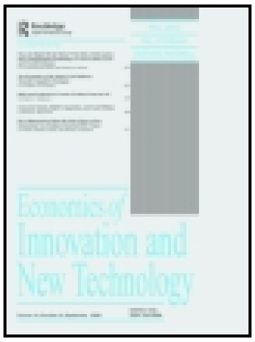

Routledge
Taylor & Francis Group

Economics of Innovation and New Technology

ISSN: 1043-8599 (Print) 1476-8364 (Online) Journal homepage: http://www.tandfonline.com/loi/gein20

Disentangling the effects of process and product innovation on cost and demand

Jordi Jaumandreu & Jacques Mairesse

To cite this article: Jordi Jaumandreu & Jacques Mairesse (2016): Disentangling the effects of process and product innovation on cost and demand, Economics of Innovation and New Technology, DOI: 10.1080/10438599.2016.1205276

To link to this article: http://dx.doi.org/10.1080/10438599.2016.1205276

Published online: 19 Aug 2016.

ECONOMICS OF INNOVATION AND NEW TECHNOLOGY, 2016
http://dx.doi.org/10.1080/10438599.2016.1205276

Disentangling the effects of process and product innovation on cost and demand

Jordi Jaumandreu[a,b] and Jacques Mairesse[c,d,e]

[a]Department of Economics, Boston University, Boston, MA, USA; [b]CEPR, London, UK; [c]CREST-ENSAE, Paris, France; [d]UNU-MERIT, Maastricht University, The Netherlands; [e]NBER-CREST-ENSAE, Malakoff Cedex, France

ABSTRACT
We explore in this note different structural models of the impact of process and product innovation on firms' demand and production cost functions. We find that the introduction of process and product innovations affects them differently as could be expected. Both product and process innovation shift forward the demand for the products of the firm. Process innovation reduces production marginal cost, but not always. A possibility, that we cannot prove or reject with the current specification of our models and available data, is that process innovation associated with product innovation raise marginal cost. Interestingly, we also find that advertising significantly augments demand but does not affect production marginal cost. To obtain broader conclusions, richer data will be needed allowing an enlargement of the model, in which process and product innovations could be specified distinctively and well identified.

ARTICLE HISTORY
Received 12 December 2015
Accepted 15 June 2016

KEYWORDS
Product innovation; process innovation; R&D

JEL CLASSIFICATION
L11; 033

1. Introduction

Firms perform R&D to obtain and introduce process and product innovations in the hope that they will eventually enhance profits. But the process of discovery and development of innovations embodies uncertainty and heterogeneity, which makes its structural analysis extremely complex. In particular, the timing of the resulting innovations and its introduction is characterized by randomness, and the effects of both types of innovations are not directly observable and presumably very different.

The distinction between process and product innovations, formalized by OECD in the Oslo manual in 1992, picks up a fundamental distinction of innovative activities. Sometimes firms want to reduce cost by altering their process of production, sometimes to enhance demand by developing and improving their products. It is also important to take into account that some process innovations may imply product changes, and some product innovations may need associated process changes.

In the last 20 years, indicators distinguishing process and product innovations have been collected in firm-level surveys in many countries such as the Community Innovation Surveys (see, e.g. Mairesse and Mohnen 2010). Researchers have struggled to use both types of indicators in productivity models, with quite diverse estimates, and have raised various problems about their use and the interpretation of results which rely on them.

Crepon, Duguet, and Mairesse (1998), CDM henceforth, proposed an econometric framework that specifies the process of activities going from research and innovation to productivity in different stages. They first allowed for an equation representing the decision of the firm to carry out R&D investment, then considered an equation of production of innovations as the result of the R&D capital (or 'knowledge production function'), and finally specified the introduction of these

CONTACT Jordi Jaumandreu jordij@bu.edu Department of Economics, Boston University, 270 Bay State Road, MA 02215, Boston, USA

innovations as impacting productivity over time in a Cobb–Douglas production function. R&D was the natural instrument to assess the role of these innovations in the production function. CDM measured innovations alternatively by patents and the share of innovative sales. Notice that the first variable is already an innovation output indicator and the second already an indicator of the impact of product innovation on production performance.

1.1. A bird's eye view of the literature on the productivity effects of product and process innovations

Since the original CDM analysis, many studies have adopted the staggered modeling of the production of innovations and the impact of innovations on productivity. In doing this, a number of them have tried to take advantage of the availability of distinct process and product innovation indicators mentioned above.

A good example is Griffith et al. (2006), henceforth GHMP, who introduce process and product innovations in a Cobb–Douglas production function after modeling separately the production of both type of innovations. GHMP use firm samples for France, Germany, Spain and the UK. They find a positive significant impact of product innovation on productivity everywhere except in Germany, and a positive significant effect of process innovation in France. They are surprised by the lack of association between productivity and process innovation in the three other countries and conjecture that ' … could correspond to the fact that we are measuring revenue productivity (deflated by industry deflators, not by individual firm deflators)'.

More extensive evidence is reported in Hall (2011) who summarizes the results of many studies regressing 'revenue productivity' on the indicators of process and product innovations, and concludes that product innovation tends to show the expected positive effect, while 'the impact of process innovation is more variable and often negative'.

More recently, Peters, Roberts, and Vuong (2015) and Peters et al. (2015) constitute a notable example of dynamic carefully modeling of the generation of process and product innovations, assuming a Markov process for productivity that shifts with their introduction. Estimating the model with a sample of German firms, product innovations turn out to be mainly significant in the increase of productivity in high-tech industries, and process innovations in low-tech industries. The productivity to be explained in these two papers is explicitly combining firm efficiency with demand shifts by nesting marginal cost in the direct demand expressed in terms of revenue and by considering persistent unobservable demand shocks. In this sense, both papers raise an issue similar to that of GHMP.[1]

A somewhat more structural use of the indicators of process and product innovation is done in Harrison et al. (2014). The authors derive a labor demand equation where there is a separated role for the increase of the efficiency of production, as a direct driver of employment reductions for a given output, and an output effect coming through the demand expansions induced by new products. Using firm samples for France, Germany, Spain and the UK, similar to GHMP, they find that the estimated effects of product innovations on employment growth are always positive and statistically significant, while the effects of process innovations are negative and often significant. They attribute the few cases of statistical insignificance to the fact that unobserved firm-level output prices are likely to fall with reductions permitted by process innovations and thus bringing about an unobserved positive output effect on employment.

Another recent example of structural modeling is the paper by Jaumandreu and Lin (2016), which focuses on the firms' marginal cost as depending on both process and product innovations and explores the transmission of marginal cost to price. The authors in this paper estimate alternative versions of their model with static and dynamic pricing, always allowing process and product innovations to impact firms' average margins or mark-ups. Preliminary estimates suggest that process innovations increase productivity, product innovations may increase or decrease productivity, and process innovations enlarge margins, while product innovations have no effect on them. These findings are complementary to those in the present study, where we assume that margins are constant.

Jaumandreu and Mairesse's (2010) paper is perhaps the first paper that tried to specify and estimate a structural model of firm process and product innovations, separating their effects on production cost and demand functions, that is on productivity and demand shifts. In this exercise, carried out with the sample of Spanish firms that we use in the present analysis, demand can be directly estimated thanks to the availability in this sample of firm-level output price indices. We have continued working on this model and we report here the estimates obtained so far on the effects of process and product innovations and what we have learned on the problems encountered in identifying these effects. A related paper is Petrin and Warzynski (2012) that models both firm demand and production functions and tries to assess simultaneously the impact of R&D on product quality and production efficiency.

