Technological Change and the Make-or-Buy Decision

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A central decision faced by firms is whether to make intermediate components internally or to buy them from specialized producers. We argue that firms producing products for which rapid technological change is characteristic will benefit from outsourcing to avoid the risk of not recouping their sunk cost investments when new production technologies appear. This risk is exacerbated when firms produce for low volume internal use, and is mitigated for those firms that sell to larger markets. Hence, products characterized by higher rates of technological change will be more likely to be produced by mass specialized firms to which other firms outsource production. Using a 1990–2002 panel data set on Spanish firms and an exogenous proxy for technological change, we provide causal evidence that technological change increases the likelihood of outsourcing. JEL Codes: O33, L24.

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1. Introduction

The "make-or-buy" decision has been the subject of much research in economics, beginning with the classic paper by Coase (1937). The transactions cost theory (Williamson 1971, 1975, 1985) explains the key roles of incomplete contracts and asset specificity in the make-or-buy decision, whereas the property rights theory considers how the incentives to integrate or outsource depend on which investments—the input supplier's or the final good producer's—are relatively more important for the success of the joint relationship (Grossman and Hart 1986; Gibbons 2005).

In this article, we abstract from the main classical concerns of incomplete contracts and specificity, and focus on the impact of technological change on the make-or-buy decision. Prior empirical work on technology and outsourcing has focused on the impact of technology intensity (measured by R&D intensity) or technological diffusion resulting from R&D spillovers.[1] Here, we take a different approach and consider how technological change in production influences a firm's outsourcing decision. New equipment and materials allow firms to produce certain products, parts, or components at a lower variable cost. However, installation of the equipment and training the workforce to use the new technology involve expenses that are sunk to the firm. Thus, the firm will invest in the new technology when it thinks it will use it intensively enough to justify paying the sunk cost. This will depend on the firm's production scale and the length of the time over which the technology will be used.

When new production technologies are more likely to appear in the future, firms will be more reluctant to buy the current machines today and produce the specific part or product in-house because these technologies will soon be obsolete. The pace at which new technologies appear affects the decision to outsource by determining the length of the time over which the investment in the new technology can be harvested. Outsourcing enables the firm to contract out and purchase products, parts, or components from supplying firms using the latest production technology while avoiding the sunk costs of adopting the new technology.[2] This reasoning can provide an explanation for the recent increases in outsourcing that have taken place in an environment characterized by rapid technological change.[3]

1. For studies of technology intensity and outsourcing, see Acemoglu et al. (2010); Lileeva and Van Biesebroeck (2008); and Mol (2005). On technological diffusion due to R&D spillovers, see Magnani (2006). Baccara (2007) studies how information leakages could affect a firm's outsourcing decision as well as its investments in R&D.

2. We will argue that supplying firms are more willing to incur the sunk costs and adopt the latest technologies because they face larger markets than the firms that buy their parts or products.

3. In the business literature, there are a number of examples that fit the predictions of our model. One example, discussed by Filman (2000) in *Business Week*, is about firms in the electronics manufacturing industry that are contracting out the manufacture of certain products in order to take advantage of the fact that "the contract manufacturing companies have invested in the manufacturing technology, so a company that's developing a product doesn't have to worry about figuring out how to make it and the company can benefit from

Using a panel data set of Spanish manufacturing firms for the time period 1990 through 2002, we study the relationship between firms' outsourcing decisions and technological change. In each year, approximately 1800 firms were asked about their outsourcing activities as well as information on a variety of other firm attributes. The data set permits us to observe changes within firms over a long period of time.

Our empirical work requires a measure of technological change in production faced by firms in the manufacturing sector. For this purpose, we use the number of patents granted by the US Patent and Trademark Office. There is a large literature, summarized in Jaffe and Trajtenberg (2002), showing that patent counts can be used to measure technological change. Patents are commonly classified by the industry in which they originate, while our analysis calls for a classification by industry of use. We map patents' technological classes to the Spanish industries in which the patents are likely to be used.[4] The reason for using this measure of technological change is that, conditional on unobserved time-invariant characteristics as well as on other observed factors (e.g., size of firm), the number of patents granted in the United States is plausibly exogenous to Spanish firms' outsourcing decisions.

Consistent with the main prediction from our conceptual framework, we find a positive and significant relationship between the probability that a firm outsources production and the number of patents used in the firm's industry. This finding is robust to the inclusion of firm-level fixed effects, alternative specifications of the patents variable, and the inclusion of dynamics in the regression. Given the exogeneity of the patents variable, we conclude that this relationship is causal. No prior study has been able to provide causal evidence of the impact of technological change on outsourcing.[5]

Since prior work on outsourcing has focused on the role played by incomplete contracts, we also consider whether our findings hold in the presence of a control for the specificity of investment. Using Nunn's (2007) measure of differentiated inputs as a proxy for the extent to which an industry is subject to industry-specific investments, we find that the patents variable remains positive and significant. In addition, we measure the impact of nontechnology variables that have been studied in the prior

leading-edge manufacturing technologies." Another example, as described by Swati (2005) in a White Paper published by a large consulting firm, is in the pharmaceutical industry where companies that had previously built all their products internally are increasingly using outsourcing because it "holds cost benefit advantage by reducing huge amounts of capital outlay for producing the latest technology in-house."

4. The mapping procedure is described in Section 3.

5. In their study of the effect of technology intensity on vertical integration in the United Kingdom, Acemoglu et al. (2010) use an approach that is similar to ours. Specifically, their exogenous measure of technology intensity is the level of capital investments in the same industry in the United States. Unlike our study, however, Acemoglu et al. (2010) do not consider the impact of technological change but rather the intensity of technology.

literature on outsourcing, such as firm size, labor costs, market volatility, and capacity utilization.[6] Unlike our results for the patents variable, we find that the relationships between the nontechnology variables and outsourcing are not robust to the inclusion of firm-level fixed effects.

Section 2 provides a conceptual framework that explains why the decision to outsource production should be related to the probability of technological change. Section 3 discusses the data and empirical specifications used to test this prediction. Results are presented in Section 4. Section 5 concludes.

2. Conceptual Framework

In this section, we provide a conceptual framework that links the decision to outsource production to technological change. A firm faces the following decision: should it assemble all of the required inputs (capital, labor, and materials) and produce in-house or should it outsource production of some of its products or their components, or the assembly of different components to outside vendors? The vendors are specialized suppliers who produce specific products or components in-house. Like other firms in our data set, vendors could also face the make-or-buy decision with regard to intermediate goods or components that they use in production.

