	(0.113)		
Ln of Demand	-0.398**	-0.400	-0.392***	0.033
	(0.167)	(0.516)	(0.0979)	(0.942)
Ln of Demand (Lag)	0.337*	0.415	0.376***	0.008
	(0.188)	(0.511)	(0.0927)	(0.967)
Ln of Pat./L (Lag)			0.805***	0.835***
			(0.0282)	(0.133)
Constant	-1.989*	-1.308*	-0.496	-0.752
	(1.135)	(0.685)	(0.408)	(0.606)
LT effect:	-0.13	0.00	-0.08	0.00
Observations:	1052	1052	1289	1289
R-squared	0.461		0.873	
Instruments/lags:		22/2-6		18/04/06
A.-B. AR Test:		0.476		0.779
Hansen J Test:		0.193		0.062

Note: All regressions include time dummies. Robust standard errors between brackets.
Significance: ***=1%; **=5%; *=10%.
Source: Authors' elaboration.

The results reported in Tables 3 and 4 point out also that demand has a stronger effect on innovation in high-tech industries than in low-tech industries. When R&D is used to measure innovative activity, the long-term demand elasticity of innovation is 1.05 for low-tech industries and 1.41 for high-tech industries. When patents are used to measure innovation, the results suggest that demand has no impact on innovation in the low-tech industries, while the long-term demand elasticity of innovation is 1.05 for high-tech industries.

The results for the relationship between demand and research intensity in the low-tech sector, reported in Table 5, are very similar to the ones reported in Table 2 for the sample of all industries. The fixed effects regressions indicate that demand has a negative effect on research intensity, while its lag has a positive effect. Using System GMM, current and past demand are no longer significant. The Arellano-Bond AR test and the Hansen J test indicate the validity of the instruments.

The results for the relationship between demand and research intensity in the high-tech sector, reported in Table 6, are slightly different. The fixed effects regression using the logarithm of R&D to value added as the dependent variable indicates that demand has a negative effect on research intensity, while its lag has a positive effect, as in the low-tech sector. When patents per hours worked is used, the fixed effects regression indicates that lagged demand has a positive and significant impact on research intensity. In both cases, however, when System GMM is used, current and past demand become not significant. Instruments are valid in both System GMM regressions.

Table 6: Demand and research intensity - High-tech industries

Dependent Variable Estimator Model	Ln of R&D/VA FE (i)	Ln of R&D/VA Sys-GMM (ii)	Ln of Pat./L FE (iii)	Ln of Pat./L Sys-GMM (iv)
Ln of R&D/VA (Lag)	0.652*** (0.0783)	0.988*** (0.0525)		
Ln of Demand	-0.396*** (0.0931)	-0.0561 (0.174)	0.0863 (0.0897)	0.303 (0.376)
Ln of Demand (Lag)	0.281*** (0.0899)	0.0413 (0.169)	0.120** (0.0595)	-0.225 (0.375)
Ln of Pat./L (Lag)			0.660*** (0.0671)	0.707*** (0.103)
Constant	0.0415 (0.380)	0.234 (0.238)	-2.500*** (0.536)	-0.924 (0.422)
LT effect:	-0.33	0.00	0.35	0.00
Observations:	533	533	648	648
R-squared	0.627		0.848	
Instruments/lags:		22/2-6		20/2-4
A.-B. AR Test:		0.079		0.427
Hansen J Test:		0.329		0.116

Note: All regressions include time dummies. Robust standard errors between brackets.
Significance: ***=1%; **=5%; *=10%.

Source: Authors' elaboration

In sum, the System GMM regressions between demand and research intensity indicate that both for low-tech and for high-tech industries, demand has no significant effect on research intensity in the long term. These findings reinforce the results found for all industries altogether, reported in Table 2. Importantly, when low-tech and high-tech industries are analysed separately, test statistics indicate the validity of the instruments.

4. Concluding Remarks

While the Schumpeterian literature on economic growth suggests that research intensity is an important determinant of productivity growth, the Kaldorian literature on economic growth stresses that demand growth is the main determinant of productivity growth.

Romero and Britto (2017) showed, however, that although demand growth is crucial for productivity growth, in sectors and/or countries with higher research intensity, productivity growth presents a stronger response to demand growth. This approach implies assuming that research intensity is exogenous, i.e. not determined by demand growth.

Since a large number of works point out that demand growth influences innovation, it is reasonable to suspect that demand might also impact on research intensity. Despite the importance of research intensity in the Schumpeterian growth literature, and notwithstanding the fact that several papers have tested the relationship between demand and innovation, very few studies investigated the relationship between demand and research intensity.

The results reported in this paper confirm that demand exerts a positive and significant impact on innovation. Moreover, the results suggest that this impact is stronger in high-tech industries than in low-tech industries. This difference brings more evidence that different sectors have specific dynamics that need to be taken into account.

Finally, this paper provides evidence that demand does not impact on research intensity, despite its impact on innovation. This finding holds both for low-tech and high-tech industries, using both R&D to value added and patents per millions of hours worked as measures of research intensity. This result reinforces Romero and Britto's (2017) findings, pointing out that research intensity is not influenced by demand growth, but most likely depends on each country's capacity to develop a mature National Innovation System.

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