In summary, one would expect a strong effect of product innovation on demand and a strong effect of process innovation on production cost although some cross effects are also likely. The evidence on these direct impacts is, however, very scarce because the data and econometric requirements to estimate separately demand and production cost are huge. As we have stressed, there have been many studies that can be considered as mixing innovation productivity and demand effects in revenue production functions and that tend to find problematic effects, particularly for process innovation. There is, hence, a lot to be gained in the understanding of the impact of innovation by trying to structurally disentangle the effects of process and product innovation. This study wants to be a step in this direction.

1.2. The present analysis

In a nutshell, we do the following. Within the encompassing framework of marginal production cost and demand functions of the firm, we consider different specifications or models for the effects of process and product innovations. We precisely focus on four models of interest: an unrestricted model where both process and product innovations affect cost and demand, and three other nested in the first but non-nested among them, in which the effects of process and product innovations are restricted. These are the following: a non-specialized model where the effects of process and product innovation are not different on cost and not different on demand; a specialized model in which process innovation affects cost and product innovation affects demand; and a mixed model, where the effects of process and product innovations are not different on demand and only process innovation affects cost. Note that we have only one innovation indicator in each of the cost and demand equations of these three restricted models.

We first consider OLS estimates for the unrestricted model and test whether the restrictions of the three nested models can be accepted. We also implement a Sargan overidentification test to decide if our process and product innovation indicators could act as good exogenous proxies in both marginal cost and demand equations. We find that even the best model among the three is not good: in several industries the estimated effects on cost are not precise enough to be significant, and the overidentification tests are not passed.

We interpret these results as showing that we cannot accept that our process and product innovation indicators act as good exogenous proxies but are endogenous, and we proceed to instrument them by R&D in the three restricted models, where we have only one innovation indicator in each equation. We cannot estimate the unrestricted model since R&D appears to be our only available good enough instrument. After testing the relative fit of the three restricted models, we favor the mixed model, although we have to recognize that some estimated effects are still not as 'structural' as we would like, since they probably mix different effects (i.e. they are 'reduced form' estimates).

We must also stress a more important caveat. In the present investigation we keep firms' mark-ups constant over time. This is a strong restriction that can be impacting our estimates in ways that are unclear. To relax this assumption calls for the modeling of firms' decisions on their markups, which could be done in an extended framework including a pricing equation together with the cost and demand equations. This is not easy and left for future research.

The rest of this paper is organized as follows. In Section 2, we describe our general framework and our four model specifications of the process and product innovations effects on cost and demand. In Section 3, we explain our sample and variables. Note that our analysis is implemented separately at the level of ten manufacturing industries. In Sections 4 and 5, respectively, we discuss the results of carrying out the estimations with exogenous and endogenous innovations. In Section 6, we briefly discuss the exclusion of advertising from the marginal cost equation. In Section 7, we conclude with remarks on the limitations of our approach and weaknesses of our results and on ways to overcome them in future researches.

2. Framework and process and product innovations

In this section, we first briefly present our framework for marginal production cost and demand for output (see also Jaumandreu and Mairesse, 2010) and then explain our choice of four model specifications of process and product innovation effects in this framework.

2.1. Framework

The two equations of our framework are precisely the following. The marginal cost is the firm short-run marginal production cost for a given capital. Assuming that the firm maximizes its profits in the short run it can be expressed as a function of capital, the prices of the variable factors labor and materials, and output. Short-run marginal production cost depends in addition on a firm unobserved productivity level ω_1. The demand for output is the demand relationship of a monopolistically competitive firm, which varies with the price set by the firm given the prices of other firms (picked up by the year dummies in the equation). Demand also depends on an unobserved demand advantage of the firm noted by ω_2.

The system of the two equations can thus be written as:

$$\begin{aligned} MC_{jt} &= MC(K_{jt}, W_{jt}, P_{Mjt}, Q_{jt}, \omega_{1jt}), \\ Q_{jt} &= Q(P_{jt}, \omega_{2jt}), \end{aligned} \tag{1}$$

with indices j and t denoting the firm and the year, and where MC stands for marginal cost, K for capital, W and P_M for the prices of labor and materials, Q for output, and P for output price.

As a link between the two equations, a pricing rule $P_{jt} = \eta/(\eta - 1)MC_{jt}$ is assumed, which implies that the firm set its price with a margin on marginal cost according to an elasticity of demand η taken in first approximation as a constant parameter. This implies the proportionality of price and marginal cost and avoids the need for a third equation allowing for a more flexible pricing behavior of the firm. We plan to relax this constraint in future research.

In this analysis, we assume that ω_1 and ω_2 follow random walk with drift processes, that is

$$\begin{aligned} \omega_{1jt} &= \omega_{1jt-1} + x_{1jt}\gamma_1 + \xi_{1jt}, \\ \omega_{2jt} &= \omega_{2jt-1} + x_{2jt}\gamma_2 + \xi_{2j}, \end{aligned} \tag{2}$$

where x_1 and x_2 represent variables that impact the unobserved productivity and demand advantages ω_1 and ω_2, and thus shift marginal cost and output demand.[2]

Equations (1) are hence subject to persistent displacements that represent changes in productivity and improvements in demand, respectively. The variables x_1 and x_2 may be endogenously determined by the firm but, as long as this determination is previous to the current period and the processes for ω_1 and ω_2 are well specified, they are orthogonal to the unforecastable random shocks ξ_1 and ξ_2. We consider here four variables that impact ω_1 and ω_2: the state of the market, firm advertising and process and product innovations.

We have chosen to estimate equations (1) in first differences. This choice has two important disadvantages: a loss of efficiency in estimation and the exacerbation of error-in-variables problems. But it has also three important advantages. First, our specification may be considered as a first-order approximation to an arbitrary differentiable production function. Second, since our prices are firm-level price indices, they are defined relatively to a specific firm-level price level in a reference year, they are not meaningful across firms and only relevant within firms, and thus in log-first differences. Third, we thus also abstract from all level fixed (or nearly fixed) effects that can be in Equations (1).

Differentiating equations (1) with respect to time, inserting equations (2), specifying the variables that shift demand and cost, and representing (log) rates of growth by lowercase letters, we obtain the following two equations system (3):

$$\begin{aligned} c_{jt} &= -\frac{\varepsilon_K}{\nu}k_{jt} + \frac{\varepsilon_L}{\nu}w_{jt} + \frac{\varepsilon_M}{\nu}p_{Mjt} + \left(\frac{1}{\nu} - 1\right)q_{jt} + \beta_{md1}md_{jt} + i_{1jt}\beta_1 + \xi_{1jt}, \\ q_{jt} &= -\eta p_{jt} + \beta_{md2}md_{jt} + \beta_a a_{jt} + i_{2jt}\beta_2 + \xi_{2jt}, \end{aligned} \tag{3}$$

where we denote the short-run elasticity of scale as $\nu\ (\equiv \varepsilon_L + \varepsilon_M)$ and variables c, p, q, k, w and p_M are the rates of growth of marginal cost, price, output, capital, and the prices of the two variable factors, labor and materials respectively. Note that, with constant short-run elasticity of scale, the growth of marginal and average costs are the same, so we simply write c for the rate of growth of marginal cost.

Variable *md* called market dynamism stands for the state of the market of the firm; it is an index which takes three values corresponding to three states: recessive, stable or expansive. Variable a is the rate of change in advertising expenditures of the firm. And variables i_1 and i_2 are generic indicators of the innovations introduced by the firm (see below for their specification).

Market dynamism is included in both cost and demand equations, and advertising only in the demand equation. It is obvious that market dynamism is a shifter of demand. But it is less clear why this variable should be included in the cost equation. We include it because, in practice, it seems to be important, which calls for two remarks.