Tadelis (2007) makes an interesting observation suggesting that what is traditionally called the "make or buy" decision could also be viewed as a "buy or buy" decision. Using an example of a carpenter who has to decide whether to produce a specialized nail or purchase it from a vendor, he argues that producing the nail in-house involves buying and managing the inputs needed to make the nail, thus the term "buy or buy." [7]

A key observation is that vendors (or specialized suppliers) offer their services to multiple firms and therefore their production levels are likely to be higher than those of the individual purchasers of their services. This means that they are likely to have a cost advantage in the production of specific products or components, relative to their customers, because they can exploit economies of scale and/or learning-by-doing.[8] This might suggest that all firms should always outsource instead of producing in-house. The fact that we do not observe all firms always outsourcing can be explained by firms incurring additional costs when outsourcing due, for

6. For prior work on the impact of nontechnology variables on outsourcing, see Abraham and Taylor 1996; Autor 2001; Girma and Gorg 2004; Diaz-Mora 2005; Ono 2007; and Holl 2008.

7. Another example, discussed by Besanko et al. 2007, is the decision by automobile manufacturers to outsource the production of customized cup holders (i.e., buy the output) or produce them in-house (i.e., buy and manage the inputs necessary to produce the cup holders).

8. Economies of scale may also occur if some firms are early adopters of a new technology, whereas others are late adopters. Suppliers could exploit this additional dimension of economies of scale by selling a given technology over a longer period of time.

example, to the loss of control over product design and production.[9] If these additional costs differ across firms, then only firms with a low enough costs will find it optimal to outsource.[10]

We consider how technological change in production influences the outsourcing decision. An example of technological change is the recent availability of IT-enhanced capital equipment for use in manufacturing.[11] While the new equipment allows production at a lower variable cost, installation of the equipment and training the workforce to use the equipment involve expenses that are sunk to the firm. In this example, the new technology is embedded in the capital equipment that is used to produce certain products or their components.

Firms need to decide whether to adopt the new technology or to continue producing with the old equipment. An important consideration in the technology adoption decision is the size of the firm's market. Vendors are therefore more likely to adopt the new technologies than the firms, which purchase their products since their larger production levels allow them to spread the sunk costs over more customers.

The firm facing the "buy-or-buy" decision as to whether to produce in-house or outsource some part of the production process must now decide between three alternatives: to produce with the old technology in-house, to invest in the new equipment and produce in-house, or to outsource production to a vendor. We already argued that this firm is less likely to adopt the new technology than the vendor because of the differences in the production levels. In addition, the vendors that adopted the latest technology can offer their product at lower prices making outsourcing more cost-effective than in-house production. These two factors will prompt some firms that did not outsource previously to begin outsourcing. Thus, technological change in production is likely to increase the fraction of firms outsourcing.[12]

9. If it is difficult to enforce the performance of the supplier, outsourcing will be unattractive (Tadelis 2002). Abramovsky and Griffith (2006) argue that information and communication technology reduce the adjustment and monitoring costs associated with outsourcing.

10. It is possible that a producing firm could decide to make some of its own components and also sell these components to other producers. In other words, the firm operates as a producer in one market and a supplier in another market. Our focus is on the role played by technological change in a firm's decision to purchase components from a supplier.

11. Computer numerically controlled machines have replaced numerically controlled machines, which had previously replaced manual machines. See Bartel et al. (2007) for a discussion of the impact of these new technologies on productivity in the valve-making industry.

12. The firm could also attempt to lower its sunk costs by outsourcing the training of its workforce. For example, the firm may need to hire an instructor to train a single operator of the advanced equipment, but the same instructor could probably train more than one person simultaneously without incurring additional costs. The combination of a sunk cost and indivisibility (of the instructor) is precisely the feature being exploited by temporary employment agencies (Autor 2001): they use the same instructor to train *several* workers in basic computer skills and offer them to firms at an attractive price because they can spread the sunk cost over a larger output (computer-skilled workers). We study the outsourcing of production and not outsourcing of training.

It is important to note that our argument complements rather than competes with the classic concerns of incomplete contracts and asset specificity explored in the make-or-buy literature. According to our argument, anything that causes economies of scale will make aggregating production in a few facilities more attractive, and this, in turn, will encourage firms to buy components for which there are strong economies of scale from a few vendors. With more rapid technological change, economies of scale become more important, and transactions for which the firm's make-or-buy choice was previously indifferent will now be outsourced. Hence, whereas, much of the incomplete contracts literature is about the costs of outsourcing (e.g., the loss of "fiat"), our framework is largely about the benefits of outsourcing, that is, the ability to take advantage of the economies of scale in production.

A similar argument applies in a dynamic context when firms expect changes in the technology over time. Firms that consider upgrading their in-house technology will be less likely to do so because, with some probability, the technology will soon become obsolete, while the sunk costs still need to be incurred. Thus, the fraction of nonadopting firms increases with the pace at which new technologies are expected to arrive in the future. For these nonadopting firms, in-house production becomes more expensive relative to what they can procure from suppliers that use the latest technology, and therefore we expect that the fraction of firms that find outsourcing profitable increases with the (expected) pace of technological change.

This argument rests, in part, on the assumption that (most) vendors always adopt the new technologies. This is a natural assumption when the technology is specific to the production process in question since a new technology would not have been developed if the expected demand for it was not large enough to enable the inventors to recoup their (sunk) costs of development. Since the technology is specific, this demand would consist mostly of the vendors as their market size is larger than that of most of their customers.

In sum, the pace at which new production technologies arrive in the market affects the decision to outsource by determining the length of time over which the investment in the new technology can be harvested. The more frequently the new technologies arrive, the less time the firm has to amortize the sunk costs. Vendors find it easier to amortize the sunk costs because of the larger markets they face, whereas outsourcing enables their customers to partake of the latest technologies while avoiding the sunk costs. In our empirical work, we test this prediction by estimating the relationship between the firm's outsourcing decision and a proxy for the arrival of new technologies to the industry in which the firm operates.

The framework we have outlined is, to some extent, related to the influential paper by Stigler (1951), which discusses the link between industry size and vertical integration.[13] According to Stigler (1951), young industries require new kinds or types of materials and hence are forced to make their own materials and design and manufacture their own specialized equipment. But, once the industry has reached a certain size, it becomes profitable for specialist firms to produce the specialized materials and equipment, and hence the industry vertically disintegrates. Our argument is similar to Stigler's in that vertical integration is driven by scale economies. The key difference between our story and Stigler's story is that ours is based on technological change, whereas Stigler's story is about the industry life cycle. As explained in the next section, our regressions include a set of variables to capture this alternative view.