First, the impact of market dynamism in the cost equation is significant but small and systematically negative. Second, we can drop this variable from the cost equation without a significant change in the estimates, but the residual term is then correlated with the cycle. The reasons for these facts are worthy of further investigation but should not bear on our findings.

We present below, in Section 6, a test confirming that advertising affects firm demand but can be excluded from its production cost function, which is to be expected since advertising is not sensu stricto a factor of production and productivity, but an investment to boost firm sales.

2.2. Specification of innovation

Our main interest in this analysis is to establish how process and product innovation should structurally enter cost and demand. In order to do so, we consider four alternative model specifications: unrestricted, non-specialized, specialized and mixed. In our data, the introduction of process and product innovations is reported separately on a yearly basis.[3] From the outset, it is not completely clear if these two types of innovations impact marginal cost, demand, or both relationships. Hence, we choose to start with a general model allowing for six possible innovation effects:

$$\begin{aligned} i_{1jt}\beta_1 &= \beta_{11}z_{jt} + \beta_{12}d_{jt} + \beta_{13}z_{jt} \times d_{jt}, \\ i_{2jt}\beta_2 &= \beta_{21}z_{jt} + \beta_{22}d_{jt} + \beta_{23}z_{jt} \times d_{jt}, \end{aligned} \tag{4}$$

where z and d are respectively binary indicators of process and product innovations.

This unrestricted model nests three sub-models of particular interest. The non-specialized model supposes that product, process and simultaneous process and product innovations have the same impact and imposes the four following linear constraints on the six innovation dummy coefficients: $\beta_{11} = \beta_{12} = -\beta_{13}$ and $\beta_{21} = \beta_{22} = -\beta_{23}$. It can simply be written as

$$\begin{aligned} i_{1jt}\beta_1 &= \beta_1 inno_{jt}, \\ i_{2jt}\beta_2 &= \beta_2 inno_{jt}, \end{aligned} \tag{5}$$

where $inno = 1(z = 1 \text{ or } d = 1)$ is a simple dummy of innovation.

The specialized model supposes that process innovation only affects marginal cost and product innovation only affects demand and imposes the four following linear constraints: $\beta_{12} = 0$, $\beta_{13} = 0$ and $\beta_{22} = 0$, $\beta_{23} = 0$. It can be written as

$$\begin{aligned} i_{1jt}\beta_1 &= \beta_1 z_{jt}, \\ i_{2jt}\beta_2 &= \beta_2 d_{jt}. \end{aligned} \tag{6}$$

There is a priori little economic sense in defining a model that reverses the role of process and product innovation (with process innovation affecting only demand and product innovation only cost). But looking at some of our first estimates has convinced us of the possible validity of a combination of models (5) and (6)

$$\begin{aligned} i_{1jt}\beta_1 &= \beta_1 z_{jt}, \\ i_{2jt}\beta_2 &= \beta_2 inno_{jt}, \end{aligned} \tag{7}$$

that we call mixed model. Process innovation is the only innovation affecting cost as in the specialized model but both process and product innovation affects demand as in the non-specialized model.

3. Data

We present estimates based on ten (unbalanced) industry samples over the period 1990–2006, which in total amount to more than 2400 Spanish manufacturing firms and 20,000 observations. All variables come from the survey ESEE (Encuesta Sobre Estrategias Empresariales), a firm-level panel survey of Spanish manufacturing starting in 1990. The survey provides a random sample of Spanish manufacturing with the largest firms exhaustively surveyed. The Data Appendix gives information on the ESEE survey and on variables definition.

Let us briefly describe here the variables that we use. On the one hand, we have the more usual variables: output (deflated production) and physical capital stock estimates. We compute variable cost as the sum of the wage bill and intermediate consumption, and estimate the hourly wage by dividing the wage bill by total hours of work. But we also have some less usual firm-level variables which play an important role in our estimations. Firstly, we have the yearly (average) output price changes as reported by the firm that we transform in firm-level price indices used both to deflate nominal production and as a variable by itself. Secondly, firms also provide an (average) estimate of the change in the cost of inputs grouped in three sets: energy, materials and services, which are combined in a price index for materials. Thirdly, firms also report yearly average rates of capacity utilization. Finally, we use a firm-specific user cost of capital as an instrument, which we compute as the sum of the interest rate paid on the long-term debt of the firm and an approximate 0.15 depreciation rate, minus the consumer prices index variation.

We rely on the following variables as shifters: the two innovation binary indicators for the introduction of process and product innovations, an index of the dynamism of the firm's specific market and the rate of increase of firm advertising.[4] Finally, we use firms' R&D investments to construct an instrument of the innovation indicators.

Tables 1 and 2 give for our ten industry samples interesting descriptive statistics on the main variables and innovation indicators respectively.

Table 1. Descriptive statistics, 1990–2006.

Industry	Sample size		Output growth (s.d.)	Price growth (s.d.)	Capital growth (s.d.)	Wage growth (s.d.)	Materials price growth (s.d)	Advertising growth (s.d.)	Market dynamism index value (s.d.)
	Obs.	Firms							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. Metals and metal products	2365	313	0.045	0.017	0.055	0.049	0.041	0.04	0.600
			(0.235)	(0.052)	(0.200)	(0.163)	(0.067)	(0.939)	(0.344)
2. Non-metallic minerals	1270	163	0.046	0.012	0.058	0.043	0.031	0.044	0.581
			(0.228)	(0.058)	(0.215)	(0.144)	(0.034)	(0.876)	(0.337)
3. Chemical products	2168	299	0.060	0.008	0.063	0.047	0.032	0.026	0.589
			(0.228)	(0.055)	(0.185)	(0.138)	(0.065)	(0.794)	(0.330)
4. Agric. and ind. machinery	1411	178	0.031	0.015	0.044	0.045	0.030	0.020	0.569
			(0.252)	(0.026)	(0.198)	(0.150)	(0.038)	(0.786)	(0.352)
5 Electrical products	1505	209	0.059	0.008	0.046	0.051	0.030	0.036	0.557
			(0.269)	(0.046)	(0.178)	(0.168)	(0.044)	(0.839)	(0.353)
6. Transport equipment	1206	161	0.060	0.008	0.050	0.047	0.028	0.029	0.569
			(0.287)	(0.031)	(0.174)	(0.162)	(0.048)	(0.857)	(0.372)
7. Food, drink and tobacco	2455	327	0.023	0.021	0.051	0.052	0.033	0.046	0.540
			(0.206)	(0.054)	(0.184)	(0.170)	(0.058)	(0.840)	(0.313)
8. Textile, leather and shoes	2368	335	0.004	0.015	0.035	0.052	0.031	0.049	0.436
			(0.229)	(0.042)	(0.197)	(0.178)	(0.044)	(0.851)	(0.343)
9. Timber and furniture	1445	207	0.025	0.020	0.049	0.054	0.035	0.048	0.530
			(0.225)	(0.031)	(0.174)	(0.166)	(0.039)	(0.940)	(0.338)
10. Paper and printing products	1414	183	0.031	0.017	0.052	0.052	0.035	0.029	0.533
			(0.187)	(0.074)	(0.226)	(0.139)	(0.076)	(0.848)	(0.324)

Table 2. Descriptive statistics on the introduction of innovations, 1991–2006.

Industry	Proportion of obs. with			Correlation Proc. and Prod.
	Proc. (s.d.)	Prod. (s.d.)	Proc. and Prod. (s.d.)	
	(1)	(2)	(3)	(4)
1. Metal and metal products	0.373	0.184	0.127	0.310
2. Non-metallic minerals	0.265	0.172	0.093	0.281
3. Chemical products	0.403	0.345	0.221	0.352
4. Agric. and ind. machinery	0.332	0.354	0.190	0.320
5. Electrical goods	0.375	0.365	0.213	0.326
6. Transport equipment	0.464	0.313	0.222	0.333
7. Food, drink and tobacco	0.305	0.223	0.154	0.443
8. Textile, leather and shoes	0.242	0.230	0.116	0.296
9. Timber and furniture	0.285	0.257	0.134	0.304
10. Paper and printing products	0.293	0.141	0.083	0.265

4. Results with exogenous innovation

We first describe how we estimate our cost and demand equations and report on their estimated coefficients. We then comment the estimated effects of process and product innovation indicators, assuming that they are exogenous, in both cost and demand equations for the unrestricted and three restricted specifications.

4.1. Marginal cost and demand functions

Quantity q and price p are the endogenous variables included in the right side of the cost and demand equations, respectively. Other variables are capital k and input prices: wage w and price of materials p_M. Both equations include a constant and 15 year dummies. Our capital variable is, in fact, capacity utilization times capital u+k.

Capital and prices should be in theory uncorrelated with the error of the equation because they are variables respectively predetermined and given for the firm. We need, however, to instrument them in the first equation, presumably because errors in variables biases are likely to be exacerbated by our choice of estimators in first differences. We employ the user cost of capital and the variable utilization of capacity as instruments aimed at picking up the variations of capital. Simultaneously, we use the levels of the wage and price of materials index to help the estimation of the price coefficients (a solution in the tradition of panel data GMM estimates). These four instruments are enough for identification, because we have to estimate only three elasticities in the first equation and the elasticity of demand in the second equation.[5]

Two important aspects should be clarified. The right variable to include in the right-hand side of the demand equation is price, but we are only able to include it in six industries. In the four other industries (i.e. industries 2, 4, 5 and 10), we did not succeed to obtain meaningful estimates using the price changes and we replaced them by the marginal cost changes. If firms' markups were invariant, replacing one by the other should be equivalent and should not affect estimation. The fact that it is not, at least for some industries, means that in the future we should model independently the price in a third equation and try to include it properly in all industries, as we already mentioned. Moreover, when we use price as explanatory variable in the demand equation, we have to drop capacity utilization as an instrument in this equation. This suggests cyclical variation in prices that could be taken care of in the third price equation. Note that we kept these changes in the specification of the demand equation and our choice of instruments in the four industries 2, 4, 5 and 10 for all our subsequent model estimations.

We report in Table 3 the estimated coefficients for the marginal cost and demand equations, and in the two first columns of Table 4 the Sargan tests of overidentifying restrictions that can be taken as a test on the validity of the instruments. We see in Table 3 that the estimated elasticities are very reasonable, although sometimes somewhat imprecise. Note that we are estimating

Table 3. Cost and demand functions with exogenous unrestricted process and product effects.[a,b]

	Cost function (dep. var.: marginal cost)[c]							Demand function (dep. var.: output)					
	Elasticities			Shifters				Price	Shifters				
Industry	ε_K (s.e.) (1)	ε_L (s.e.) (2)	ε_M (s.e.) (3)	Market dyn. (s.e) (4)	Process innov. (s.e.) (5)	Product innov. (s.e.) (6)	Prc.×Prd. (s.e.) (7)	elasticity η (s.e) (8)	Market dyn. (s.e) (9)	Adv. (s.e.) (10)	Product innov. (s.e) (11)	Process innov. (s.e.) (12)	Prc.×Prd. (s.e.) (13)
1. Metals and metal products	0.117	0.057	0.591	−0.096	−0.010	−0.018	0.002	2.158	0.180	0.008	0.030	0.025	−0.013
	(0.034)	(0.043)	(0.099)	(0.032)	(0.011)	(0.014)	(0.018)	(0.657)	(0.018)	(0.005)	(0.011)	(0.018)	(0.022)
2. Non-metallic minerals	0.062	0.236	0.929	−0.036	0.010	−0.014	0.018	2.268	0.009	0.017	0.024	−0.060	0.044
	(0.059)	(0.161)	(0.290)	(0.028)	(0.012)	(0.017)	(0.024)	(1.293)	(0.073)	(0.014)	(0.031)	(0.035)	(0.048)
3. Chemical products	0.105	0.084	0.648	−0.048	−0.017	−0.004	0.008	1.789	0.132	0.024	0.039	0.004	−0.020
	(0.022)	(0.082)	(0.081)	(0.016)	(0.012)	(0.012)	(0.016)	(0.556)	(0.017)	(0.008)	(0.013)	(0.014)	(0.020)
4. Agric. and ind. machinery	0.091	0.172	0.884	−0.026	0.012	−0.009	0.015	3.305	0.023	0.024	0.031	0.010	−0.012
	(0.113)	(0.146)	(0.355)	(0.063)	(0.012)	(0.012)	(0.025)	(0.989)	(0.055)	(0.019)	(0.026)	(0.025)	(0.041)
5. Electrical products	0.052	0.330	0.614	−0.048	−0.010	−0.004	0.020	2.009	0.084	0.045	0.008	−0.044	0.065
	(0.049)	(0.095)	(0.159)	(0.026)	(0.014)	(0.010)	(0.015)	(0.866)	(0.035)	(0.014)	(0.027)	(0.019)	(0.037)
6. Transport equipment	0.178	0.285	0.463	−0.074	−0.010	0.010	−0.020	3.021	0.166	0.018	0.007	0.021	0.004
	(0.057)	(0.060)	(0.104)	(0.024)	(0.011)	(0.013)	(0.020)	(1.414)	(0.023)	(0.010)	(0.024)	(0.022)	(0.035)
7. Food, drink and tobacco	0.057	0.111	0.767	−0.026	−0.002	−0.016	0.008	2.291	0.112	0.024	0.019	0.040	−0.016
	(0.024)	(0.057)	(0.081)	(0.013)	(0.009)	(0.008)	(0.012)	(0.608)	(0.014)	(0.007)	(0.010)	(0.011)	(0.018)
8. Textile, leather and shoes	0.070	0.074	0.648	−0.082	−0.012	−0.012	0.030	4.299	0.240	0.027	0.027	0.018	−0.056
	(0.033)	(0.055)	(0.110)	(0.033)	(0.011)	(0.010)	(0.018)	(2.669)	(0.049)	(0.008)	(0.017)	(0.026)	(0.037)
9. Timber and furniture	0.074	0.135	0.606	−0.083	−0.021	−0.016	0.018	3.149	0.171	0.013	0.053	0.042	−0.028
	(0.023)	(0.057)	(0.138)	(0.039)	(0.018)	(0.017)	(0.025)	(1.447)	(0.020)	(0.007)	(0.016)	(0.023)	(0.030)
10. Paper and printing products	0.041	0.198	0.663	−0.043	0.008	0.015	−0.026	1.875	0.058	0.019	0.043	0.031	−0.069
	(0.020)	(0.120)	(0.206)	(0.025)	(0.011)	(0.017)	(0.022)	(1.106)	(0.034)	(0.012)	(0.025)	(0.043)	(0.067)

[a]Nonlinear GMM.
[b]Standard errors in parentheses, robust to arbitrary autocorrelation over time and heteroskedasticity across firms.
[c]Coefficient of output is $(1/(\varepsilon_L + \varepsilon_M) - 1)$.

Table 4. Testing the specification and restrictions.