3. Data and Empirical Specification

3.1 Outsourcing Data

We use data for 1990–2002 from the Encuesta sobre Estrategias Empresariales (ESEE or Survey on Business Strategies), a survey of 3195 Spanish manufacturing firms conducted by the Fundacion SEPI with the support of the Ministry of Industry, Tourism, and Trade. The survey has been conducted annually since 1990 and is an unbalanced panel. The ESEE is designed to be representative of the population of Spanish manufacturing firms and includes around 1800 firms per year (aiming to survey all firms with more than 200 employees and a stratified sample of smaller firms). The response rate is 80–100% each year and, as firms dropped from the survey, new firms were incorporated into the sample (using the same sampling criteria as in the base year) to ensure that the panel remains representative.[14]

The survey includes annual information on firms' production outsourcing decisions. The specific question in each of the annual surveys is: "Did you contract with third parties the manufacture of custom-made finished products, parts or components"? Production outsourcing does not include purchases of noncustomized products, parts, or components and therefore does not include the manufacturer's purchases of any standard inputs that are not customized to its specifications. We use this information to create a dummy variable for whether or not the firm outsources production. Then, using the firm's accounting data, we calculate the following ratio: the value of the custom-made finished products, parts, or components that the firm bought from third parties divided by the sum of the expenditures on: (a) external services (R&D, advertising, public relations, and other); (b) raw materials and other consumables; (c) purchases of goods for sale in the

13. Stigler's paper is titled "The Division of Labor is Limited by the Extent of the Market" because he shows how Adam Smith's famous theorem can be used to understand fundamental principles of economic organization.

14. This data set has been used by Holl (2008) who studies the effect of agglomeration economies on outsourcing, Lopez (2002) who studies the impact of outsourcing on wages, and Guadalupe et al. (2012) who study the impact of foreign direct investment on innovation.

same condition in which they were acquired; and (d) work carried out by subcontractors. The items in (b–d) are reported in the survey as an aggregate figure. Note that the definition of outsourcing in the survey does not distinguish between domestic and foreign outsourcing. This is not of concern to us because our framework is focused on the role played by technological change in the decision to outsource; whether the firm outsources to a domestic or foreign provider is not material to our study.

Table 1 shows the percentage of firms that reported outsourcing at least some part of production between 1990 and 2002, and the mean value of the outsourced production as a percentage of total cost.[15] On average, 43% of the firms reported that they outsourced production during this time period. The outsourcing percentage rose from 36% in 1990 to 42% in 2002, with even higher values in some of the intervening years. There is significant variation in the likelihood of outsourcing across industries ranging from a low of 4% for "man-made fibers" to a high of 77.2% for "agricultural and forestry machinery." The average value of the outsourced production as a percentage of total costs is 6.8% during this time period; for firms that did outsource production, the mean value of outsourced production as a percentage of total costs is 16%, with a minimum value of 1.4% (man-made fibers) and a maximum value of 29.7% (agricultural and forestry machinery).

3.2 Technological Change and Patent Data

The rate of technological change faced by the firm is unobservable. Our estimation strategy is to use a variable that is likely to be correlated with that latent variable. While the ESEE includes firm-level information on variables, such as R&D activity and process innovation, both of which are likely to be correlated with the technological changes used by the firm,[16] these variables could be endogenous if unobserved factors drive these decisions as well as the decision to outsource. For example, firms that are more "innovative" or "creative" —characteristics that are not measured in our data—may be engaging in more R&D, process innovations, and production outsourcing. While the inclusion of fixed effects would enable us to control for time-invariant unobserved factors that affect both the decision to engage in R&D (or process innovation) and to outsource, this would not address possible reverse causation.[17] Thus, although our data set contains firm-level information on variables that are likely to be

15. Firms that appeared in only 1 year in the data set are eliminated from Table 1 and from all of the regressions.

16. Cohen and Levinthal (1989) argue that investments in R&D are not only needed to develop new products and processes but also to adapt new production technologies to the specific requirements of the firm. Similarly, whether the firm engages in process innovation could be a proxy for technological change since process innovation could be facilitated by exogenous changes in production technologies.

17. For example, outsourcing components may be an alternative to engage in cost-reducing R&D and therefore affect the firm's decision to invest in R&D.

Table 1. Outsourcing by Industry (1990–2002)

Industry	Incidence of outsourcing		Value of outsourcing/ total costs	
	Mean (SD)	*N*	All	If > 0
Food and beverages	0.210 (0.407)	3387	0.022	0.108
Tobacco products	0.567 (0.499)	67	0.034	0.067
Textile	0.451 (0.498)	1107	0.056	0.125
Wearing apparel	0.548 (0.498)	1333	0.133	0.241
Leather articles	0.398 (0.490)	723	0.072	0.181
Wood products	0.275 (0.447)	579	0.042	0.152
Paper	0.345 (0.476)	626	0.043	0.129
Publishing and printing	0.584 (0.493)	1148	0.119	0.208
Petroleum products and nuclear fuel	0.444 (0.527)	9	0.088	0.236
Basic chemical	0.245 (0.430)	364	0.017	0.071
Paints and varnishes	0.179 (0.385)	223	0.007	0.039
Pharmaceuticals	0.595 (0.491)	588	0.049	0.085
Soaps, detergents, and toilet preparation	0.510 (0.501)	255	0.039	0.078
Other chemicals	0.400 (0.492)	150	0.017	0.043
Man-made fibers	0.040 (0.200)	25	0.001	0.014
Rubber and plastics products	0.480 (0.500)	1159	0.058	0.122
Nonmetallic mineral products	0.270 (0.444)	1559	0.032	0.120
Basic metals	0.302 (0.459)	703	0.030	0.108
Fabricated metal products	0.484 (0.500)	1949	0.075	0.157
Energy machinery	0.507 (0.501)	225	0.076	0.154
Nonspecific purpose machinery	0.711 (0.454)	342	0.122	0.176
Agricultural and forestry machinery	0.772 (0.422)	92	0.219	0.297
Machine tools	0.717 (0.453)	113	0.145	0.207
Special purpose machinery	0.609 (0.489)	468	0.139	0.237
Weapons and ammunition	0.755 (0.434)	49	0.216	0.289
Domestic appliances	0.592 (0.492)	238	0.159	0.275
Office machinery and computers	0.395 (0.492)	76	0.038	0.097
Electric motors, generators, and transformers	0.644 (0.481)	118	0.066	0.112
Electric distribution, control, and wire	0.632 (0.483)	277	0.081	0.125
Accumulators and battery	0.646 (0.481)	79	0.151	0.235
Lighting equipment	0.541 (0.500)	185	0.086	0.167
Other electrical equipment	0.792 (0.407)	159	0.092	0.121
Electronic components	0.436 (0.497)	172	0.050	0.116
Signal transmission and telecommunication	0.727 (0.447)	132	0.089	0.127
TV and radio receivers and audiovisual electronics	0.580 (0.497)	81	0.112	0.204
Medical equipment	0.517 (0.504)	58	0.056	0.111
Measuring instruments	0.719 (0.451)	160	0.148	0.209