Industry	Specif. test[a]		Restricting the effects to model[b]					
			Non-specialized		Specialized		Mixed	
	χ^2 (df) (1)	p val. (2)	χ^2 (4) (3)	p val. (4)	χ^2 (4) (5)	p val. (6)	χ^2 (4) (7)	p val. (8)
1. Metals and metal products	5.855	0.210 (4)	3.610	0.461	17.000	0.002	6.379	0.173
2. Non-metallic minerals	11.264	0.046 (5)	6.944	0.139	4.557	0.336	5.923	0.205
3. Chemical products	14.445	0.006 (4)	8.622	0.071	16.975	0.002	12.051	0.017
4. Agric. and ind. machinery	10.138	0.071 (5)	3.554	0.470	4.964	0.291	1.565	0.815
5. Electrical products	16.406	0.006 (5)	24.930	0.000	24.141	0.000	24.889	0.000
6. Transport equipment	18.381	0.001 (4)	9.028	0.060	3.144	0.534	2.501	0.644
7. Food, drink and tobacco	13.756	0.008 (4)	6.813	0.146	11.678	0.020	11.303	0.023
8. Textile, leather and shoes	0.348	0.986 (4)	4.525	0.340	5.626	0.229	5.541	0.236
9. Timber and furniture	5.130	0.274 (4)	2.341	0.673	20.140	0.000	7.537	0.110
10. Paper and printing products	4.156	0.245 (3)	1.998	0.736	5.569	0.234	2.792	0.593

[a]Sargan test of overidentifying restrictions.
[b]Difference in the GMM criterion. Degrees of freedom are the number of restrictions.

here production elasticities on the basis of variations in output prices and variable factors prices, an approach fully supported by duality but not usual in practice on firm data. In particular, long-run returns to scale in the cost function are reasonable, being for most of them not significantly different from unity, and output price demand elasticities significantly above unity as expected. However, we find that the Sargan tests in the two first columns of Table 4 are not passed at standard levels of significance in five industries. We may hopefully attribute part of this failure to the unrestricted specification of the innovation shifters in both equations.

4.2. Unrestricted innovation effects

The estimated innovation effects reported in Table 3 are the ones obtained for the unrestricted model specification (4). We find that they are very imprecise, a result most likely reflecting the high degree of multicollinearity of the process and product innovation dummies (as shown by their high correlations of about 0.30 reported in the last column of Table 2). However, in spite of their lack of precision, these estimates also point to high heterogeneity of innovation effects in the different industries. A detailed reading of the cost effects shows a somewhat dominant pattern, whereby in six industries both process and product innovations have negative signs together with positive interaction effects. Similarly, a detailed reading of the demand effects reveals an opposite dominant pattern, with estimated effects slightly more significant. In seven industries, both process and product innovations are positive while their interaction effects are negative. We can very tentatively conclude that both types of innovations tend to reduce cost in isolation but less so when process and product innovation are associated. Similarly but with opposite sign, both types of innovations tend to increase demand in isolation and less so when associated.

We may expect to have a more precise idea of the specific industry pattern of innovation effects on cost and demand by estimating the non-specialized, specialized and mixed models (5), (6) and (7). Since they are nested in the unrestricted model (4), we can test whether their respective restrictions can be accepted by means of differences of the values of the second

Table 5. Cost and demand functions with exogenous innovation dummies.[a,b]

	Cost function (dep. var.: marginal cost)[c]					Demand function (dep. var.: output)				Specification test[d]	
	Elasticities			Shifters		Price elasticity	Shifters				
				Market dynamism	Innovation at $(t-1)$		Market dynamism	Advertising	Innovation		
Industry	ε_K (s.e.) (1)	ε_L (s.e.) (2)	ε_M (s.e.) (3)	(s.e.) (4)	(s.e.) (5)	η (s.e) (6)	(s.e) (7)	(s.e.) (8)	(s.e) (9)	$\chi^2(df)$ (10)	p val. (11)
1. Metals and metal products	0.115	0.036	0.634	−0.092	−0.004	2.293	0.183	0.009	0.032	6.970	0.137
	(0.035)	(0.054)	(0.094)	(0.032)	(0.007)	(0.634)	(0.018)	(0.005)	(0.009)	(4)	
2. Non-metallic minerals	0.064	0.270	0.853	−0.038	−0.004	2.097	0.016	0.020	0.004	13.391	0.020
	(0.065)	(0.189)	(0.275)	(0.030)	(0.010)	(1.144)	(0.065)	(0.013)	(0.018)	(5)	
3. Chemical products	0.104	0.061	0.679	−0.048	0.003	1.814	0.131	0.024	0.023	15.002	0.005
	(0.022)	(0.084)	(0.080)	(0.016)	(0.006)	(0.567)	(0.017)	(0.008)	(0.010)	(4)	
4. Agric. and ind. machinery	0.050	0.220	0.991	−0.004	0.001	3.409	0.022	0.021	0.025	12.339	0.030
	(0.129)	(0.172)	(0.403)	(0.055)	(0.008)	(1.026)	(0.054)	(0.019)	(0.019)	(5)	
5. Electrical products	0.054	0.301	0.611	−0.054	0.011	1.962	0.092	0.046	0.001	15.981	0.007
	(0.048)	(0.092)	(0.150)	(0.027)	(0.007)	(0.859)	(0.034)	(0.014)	(0.015)	(5)	
6. Transport equipment	0.181	0.264	0.487	−0.073	0.003	3.119	0.164	0.018	0.017	18.958	0.001
	(0.062)	(0.069)	(0.104)	(0.025)	(0.011)	(1.398)	(0.023)	(0.010)	(0.016)	(4)	
7. Food, drink and tobacco	0.055	0.095	0.801	−0.024	−0.004	2.284	0.114	0.025	0.033	14.286	0.006
	(0.025)	(0.057)	(0.078)	(0.014)	(0.005)	(0.610)	(0.014)	(0.007)	(0.007)	(4)	
8. Textile, leather and shoes	0.071	0.057	0.664	−0.082	0.004	4.058	0.234	0.026	0.012	0.737	0.947
	(0.033)	(0.055)	(0.109)	(0.033)	(0.008)	(2.574)	(0.046)	(0.008)	(0.012)	(4)	
9. Timber and furniture	0.074	0.097	0.689	−0.074	0.010	3.685	0.175	0.015	0.057	4.450	0.349
	(0.024)	(0.059)	(0.139)	(0.037)	(0.007)	(1.438)	(0.021)	(0.007)	(0.015)	(4)	
10. Paper and printing products	0.041	0.217	0.628	−0.044	−0.007	1.821	0.058	0.019	0.031	4.604	0.203
	(0.020)	(0.118)	(0.201)	(0.025)	(0.008)	(1.117)	(0.035)	(0.013)	(0.021)	(3)	

[a]Nonlinear GMM.
[b]Standard errors in parentheses, robust to arbitrary autocorrelation over time and heteroskedasticity across firms.
[c]Coefficient of output is $(1/(\varepsilon_L + \varepsilon_M) - 1)$.
[d]The Sargan test of overidentifying restrictions.

stage objective functions, when they are scaled, using the weighting matrix of the unrestricted estimates. These differences are distributed as a χ^2 with four degrees of freedom equal to 4, the number of restrictions imposed in the unrestricted model. The results of these tests are reported in columns 3–8 of Table 4.

The specialized model gives the worst results. In five industries, the restriction is statistically rejected at standard levels of significance. More favorable are the results of the non-specialized and mixed models. The non-specialized model is only rejected in one industry and the mixed model in three. However, we cannot consider that the first is clearly better than the second.

These results suggest that there is a chance that the non-specialized model, which simply includes an (exogenous) indicator of innovation in the cost and demand equations, works properly. Table 5, which reports all the estimates in the case of this innovation model, reveals, however, that the results are not good. We have tried to include innovation in the cost function both contemporaneously and lagged, and have chosen to retain the specification with lagged innovation since the estimated innovation effects appear slightly better. The estimated elasticities and the estimated coefficients of market dynamism and advertising remain basically unchanged. Nonetheless, innovation effects are fully significant in the demand equation for only six industries, and process innovation is significant in none. Moreover, the Sargan test of overidentifying restrictions, reported in columns 10 and 11 of Table 5, rejects the specification in six industries.