(continued)

Table 1. Continued

Industry	Incidence of outsourcing		Value of outsourcing/ total costs	
	Mean (SD)	*N*	All	If > 0
Industrial process control equipment	0.167 (0.408)	6	0.000	0.001
Optical instruments	0.714 (0.456)	56	0.135	0.195
Motor vehicles	0.544 (0.498)	1025	0.099	0.188
Other transport equipment	0.676 (0.469)	447	0.147	0.223
Furniture and other Mfg.	0.378 (0.485)	1070	0.062	0.165
Year				
1990	0.364 (0.481)	1633	0.061	0.169
1991	0.477 (0.500)	1810	0.063	0.145
1992	0.442 (0.497)	1763	0.069	0.163
1993	0.423 (0.494)	1659	0.067	0.164
1994	0.410 (0.492)	1682	0.062	0.153
1995	0.417 (0.493)	1552	0.064	0.156
1996	0.423 (0.494)	1553	0.068	0.164
1997	0.448 (0.497)	1725	0.074	0.167
1998	0.465 (0.499)	1653	0.076	0.164
1999	0.431 (0.495)	1628	0.075	0.177
2000	0.447 (0.497)	1731	0.069	0.157
2001	0.430 (0.495)	1598	0.067	0.159
2002	0.426 (0.495)	1595	0.067	0.156
All observations	0.432 (0.495)	21,582	0.068	0.161

correlated with technological change, we do not use these variables because they might not be exogenous to the outsourcing decision.

Hence, we take a different approach and use a proxy for technological change, which is plausibly exogenous to the firm. This proxy is the annual number of patents applied for (and subsequently granted) by the US Patent and Trademark Office and mapped to the Spanish industry in which the patents are used.[18] The conceptual framework developed in Section 2 showed that the firm's outsourcing decision would be influenced by the firm's expectations about the arrival of innovations. By using a count of the number of patents used in the firm's industry, we are assuming a positive correlation between the firm's expectations regarding the probability of technological change and the number of patents that are used in the industry in which the firm operates. The patents assigned to an industry of use represent innovative ideas that are relevant to the activities of the firms operating in that industry. The implicit assumption is that a

18. Since there is no reciprocal relationship between the US patents office and the Spanish patents office, patents granted in the United States are likely to be exogenous from the perspective of Spanish firms.

larger number of such patents implies a higher probability of technological change in the future.[19]

The US patent data are available through 2006 from the NBER Patent Citations Data File.[20] In this data set, each patent is assigned a US Patent Class and an International Patent Classification (IPC). The industrial sector to which a patent is assigned is usually not identical to the sector using the patented invention. Hence, it is necessary to convert the data on the number of patents originating in an industry into the number of patents used by an industry.

As described in Johnson (2002), between 1978 and 1993, the Canadian Intellectual Property Office simultaneously assigned an IPC code along with a Canadian industry of manufacture and a Canadian sector of use to each of over 300,000 patents granted in Canada. Using the data on patents granted between 1990 and 1993 (a total of 148,000 patents), Silverman (1999) linked the Canadian SIC codes to US SIC codes. Thus, for each IPC, Silverman (1999) reported the likelihood of any random patent in that IPC having a particular industry of manufacture–sector of use combination based on the US SIC codes.[21] Finally, for his study of international technology diffusion, Kerr (2008) linked the US SIC codes to their corresponding International Standard Industrial Classification (ISIC) classifications. We applied the probabilities developed by Silverman (1999) and updated by Kerr (2008) to the US patent data to predict the number of patents with each industry of manufacture–sector of use combination for each of the 142 ISICs in the manufacturing sector and then matched these to the 44 categories in the manufacturing sector in the ESEE.[22]

Although the concordance between patents, industry of manufacture, and industry of use is based on Canadian data, using this algorithm does not superimpose the industrial structure of Canadian inventions on data for other countries. The probabilities are based on a technical relationship between the patent code and industry of manufacture and sector of use. In Appendix Table A1, we provide two examples of the concordance

19. The underlying notion is that "knowledge" at a point in time is the accumulated number of ideas as measured by the patents counts. For example, it is customary to assume that knowledge at time t in industry i, K_{it}, is given by $K_{it} = K_{it-1} + P_{it}$, where P_{it} is the number of patents granted in year t and used in industry i, and where we have ignored the obsolescence of ideas. Thus, $P_{it} = K_{it} - K_{it-1}$ measures the change in knowledge: a larger P represents a faster pace of knowledge accumulation.

20. We downloaded the patent data from http://www.nber.org/patents/. For a description of the data, see Hall et al. (2001) and http://elsa.berkeley.edu/~bhhall/NBER06.html.

21. Hausman (2010) used this concordance in her study of the effects of university innovation on local economic growth and entrepreneurship in the United States.

22. Other researchers (e.g., Jaffe and Trajtenberg 2002) have studied the importance of patents using data on patent citations. We cannot use citation counts since citations are specific to a patent and they vary a lot across individual patents. Recall that we do not assign individual patents to a sector of use but rather assign a fraction of patents in an IPC to a particular sector of use.

between specific patents and the manufacturing industries in which they are used.

One concern might be that we are studying the 1990–2002 time period, but we are using a concordance based on the patent examiners' analysis of patents that were applied for between 1990 and 1993. If the technology mappings from the early 1990s are not representative of the mappings for the latter part of the time period we study, then our constructed measure of technological change will be a noisy measure. If this measurement error is of the "classical" type, it will attenuate the effect of patents on outsourcing toward zero. Finding a significant coefficient would therefore be strong evidence of a meaningful relationship between technological change and outsourcing.

Appendix Table A2 shows annual patents from 1990 through 2002 assigned to each of the Spanish manufacturing sectors. Since the patent data set is from 2006, we are confident that, even for the later years, the patent counts are complete because the typical time interval between patent application and patent granting is usually no more than 4 years. Note that there are two groups of industries: energy machinery, nonspecific purpose machinery, agricultural and forestry machinery, machine tools, special purpose machinery, weapons and ammunition, and domestic appliances; and electric motors, electric distribution, accumulators, lighting equipment, and other electrical equipment, for which each industry member is assigned the same patent counts because matching the three-digit ISIC classifications to the corresponding Spanish field was often ambiguous. For these industries, we therefore used two-digit ISICs and at this level, the industries are grouped together. In the case of furniture and other manufacturing industries, these two industries are in the same Spanish field and are therefore assigned the same patent counts.