5. Results instrumenting innovation

From our previous results with exogenous innovation, we conclude that, in addition to heterogeneous innovation effects, we have at least a problem of errors in variables generating negative correlations of the innovation indicators with the residuals and hence attenuation biases. Errors in variables in the process and product indicators as well as in the overall innovation indicator are likely to arise for several motives. One major reason is the unweighted character of these count indicators. The size of cost reduction and size of demand increase are likely to change with the characteristics of innovation, in particular the type and intensity of underlying research and its novelty. This generates a missing variable problem and one can argue that the replacement of the relevant quantitative innovation variable by a binary indicator is likely to bias the estimated coefficient.[6] Another important reason is that yearly binary indicators can hardly capture the relevant timing of the introduction of innovations and the lags in their impact.

Part of the problem can be addressed by using R&D expenditures as an instrument. While the simple use of the innovation indicators is what can be called a 'proxy' solution to a missing variable, this is an arrangement of the type that Wooldridge (2010, pages 67 and 112) calls 'multiple indicator solution'. In this study, we construct an instrument that is equal to the (log of the) sum of the R&D investments accumulated by the firm since the latest innovation if there is an innovation, and equal to zero if there is no innovation. This instrument can help to address the problem because R&D is likely to be correlated with the size of the innovation effect. Unfortunately we cannot distinguish between R&D investment in process and product innovation and hence we have only one instrument. This puts a severe limitation on what we can do in practice, because we cannot hope to instrument unrestricted innovation effects with only one instrument. Finding a solution would not only need to find out other relevant instruments but also to set up an appropriate structural model of process and product innovations. This task is not a simple one and it lies out of the scope of this exploratory analysis.

5.1. Models, instruments and tests

What we can do and are doing here is to compare the results for the three restricted models that only include one innovation indicator in the cost and demand equations, when we estimate them using the same set of instruments as before for the 'non-innovation' part of the cost and demand

Table 6. Testing the restricted models against each other.

	Value functions			Specialized vs non-spec.[a]	Specialized vs mixed[a]	Non-spec. vs mixed[a]	Advertising exclusion in the cost function[b]	
	Spec. (1)	Non-spec. (2)	Mixed (3)	$N(0, 1)$ (p val.) (4)	$N(0, 1)$ (p val.) (5)	$N(0, 1)$ (p val.) (6)	$\chi^2(1)$ (7)	p val. (8)
1. Metals and metal products	0.545	0.181	0.195	1.660 (0.048)	1.637 (0.051)	−0.749 (0.227)	1.984	0.159
2. Non-metallic minerals	1.290	1.104	1.075	0.523 (0.331)	0.606 (0.272)	0.832 (0.203)	0.906	0.341
3. Chemical products	0.632	0.357	0.347	1.524 (0.064)	1.561 (0.059)	0.513 (0.304)	0.475	0.491
4. Agric. and ind. machinery	0.169	0.204	0.167	−0.134 (0.447)	0.006 (0.497)	0.689 (0.245)	5.362	0.021
5. Electrical products	0.381	0.378	0.382	0.017 (0.493)	−0.008 (0.497)	0.263 (0.604)	17.360	0.000
6. Transport equipment	0.764	0.726	0.707	0.298 (0.383)	0.458 (0.324)	0.874 (0.191)	4.540	0.033
7. Food, drink and tobacco	0.322	0.192	0.191	1.072 (0.142)	1.070 (0.142)	0.115 (0.454)	3.525	0.060
8. Textile, leather and shoes	0.086	0.131	0.131	−0.496 (0.310)	−0.488 (0.313)	0.003 (0.499)	0.016	0.899
9. Timber and furniture	0.558	0.214	0.225	1.204 (0.114)	1.165 (0.122)	−0.470 (0.319)	0.022	0.882
10. Paper and printing products	0.407	0.236	0.231	0.931 (0.069)	0.9787 (0.164)	0.397 (0.346)	0.245	0.621

[a]Rivers–Vuong model selection test for non-nested models.
[b]Difference in the GMM criterion. One degree of freedom.

equations, that is the user cost of capital, capacity utilization rates, wage level and price index of materials.

As concerns the 'innovation' part of the cost and demand equations in our three restricted models, we consider the following additional instruments. On the one hand, we use product innovation as instrument in the cost equation and process innovation as instrument in the demand equation. The assumption here is that the error in the variable used as instrument is uncorrelated with the error induced by the variable included in the regression. For example, the error generated by the lack of a size measure of process innovation, which we use to instrument the demand equation in which we include the product innovation dummy, is not correlated with the error induced by the lack of a size measure of product innovation. On the other hand, we use as instrument the cumulated R&D variable in both equations, lagged in the cost equation since the innovation dummy in this regression is lagged, as we already mentioned.

Because we use the same set of instruments, we can implement of a Rivers–Vuong test to compare our three non-nested models (Rivers and Vuong 2002). The test consists in computing for each of the three pair of models the difference in the values of the objective functions of the first stage estimates, divided by the estimated variance of such difference. The test follows a standard Normal distribution, a positive (negative) significant value implying that the second (first) model is significantly better than the other. Table 6 reports the values of the objective functions (columns 1–3) and the values of the tests (columns 4–6). The non-specialized model turns out to be significantly better than the specialized model in four industries, at different degrees of signification (5% in industry 1, 10% in industry 3, and 15% in industries 7 and 9). The mixed model is also significantly better than the specialized model in the same four industries (10% in industries 1 and 3, and 15% in industries 7 and 9). The non-specialized and mixed models appear non significantly different in all ten industries. However, as we shall see now, we have some preference for the mixed model which seems to give better results.

Table 7. Cost and demand functions with endogenous process innovation and innovation dummies.[a,b]

	Cost function (dep. var.: marginal cost)[c]					Demand function (dep. var.: output)					
	Elasticities			Shifters		Price elasticity	Shifters			Specification test[d]	
				Market dynamism	Process In. at $(t-1)$		Market dynamism	Advertising	Innovation		
Industry	ε_K (s.e.) (1)	ε_L (s.e.) (2)	ε_M (s.e.) (3)	(s.e.) (4)	(s.e.) (5)	η (s.e) (6)	(s.e) (7)	(s.e.) (8)	(s.e) (9)	$\chi^2(df)$ (10)	p val. (11)
1. Metals and metal products	0.107	0.139	0.583	−0.079	−0.033	1.984	0.178	0.010	0.032	9.873	0.130
	(0.036)	(0.048)	(0.095)	(0.027)	(0.014)	(0.619)	(0.018)	(0.005)	(0.009)	(6)	
2. Non-metallic minerals	0.094	0.147	0.747	−0.059	0.040	2.158	0.015	0.023	0.033	10.400	0.167
	(0.048)	(0.127)	(0.174)	(0.029)	(0.019)	(1.125)	(0.069)	(0.013)	(0.021)	(7)	
3. Chemical products	0.108	0.103	0.620	−0.050	−0.028	1.599	0.130	0.023	0.032	15.887	0.014
	(0.022)	(0.075)	(0.080)	(0.016)	(0.017)	(0.554)	(0.017)	(0.008)	(0.012)	(6)	
4. Agric. and ind. machinery	0.096	0.110	0.837	−0.044	0.042	3.766	0.006	0.032	0.047	12.482	0.086
	(0.087)	(0.101)	(0.266)	(0.050)	(0.018)	(1.057)	(0.057)	(0.019)	(0.024)	(7)	
5. Electrical products	0.053	0.296	0.606	−0.056	0.020	1.994	0.085	0.045	0.041	16.232	0.013
	(0.044)	(0.087)	(0.134)	(0.021)	(0.017)	(0.885)	(0.036)	(0.015)	(0.020)	(6)	
6. Transport equipment	0.158	0.276	0.514	−0.061	0.018	3.440	0.159	0.018	0.007	22.827	0.001
	(0.052)	(0.062)	(0.114)	(0.024)	(0.017)	(1.413)	(0.023)	(0.010)	(0.019)	(6)	
7. Food, drink and tobacco	0.056	0.126	0.811	−0.018	−0.014	2.280	0.116	0.026	0.031	15.612	0.016
	(0.025)	(0.058)	(0.080)	(0.012)	(0.010)	(0.606)	(0.014)	(0.007)	(0.008)	(6)	
8. Textile, leather and shoes	0.071	0.051	0.644	−0.089	0.006	2.936	0.215	0.025	0.011	1.998	0.920
	(0.032)	(0.048)	(0.103)	(0.032)	(0.016)	(1.481)	(0.029)	(0.007)	(0.012)	(6)	
9. Timber and furniture	0.073	0.123	0.563	−0.098	−0.024	3.178	0.172	0.013	0.065	6.740	0.346
	(0.023)	(0.057)	(0.167)	(0.047)	(0.038)	(1.346)	(0.020)	(0.007)	(0.015)	(6)	
10. Paper and printing products	0.027	0.252	0.658	−0.036	−0.026	1.904	0.053	0.017	0.031	7.106	0.130
	(0.022)	(0.121)	(0.207)	(0.024)	(0.024)	(1.129)	(0.034)	(0.013)	(0.022)	(4)	