For each year, we calculated the average number of patents used in the sector during the previous 3 years and assigned this value to each Spanish firm based on its industrial sector. The three period lag is used instead of the contemporaneous number of patents for two reasons. First, year-to-year variations in patents are volatile and using information over a 3-year period smoothes the data.[23] Second, given the time lag between patent application and patent granting, using the average of patent counts over the prior 3 years, rather than a 3-year period which encompasses the current year plus the prior 2 years, makes a truncation problem for the later years, if it exists, less severe. Using the patents counts from an outside source as a proxy for the unobserved rate of technological change in the production faced by the firm guarantees that our proxy is exogenous and that we can interpret the estimated effect as causal. But, since this proxy is measured at the industry level, its effect is likely to be weaker than a variable measured at the firm level.

23. We tried shorter and longer time horizons and our results were unchanged. See subsection 4.3.

3.3 Additional Controls

We add a control for firm size but note that the relationship between firm size and outsourcing is not obvious. On the one hand, larger firms can take advantage of economies of scale and/or learning by doing and therefore be less likely to outsource than smaller firms. They are also more likely than smaller firms to upgrade to the latest technology because the sunk costs are spread over a larger base of production. On the other hand, as suggested by Ono (2007), large firms may be more likely to outsource if outsourcing requires some fixed transactions costs or fixed costs in searching for compatible suppliers.

As discussed in Section 2, the scale of operations of the industry in which the firm is located may impact the firm's outsourcing decision. We add a variable that measures the total sales of the firm's industry; according to Stigler (1951), this variable should have a positive and significant effect on outsourcing. Total sales in the industry are calculated by first reweighting each firm in the ESEE according to the information on the sample coverage by industry by firm size category reported in the ESEE, and then summing up the reweighted sales values.[24] In addition, since market structure and innovation are related, and market structure can also affect firms' decision to outsource, we use the reweighted sales values to calculate each industry's Herfindahl–Hirschman index and add it as a control for the extent of competition in the firm's industry.

We also control for a set of variables that have been the subject of previous research on the determinants of outsourcing. Since firms may use outsourcing as a way of economizing on labor costs (see Abraham and Taylor 1996), we include the firm's average labor cost defined as total annual spending on wages and benefits divided by total employment. Outsourcing may also be used to smooth the workload of the core workforce during peaks of demand (Abraham and Taylor 1996; Holl 2008). Hence, we add a measure of capacity utilization defined as the average percentage of the standard production capacity used during the year. Another factor that can increase the propensity to outsource is the volatility in demand for the product (Abraham and Taylor 1996; Holl 2008). We proxy volatility using two dummy variables that indicate whether the firm's main market expanded or declined during the year.[25] Summary statistics on all of these variables are shown in Appendix Table A3.

24. The ESEE reports the percentage of firms in each industry in five size categories (less than 20 employees, 21–50, 51–100, 101–200, and more than 200) in the Spanish Social Security Census, which are represented in the survey.

25. The firm's location could also serve as a proxy for the ease with which outsourcing can be done (see Ono 2007). Our data do not provide this information, but a firm's location is likely to be time-invariant and its potential effect on outsourcing is absorbed by the firm fixed effect in our regressions.

4. Results

We use two dependent variables: an indicator of whether the firm is engaged in outsourcing production and outsourcing expenditures divided by the sum of expenditures on external services, raw materials, purchases of goods for sale in same condition in which they were acquired, and work carried out by the subcontractors. Results for the two dependent variables are presented in Tables 2 and 3, respectively. The equation we wish to estimate has the following form:

$$Y_{\mathrm{it}} = \alpha_0 + \alpha_1 \text{ Tech Change}_{j(i)t} + x_{\mathrm{it}}\,\alpha_2 + \alpha_3 \mathrm{Year}_t + \theta_i + u_{\mathrm{it}} \tag{1}$$

where i indexes the firm and j indexes the industry in which firm i operates, Y_{it} is an indicator for outsourcing or the value of outsourcing divided by total costs, x_{it} is the vector of control variables described in the previous section, $\mathrm{Year_t}$ is a year effect, θ_i is a firm fixed effect, and u_{it} is the error term.

As discussed in Section 3, we use patents as a proxy for the unobserved technological change in production. Specifically, following Wooldridge's (2002) definition of a proxy variable, we assume that

$$\text{Tech Change}_{j(i)t} = \beta_0 + \beta_1 \text{ Patents}_{j(i)t} + r_{j(i)t}$$

where $\text{Patents}_{j(i)t}$ is the "use of patents" variable constructed at the level of the industry in which firm i operates, and is uncorrelated with the disturbance $r_{j(i)t}$ by construction.[26]

Substituting this into equation (1) results in our estimating the following equation:

$$Y_{\mathrm{it}} = (\alpha_0 + \alpha_1\beta_0) + \alpha_1\beta_1 \mathrm{Patents}_{j(i)t} + x_{\mathrm{it}}\alpha_2 + \alpha_3 \mathrm{Year}_t + \theta_i + u_{\mathrm{it}} + \alpha_1 r_{j(i)t} \tag{2}$$

Note that by using a proxy for unobserved technological change, we can only estimate the effect of patents on outsourcing, $(\alpha_1\beta_1)$. In equation (2), an industry-level error $\alpha_1 r_{j(i)t}$ is added to the overall disturbance. To allow for arbitrary serial correlation, we cluster the standard errors (SEs) by industry.

In Section 3, we mentioned that the available data on R&D and process innovation could also proxy for technological change but these variables could be endogenous in the outsourcing equation. One could then use the patent variable as an instrument for these endogenous proxies. The problem with this strategy is that patents are not likely to be exogenous unless R&D and process innovation are very good proxies for technological change. To be precise, let the proxy equation be $\mathrm{TechChange}_{j(i)t} = \delta_0 + \delta_1 \mathrm{R\&D}_{\mathrm{it}} + \delta_2 \mathrm{Process}_{\mathrm{it}} + r^1_{j(i)t}$. Then, for patents to be a valid instrument, they should be uncorrelated with $r^1_{j(i)t}$. This,

26. The key assumption is that the other regressors in equation (1), x_{it}, do not provide information on technological change given patents, that is they do not appear in the proxy equation once patents are included. This guarantees that we can estimate α_2 consistently. If this assumption fails, then our estimator of α_2 will not be consistent. Since α_2 is not the focus of this article this assumption is not restrictive.

however, is a very strong assumption since R&D and process innovation do not capture all aspects of technological change and it is quite likely that part of the unexplained residual will be correlated with the patent variable.

The within-firm standard deviation (SD) in the outsourcing incidence variable is 0.319 (recall from Table 1 that the overall SD is 0.495), whereas the within-firm SD in the value of outsourcing divided by total costs is 0.091 (compared to the overall SD of 0.161). Furthermore, examining year-to-year changes in the outsourcing decision, we found that 16.5% of the year-to-year changes were nonzero (i.e., the firm changed from outsourcing to not outsourcing or vice versa). Hence, we have considerable within-firm variation in the dependent variable. In contrast, the within-firm SD in the patents variable is considerably smaller than the overall SD (0.161 compared to 0.889). This should weaken our ability to find a significant relationship between outsourcing and patents in our fixed effects framework.

4.1 Technological Change

Table 2 shows the results of estimating equation (2) in which the dependent variable is the incidence of outsourcing. To demonstrate the importance of including firm fixed effects, column (1) shows the results of estimating equation (2) without the fixed effects and we find that patents are positive and significant. Adding firm fixed effects in column (2) results in an even larger effect of patents on outsourcing. The coefficient on the patents variable in column (2) shows that an increase of 10% in the number of patents granted increases the probability of outsourcing by 1.7 percentage points.[27] This effect is not unreasonable in light of the fact that, in our data set, the fraction of firms outsourcing is, on average, 43% (Table 1). The point estimate of patents on outsourcing is robust to the precise specification of the control variables. In column (3), we do not control for any observable characteristics of the firm and find a very similar coefficient on patents. This suggests that the inclusion of additional time-varying firm attributes should not significantly change our results.[28] Given the exogeneity of the patents variable, we interpret the results

27. Recall from our discussion in subsection 3.3 that larger firms are more likely than smaller firms to upgrade to the latest technology because the sunk costs are spread over a larger based of production. As a consequence, they are less likely to outsource when technological change occurs. This suggests a negative interaction term between sales and patents, which is indeed what we observed in results not reported here.

28. As previously discussed, R&D and process innovation are likely to be correlated with the firm's expected rate of technological change but these variables are also likely to be endogenous. Although we are fully aware of the endogeneity problem, we estimated regressions that include these two variables and found that both were positively correlated with the firm's outsourcing decision; furthermore, including these variables did not reduce the significance level of the patents coefficient. We also added interaction terms between patents and each of the other independent variables and found that this did not affect the finding that patents have a positive and significant effect on outsourcing. In addition to the patent–sales interaction term discussed in note 27, the interaction terms that were significant were those

Table 2. Dependent Variable is Incidence of Outsourcing, 1990–2002[a]

	(1)	(2)	(3)	(4)[b]
log patents (3 years average)	0.0621***	0.1709**	0.1533*	0.1377**
	(0.0217)	(0.0837)	(0.0821)	(0.0663)
Sales	0.1243***	−0.0453		−0.0853
	(0.0430)	(0.0302)		(0.1059)
Capacity usage (%)	0.0007*	−0.0003		0.0019
	(0.0004)	(0.0003)		(0.0019)
Average labor cost	0.0003	0.0000		0.0005
	(0.0002)	(0.0000)		(0.0012)
Market expanded	0.0633***	0.0099		0.0511
	(0.0127)	(0.0069)		(0.0390)
Market declined	0.0329**	0.0075		0.0744*
	(0.0140)	(0.0087)		(0.0415)
Herfindahl Index	0.3051*	−0.0857		−0.0216
	(0.1734)	(0.1309)		(0.1117)
Total industry sales	−0.0040**	0.0005		0.0007
	(0.0015)	(0.0004)		(0.0007)
Firm fixed effect	No	Yes	Yes	No
Industry fixed effect	No	No	No	Yes
R^2	0.054	0.008	0.007	0.207
Observations	21,582	21,582	21,582	535

[a]Reported are estimated coefficients and Standard Errors in parentheses. SEs are clustered by industry. All regressions are estimated using linear probability and include year dummies. Sales are in thousands of Euros. Wages are in hundreds.

[b]In this column, the data are collapsed to the industry level.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

in Table 3 as strong evidence of a causal relationship between technological change in production and the outsourcing decision. Finally, since we are using a 3 years average of patents measured at the industry level, our approach identifies the effects of technological change by exploiting long differences in the patents. In column (4), we collapse the data to the industry level and again find a positive and significant effect of patents.[29]

The results in Table 2 confirm our hypothesis that the pace at which new technologies appear affects the decision to outsource. We also explored which industries more closely fit this story and which industries do not. In order to do this, we measured the "influence" of each industry on the estimated relationship between the dependent variable and a single regressor, in this case, patents.[30] We found that the industries with the

with the Herfindahl index and the total sales in the industry (both of these interaction terms were positive).

29. We re-estimated the regression in column (2) of Table 2 using first differences and found that the point estimate on the patents variable was 0.1514 (very close to the coefficient reported in column (2) of Table 2), though it was less precisely estimated (SD of 0.127).

30. We calculated the "dfbeta" influence statistic. See http://www.stata.com/help.cgi?regress + postestimation for the procedure for calculating this statistic. "Dfbeta" is the standardized difference in the parameter estimates due to deleting an observation.

Table 3. Marginal Effects on Extent of Outsourcing Conditional on Positive Outsourcing

	(1)	(2)	(3)	(4)[a]
log patents (3 years average)	0.0091*	0.0184*	0.0179*	0.0488**
	(0.0050)	(0.0109)	(0.0098)	(0.0244)
Sales	0.0186***	−0.0084		−0.0002
	(0.0051)	(0.0120)		(0.0633)
Capacity usage (%)	0.0002***	−0.0000		0.0002
	(0.0001)	(0.0001)		(0.0007)
Average labor cost	0.0000	0.0000		−0.0005
	(0.0000)	(0.0001)		(0.0004)
Market expanded	0.0097***	0.0029**		0.0267*
	(0.0026)	(0.0013)		(0.0160)
Market declined	0.0060**	0.0015		0.0151
	(0.0027)	(0.0015)		(0.0285)
Herfindahl Index	0.0413	0.0086		0.0052
	(0.0345)	(0.0192)		(0.0482)
Total industry sales	−0.0008**	0.0001		0.0002
	(0.0004)	(0.0003)		(0.0006)
Firm fixed effect	No	Yes	Yes	No
Industry fixed effect	No	No	No	Yes
Observations	21,205	21,205	21,205	534

Reported are estimated coefficients and standard errors in parentheses. Dependent variable: outsourcing costs/total costs, 1990–2002. SEs are clustered by industry and were estimated using bootstrapping with 500 replications. Except for column (1), regressions were estimated using Tobit and include year dummies. Marginal effects from the regressions are shown in the table. Sales are in thousands of Euros. Wages are in hundreds.
[a]In this column, the data are collapsed to the industry level.
*$p<0.10$, **$p<0.05$, ***$p<0.01$.

greatest "influence" are (a) electronic components, (b) electric distribution, (c) pharmaceuticals, (d) domestic appliances, and (e) optical instruments. The industries that most poorly fit our model are (a) furniture, (b) electric motors, (c) rubber and plastics products, (d) other transport equipment, and (e) tobacco products.