[a]Nonlinear GMM.
[b]Standard errors in parentheses, robust to arbitrary autocorrelation over time and heteroskedasticity across firms.
[c]Coefficient of output is $(1/(\varepsilon_L + \varepsilon_M) - 1)$.
[d]The Sargan test of overidentifying restrictions.

5.2. A structural model of product and process innovation

We report in Table 7 the results we obtained when we considered the mixed model, which we now estimate using two additional instruments ('cross' innovation and R&D) for both the cost and demand equations, so that we have two overidentifying restrictions for each equation. Together with the previously used instruments this makes a total of six or seven restrictions in most of industries (see footnote 5). The Sargan tests of overidentifying restrictions are given in columns (10) and (11) of Table 7. We see that the test still does not pass in four industries.

The estimated elasticities of the cost and demand equations are reasonable, with little changes with respect to the previous estimates, but again sometimes rather imprecisely estimated. The market dynamism variable diminishes cost and increases demand in all industries, and significantly so for eight industries, with an average impact of 11%. The advertising variable shifts demand significantly in all ten industries. Note that its coefficient can be read as an elasticity, and that the average elasticity we find of 2.3% is a very reasonable number. Product innovation increases demand in all industries, and significantly so in eight industries, with an average effect of 3.3%. Process innovation in year $t-1$ has statistically significant or nearly significant impacts that are negative in five industries and positive in four industries.

Our interpretation is that we have not been able to disentangle all the effects, at least in the case of the cost function. It is likely that we do not fully control for the endogeneity of process innovations. One possibility is that process innovations associated with product innovations increase the cost of the firm. This seems reasonable, as these new processes may well imply changes in the inputs that we do not take into account (as labor skills, quality of materials, managerial abilities or production organization).

6. Advertising

We have included market dynamism in both equations and discussed the best specification for the innovation dummies but is advertising rightly excluded from the cost equation? To answer this question, we estimate our preferred model extended to include advertising in both equations. Using this unrestricted estimate, we apply the same test as we did for innovation effects (in Table 5). What we test in this case is whether we can impose the restriction that the coefficient on advertising in the cost equation is zero.

The result of the test is quite drastic, as can be checked in Table 6 columns 7 and 8. In seven industries, we can accept the exclusion of advertising in the cost equation with high levels of confidence. The case of the three remaining three industries is peculiar. In industries 4 and 5, advertising has a significant positive effect on cost at the expense of the coefficient on capital which becomes negative or null. In industry 6, the impact of advertising on cost is negative. We can safely conclude that the a-priori exclusion of advertising from the cost equation on our cost and demand framework is very well accepted by the data.

7. Concluding remarks

We have tried in this paper to identify and estimate the effects of innovation in the productivity-induced variations of the marginal cost function of the firm and in the shifts of its demand function. To do so we have explored four structural model specifications of innovation effects by means of dummy variables representing the introduction of process innovations, product innovations or simply innovations.

The unrestricted exogenous innovation effects model provide evidence of heterogeneity, which cannot be fully assessed because of the strong colinearity in the innovation indicators and a very likely problem of errors in variables. The estimation of the three restricted models suffers from the fact that the only good variable we can use to instrument the innovation indicators is constructed on the basis of R&D investments which contribute to both process and product innovations (and is not known at a project level).

However, comparing the different instrument variable estimates of the restricted models, although tentative, we arrive at two main conclusions. On the one hand, we find there is not much difference in the impact on demand of product innovation only, process innovation only and simultaneous process and product innovations. On the other hand, we observe that process innovations sometimes reduce cost and sometimes increase cost. Clearly we have not been able to completely separate the effects of process and product innovation. The conjecture, that we cannot prove with our unique good instrument, is that some process innovations associated with product innovations raise costs.

These findings can explain the lack of robustness of the innovation effects estimated in less structural productivity equations. First, if the researcher includes both process and product innovation in a specification that embodies both productivity evolution and demand shifts, the results can be very different according to the correlations which dominate in the data. Process innovation can be picking up efficiency and demand shifts but may also turn out to have no effect or a less significant effect if it is negatively related to efficiency. At the same time, a product innovation dummy may be mainly estimating the demand effect but may also show a reduced or even non-significant effect because of its possible negative efficiency effect. Second, if the productivity equation can be argued not to significantly include demand shifts (e.g. because revenue has been effectively deflated), a positive significant productivity effect for process innovation is not warranted and much harder to find for product innovation. Third, considering an overall innovation instead of separate process and product innovations is likely to mix their effects in unpredictable ways.

Are there appropriate solutions for a structural estimation of process and product innovation effects? One possible solution, as we tried to do here, is the enlargement of the set of available instruments. A reasonable way to do this is specifying and estimating equations for the production of process and product innovations that can select some exogenous variables particularly correlated with the introduction of one or the other type of innovations, and thus would provide suitable instruments. These equations are not easy to specify because, with panel data, in addition to the problem of the types of innovations we need to predict the timing of their introduction. A second possible solution would be to construct a sort of latent variable model, in which the effects of the unique dummy introduced in each equation correspond to a particular theoretically restricted combination of process and product effects. On the basis of such a model one might possibly infer structural effects from the estimated coefficients and correlations in the data. Both avenues seem worthy of being pursued in future research.

Finally, but not the least, as we stressed, our model should be enlarged with a pricing equation that allows for cyclical effects and could take into account different impacts of process and product innovations on firms' margins. This can also potentially improve the identification of these impacts.

Notes

1. There is a literature started with Klette and Griliches (1996) which tries to solve the problem of estimating the firm production function without firm output prices by nesting it in the firm (inverted) demand function. A recent example is De Loecker (2011). On this question see also Mairesse and Jaumandreu (2005).
2. The random walk process is only a simplifying assumption that can be relaxed and tested in more complex specifications. Notice, however, that a number of studies that assume an autoregressive process in productivity get as a result an autoregressive coefficient quite near to one (see, e.g. Peters et al. 2015). Productivity is also persistent in nonlinear processes as in Doraszelski and Jaumandreu (2013).
3. Notice that this information differs from the information usually available in CIS data, where the introduction of one or more process and product innovations are reported over the last three years.
4. The rate of growth seems a sensible specification when we are explaining output changes over time. It is likely to be not very different than the rate of growth of a firm-level 'accumulated goodwill' intangible capital stock and avoids all the complications in defining and measuring such a variable.