Table 3 presents results of estimating equation (2) where the dependent variable is outsourcing expenditures divided by the sum of expenditures on external services, raw materials, purchases of goods for sale in same condition in which they were acquired, and work carried out by the subcontractors.[31] We follow Wooldridge (2002) in specifying a homoskedastic normal density for the unobserved firm effect conditional on the regressors. The unobserved effect is expressed as a linear combination of the time averages of all the regressors except patents, and a normal error term which is then integrated out from the likelihood function. We then use a standard random effects Tobit estimator to estimate equation (2). The coefficients shown in Table 3 are the marginal effects of the exogenous variables on the ratio of outsourcing costs to total costs,

31. The number of observations in Table 3 is less than that in Table 2 because some firms that reported positive outsourcing did not report the value of the outsourcing.

conditional on positive outsourcing; the coefficients and SEs on the time averages of the exogenous variables are not included in the table.

In all specifications in Table 3, the patents variable is positive, but weakly significant. Referring to column (2), we find that conditional on positive outsourcing, a 10% increase in the number of patents granted increases the ratio of outsourcing costs to total costs by 0.184 percentage points, which is a small effect relative to the mean outsourcing cost ratio of 16%. Note that although the point estimate of the patents' coefficient is larger when the data are aggregated to the industry level, the difference between the estimates in columns (2) and (4) is not statistically significant. Combining the results in Tables 2 and 3 indicate that the effect of technological change on outsourcing is largely at the extensive margin.

4.2 Robustness Checks

In Table 4, we consider whether the positive relationship between the patents variable and the incidence of outsourcing is robust to different specifications of the patents variable and to the inclusion of dynamics in the equation. For these robustness checks, we use the specification in column (2) of Table 2. Column (1) adds the quadratic of the patents variable. Column (2) replaces the patents variable with the average of the number of patents used over the previous 2 years, whereas Column (3) replaces it with the average of the number of patents used over the previous 4 years. In column (4), we use the average of patents over the previous 3 years and also add the average over years $t-4$, $t-5$, and $t-6$. Column (5) reports the marginal effect calculated from estimating equation (2) using logit. We find that the quadratic patents variable is insignificant while the linear and quadratic patents variables in column (1) are jointly significant ($F=4.98$, $p=0.0072$). Defining our patent variable by averaging over the last 2 or 4 years or using a logit model does not affect the prior conclusion that the patents variable has a positive and significant impact on the likelihood of outsourcing.[32] We should also expect that if patents—however defined—are capturing expectations about technological change then, given current patents, lagged patents should not affect the decision to outsource. It is therefore reassuring that the average count of patents on years $t-4$, $t-5$, and $t-6$ is not significant when added to the baseline specification. Finally, in column (6), we add dynamics to the equation. We use the Arellano–Bond methodology for estimating dynamic panel models, adding moments based on the level equation (i.e., the system estimator), and find a positive and significant coefficient on patents. In sum, the positive and significant effect of patents on the outsourcing decision is robust to all of the specifications in Table 4.

32. These results also hold when we use a five-period lag.

Table 4. Robustness Checks[a]

	(1) Add quadratic patents	(2) 2-year moving average	(3) 4-year moving average	(4) Add lagged patents	(5) Logit marginal effects	(6) Dynamic model
log patents (3 years avg)	0.1826*			0.2168*	0.2129***	0.0400***
	(0.1001)			(0.1162)	(0.0517)	(0.0138)
[log patents (3 years avg)]^2	−0.0035					
	(0.0149)					
log patents (2 years avg)		0.1570*				
		(0.0844)				
log patents (4 years avg)			0.1686*			
			(0.0844)			
log patents (lagged)				−0.0651		
				(0.1062)		
Outsourcing ($t-1$)						0.3698***
						(0.0243)
Sales	−0.0446	−0.0450	−0.0448	−0.0448	−0.1017*	0.0834***
	(0.0305)	(0.0307)	(0.0299)	(0.0306)	(0.0614)	(0.0292)
Capacity usage (%)	−0.0003	−0.0003	−0.0003	−0.0003	−0.0004	0.0006
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0005)
Average labor cost	0.0000	0.0000	0.0000	0.0000	0.0008*	−0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0005)	(0.0000)
Market expanded	0.0099	0.0099	0.0098	0.0099	0.0132	0.0109
	(0.0069)	(0.0069)	(0.0069)	(0.0068)	(0.0104)	(0.0102)
Market declined	0.0074	0.0076	0.0075	0.0075	0.0078	0.0130
	(0.0087)	(0.0087)	(0.0087)	(0.0087)	(0.0116)	(0.0120)
Herfindahl Index	−0.0865	−0.0749	−0.0848	−0.0780	−0.1162	0.3334*
	(0.1324)	(0.1303)	(0.1312)	(0.1300)	(0.1566)	(0.1850)
Total industry sales	0.0005	0.0005	0.0005	0.0004	0.0006	−0.0025**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0011)
ARm1						−21.22
p-value						0.000
ARm2						1.78
p-value						0.075
R^2	0.008	0.008	0.008	0.008	0.014	
Observations	21,582	21,582	21,582	21,582	12,851	18,488

Reported are estimated coefficients and standard errors in parenthesis. Dependent variable is incidence of outsourcing, 1990–2002. SEs are clustered by industry. In column (6), SEs are estimated using bootstraping with 500 replications. All regressions include year dummies. Sales are in thousands of Euros. Wages are in hundreds. The variable log(patents—lagged) is the average number of patents used in the sector during the years: $t-4$, $t-5$, and $t-6$. Columns (1) through (5) include fixed effects. Column (6) uses the Arellano–Bond method with moments based on differences and level equations (System GMM). Lags 2 and 3 of the outsourcing indicator are used as instruments for lagged outsourcing. All other regressors are treated as predetermined and lags 1 and 2 are used as instruments. Column (5) has a smaller sample size than in columns (1–4) because Conditional Logit excludes panels where the dependent variable remains constant. The number of observations in column (6) is smaller than in columns (1–4) because we lose the initial observation for each firm to account for the lag structure and because we estimate the equations in first differences.
*$p<0.10$, **$p<0.05$, ***$p<0.01$.