5. In fact, since we use the moments corresponding to two equations, we have some overidentifying restrictions. Four instruments and three elasticities give one restriction in the first equation, and four instruments and one parameter to estimate give three restrictions in the second. When we include the variables that shift the equations we get another overidentifying restriction in the first equation since we add four instruments and there are only three additional parameters to be estimated (advertising being excluded from the equation). This gives a total of five restrictions, which drop to four when we do not use utilization of capacity to instrument the second equation (see below). In industry 10, the restrictions fall further because we take capital as exogenous. The number of these restrictions is the degrees of freedom of the Sargan specification tests test reported in the first columns of Table 4.
6. Let us assume that the true model should include a variable size with the coefficient β, that this variable size is replaced in the estimated model by a binary indicator dummy related to size by the linear predictor $dummy = \gamma_0 + \gamma_1 size + \varepsilon$. The disturbance of the estimated equation will contain an error component equal to $-\beta\varepsilon/\gamma_1$ showing that the dummy proxy indicator is negatively correlated with this component.

Acknowledgments

We thank Xin Qi for research assistance. We are also grateful for comments to Sabien Dobbelaere, Ivan Fernadez-Val, Bronwyn Hall, Shuheng Lin, Pierre Mohnen, Bettina Peters, Mark Roberts, Van Anh Vuong and other participants of the London, Paris and Maastricht CDM workshops, and other seminars where preliminary versions of the paper were presented.

Disclosure statement

No potential conflict of interest was reported by the authors.

References

Crepon, B., E. Duguet, and J. Mairesse. 1998. "Research, Innovation, and Productivity: An Econometric Analysis at the Firm Level." *Economics of Innovation and new Technology* 7: 115–158.
De Loecker, J. 2011. "Product Differentiation, Multiproduct Firms, and Estimating the Impact of Trade Liberalization on Productivity." *Econometrica* 79: 1407–1451.
Doraszelski, U., and J. Jaumandreu. 2013. "R&D and Productivity: Estimating Endogenous Productivity." *Review of Economic Studies* 80: 1338–1383.
Griffith, R., R. Harrison, J. Mairesse, and B. Peters. 2006. "Innovation and Productivity across Four European Countries." *Oxford Review of Economic Policy* 22: 483–498.
Hall, B. H. 2011. "Innovation and Productivity." *Nordic Economic Policy Review* 2: 167–204.
Harrison, R., J. Jaumandreu, J. Mairesse, and B. Peters. 2014. "Does Innovation Stimulate Employment? A Firm-level Analysis using Comparable Micro Data on Four European Countries." *International Journal of Industrial Organization* 35: 29–43.
Jaumandreu, J., and J. Mairesse. 2010. "Innovation and Welfare: Results from Joint Estimation of Production and Demand Functions." Working Paper no. 16221, NEBR, Cambridge.
Jaumandreu, J., and S. Lin. 2016. "Innovation and Prices." Mimeo, Boston University.
Klette, J., and Z. Griliches. 1996. "The Inconsistency of Common Scale Estimators when Output Prices are Unobserved and Endogenous." *Journal of Applied Econometrics* 11: 343–361.
Mairesse, J., and J. Jaumandreu. 2005. "Panel-data Estimates of the Production Function and the Revenue Function: What Difference Does it Make?" *The Scandinavian Journal of Economics* 107: 651–672.
Mairesse, J., and P. Mohnen. 2010. "Using Innovation Surveys for Econometric Analysis." B. Hall, and N. Rosenberg eds., *Handbook of the Economics of Innovation*, Burlington Academic Press, Chapter 26, 1129–1155.
Peters, B., M. Roberts, V. A. Vuong, and H. Fryges. 2015. "Estimating Dynamic R&D Choice: An Analysis of Cost and Long-Run Benefits." Mimeo, Penn State University.
Peters, B., M. Roberts, and V. A. Vuong. 2015. "Dynamic R&D Choice and the Impact of Firms' Financial Strength." *Economics of Innovation and New Technology* (this issue). doi: 10.1080/10438599.2016.1202516.
Petrin, A., and F. Warzynski. 2012. "The Impact of R&D on Quality, Productivity and Welfare." Mimeo, University of Minnesota.
Rivers, D., and Q. Vuong. 2002. "Model Selection Tests for Nonlinear Dynamic Models." *Econometrics Journal* 5: 1–39.
Wooldridge, J. 2010. *Econometric Analysis of Cross-section and Panel Data*. Cambridge, MA: MIT Press.

Appendix. Data appendix

Sample

All employed variables come from the information furnished by firms to the ESEE survey (Encuesta Sobre Estrategias Empresariales), a firm-level panel survey of Spanish manufacturing starting in 1990 and sponsored by the Ministry of Industry. The unit surveyed is the firm, not the plant or establishment. For firms belonging to a group, some answers are relative to this group. In the first year of the survey, firms with fewer than 200 workers were sampled randomly by industry and size strata with a rate of 5%, while firms with more than 200 workers all requested to participate responded with a rate of about 60%. To preserve representativeness, samples of newly created firms were added to the initial sample every subsequent year. Exit from the sample, coming from both death and attrition can be distinguished and attrition was maintained to sensible limits. Table A.1. gives the composition of the overall unbalanced sample according to the number of years of firms' presence.

Table A.1. Composition of overall sample by number of years.

	1990–2006	
No. of years in sample	No. of firms	Observations
3	319	957
4	244	976
5	221	1105
6	217	1302
7	213	1491
8	178	1424
9	123	1107
10	194	1940
11	131	1441
12	91	1092
13	106	1378
14	57	798
15	73	1095
16	97	1552
17	162	2754
Total	2426	20,412

Definition of variables

Advertising: Firm's advertising expenditure. Rates of growth between year t and year (t-1) are computed using an average of expenditures in these two years in the denominator.

Average cost: Firm's variable costs (wage bill and cost of materials) divided by output.

Capital: Capital at current replacement values is computed recursively from an initial estimate and the data on current firms' investments in equipment goods (but not buildings or financial assets), updated by means of a price index of capital goods, and using industry estimates of the rates of depreciation. Real capital is then obtained by deflating the current replacement values. In the regressions, we use the utilization of capacity times capital (see below for utilization of capacity).

Market dynamism: Weighted index of the market dynamism reported by the firm for the markets in which it operates. The index can take the values 0 (slump), 0.5 (stable markets) and 1 (expansion).

Output: Production of goods and services. Sales plus the variation of inventories, deflated by the firm's output price index.

Price of materials: Paasche-type price index computed starting from the percentage variations in the prices of purchased materials, energy and services reported by the firms.

Price of output: Paasche-type price index computed starting from the percentage price changes that the firm reports to have made in the markets in which it operates.

Product innovation: Dummy variable that takes the value 1 when the firm reports the introduction of product innovations.

Process innovation: Dummy variable that takes the value 1 when the firm reports the introduction of process innovations in its productive process.

R&D: Total R&D expenditure of the firm. From these expenses and the innovation counts, we construct for each year t an instrument that is equal to the (log of) sum of the R&D expenses accumulated by the firm since the latest innovation until year t, if the firm reports an innovation in year t, and zero if not.

Utilization of capacity: Yearly average rate of capacity utilization as reported by the firm.

User cost of capital: Weighted sum of the cost of the firm values for two types of long-term debt (long-term debt with banks and other long-term debt), plus a common depreciation rate of 0.15 and minus the rate of growth of the consumer price index.

Wage: Firm's hourly wage rate (wage bill divided by effective total hours of work).