As an additional robustness check, we also performed a number of placebo tests to demonstrate that the relationship between patents and outsourcing is causal and not due to an unobserved characteristic of the industry that is correlated with technological change and outsourcing. Specifically, we tried two alternative approaches to divide the 44 industries in our sample into several broad industry sectors. The first method created three broad industry sectors, whereas the second created eight sectors.[33] For each firm *i*, we randomly assigned patents from the industries that are in the same broad industry sector as firm *i*'s industry, excluding firm *i*'s industry as an option. If the results in Table 2 are indeed causal, we would expect that using this alternative method of assigning patents should result in an insignificant relationship between patents and outsourcing. Five hundred random assignments were done for each firm. We found that the estimated relationship between patents and outsourcing was insignificant 92% (Method 1) or 99% (Method 2) of the time. These results strengthen our conclusion that the results in Table 2 are indeed causal.

4.3 Alternative Explanations

The prior literature on the make-or-buy decision has focused on the role played by relationship-specific investments in a context where at least some part of the contract is nonverifiable ex post and hence noncontractible ex ante (Williamson 1971, 1975, 1985; Grossman and Hart 1986). Our framework focuses on technological change in production and implicitly assumes full contractibility. Both approaches—technological change and the existence of asset specificity and incomplete contracts—play a role in explaining outsourcing. Since we have not controlled for the specificity of investment, it is possible that our estimates of the effect of technological change may be reflecting the effect of incomplete contracts on outsourcing.

In order to control for the effect of incomplete contracts on outsourcing, we use the proxy for relationship-specific investments created by Nunn (2007). Nunn used 1997 data to calculate the proportion of each industry's intermediate inputs that are sold on an organized exchange or reference priced in a trade publication. He defines "differentiated inputs" as inputs that are neither sold on an organized exchange nor reference priced in a trade publication. As in Nunn (2007), we use the measure of differentiated inputs as a proxy for the extent to which an industry is subject to industry-specific investments. We matched Nunn's data to the industrial sectors in the ESEE. The Nunn data are available only for 1997 but we assume that this measure of differentiated inputs is constant over our sample period (1990–2002). We can then use all observations in our sample to re-estimate the regressions in Table 2 adding the differentiated inputs variable.

Fixed effects cannot be used because this will wipe out the time-invariant Nunn proxy; we therefore use random effects. Thus, the

33. The first approach created three sectors defined as (a) Industries 1–5, (b) Industries 6–20 and 21–27, and (c) Industries 28–44. The eight sectors used in the second method are: (a) industries 1 and 2; (b) industries 3, 4, and 5; (d) industries 6, 17, 18, and 44; (e) industries 7 and 8; (f) industries 9–16; (g) industries 19–27; (h) industries 28–41; and (i) industries 42 and 43. For industry numbers, see Appendix Table A2.

Table 5. Controlling for Relationship-specific Inputs

	(1)	(2)	(3)	(4)
	All industries		Below median relationship-specific inputs	
log patents (3 years average)	0.0583***	0.0565***	0.0760***	0.0828***
	(0.0217)	(0.0184)	(0.0270)	(0.0279)
Relationship-specific input		0.4588***		0.2231
		(0.0842)		(0.2331)
Sales	0.0728***	0.0642**	0.0658	0.0683
	(0.0281)	(0.0265)	(0.0495)	(0.0486)
Capacity usage (%)	0.0000	−0.0000	−0.0003	−0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Average labor cost	0.0001	0.0001	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Market expanded	0.0194***	0.0192***	0.0210***	0.0202***
	(0.0068)	(0.0070)	(0.0074)	(0.0075)
Market declined	0.0106	0.0096	0.0076	0.0075
	(0.0084)	(0.0082)	(0.0105)	(0.0105)
Herfindahl Index	0.2141**	0.0379	0.1539	0.2237
	(0.1078)	(0.0998)	(0.1229)	(0.1405)
Total industry sales	−0.0023	−0.0021*	−0.0043***	−0.0040***
	(0.0018)	(0.0011)	(0.0006)	(0.0006)
R^2	0.005	0.006	0.007	0.007
Observations	21,582	21,332	15,466	15,216

Reported are estimated coefficients and standard errors in parentheses. Dependent Variable is Incidence of Outsourcing, 1990–2002. SEs are clustered by industry. All regressions are estimated using linear probability random effects and include year dummies. Sales are in thousands of Euros. Wages are in hundreds. See text for definition of "Relationship Specific Input."
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

estimated effects are likely to be biased because of the omitted time-invariant firm characteristics. Nevertheless, our exercise consists in comparing the estimated coefficient on patents with and without the differentiated input measure in the equation.

The results, shown in columns (1) and (2) of Table 5, demonstrate that the patent variable remains positive and significant but the coefficient is much smaller than the patent coefficient in column (2) of Table 2 where we controlled for firm fixed effects. More importantly, the estimated coefficient is essentially not affected by the inclusion of the Nunn variable.[34] Note also that the effect of the differentiated inputs variable is positive and significant.[35]

34. The Nunn variable is positively correlated with the patent measure we use for 1997 (i.e., the mean over 1994–96) as well as with the mean number of patents over the 1990–2002 time period (0.268 and 0.243, respectively, but the significance levels are only 9% and 13%, respectively.).

35. This result is inconsistent with the transactions costs theory because this theory predicts that vertical integration is more likely in the presence of relationship-specific investments. The result is consistent with the version of the property rights theory described

In columns (3) and (4), we re-estimate the regressions restricting the sample to firms that are in industries that have a value below the median for the Nunn variable, that is, industries that have a small share of relationship-specific inputs. By focusing on industries where relationship-specific inputs are less important, incomplete contracts should be less relevant for these industries. While positive, the coefficient on relationship-specific inputs is smaller than it was for the entire sample and is no longer significant. Again, there is not much difference in the estimated effect of patents when the Nunn variable is included and the patents variable is positive and significant in both columns (3) and (4).[36]

Admittedly, the analysis in this section is based on random effects regressions rather than the preferred fixed effects approach. The random effects regressions indicate that the measured effects of technological change on outsourcing are unlikely to reflect the effect of incomplete contracts. Of course, if data were available to enable us to estimate fixed effects regressions, it is possible that this conclusion could change.

4.4 Nontechnology Variables

Although the focus of this article is the impact of technological change on outsourcing, our analysis also provides evidence on the impact of nontechnology variables that have been studied in the prior empirical literature. In the previous literature on the nontechnology determinants of outsourcing, panel data sets have been used infrequently.[37] In column (1) of Table 2, we estimate a version of equation (2) that does not include firm fixed effects and the results in this column replicate some of the findings from the previous literature (Abraham and Taylor 1996; Holl 2008). Market volatility is positive and significant. Capacity utilization is positive and weakly significant, whereas average labor cost has the predicted positive sign but is insignificant. The sign on firm sales in these regressions is positive and consistent with the findings of Ono (2007) and Holl (2008) indicating the relevance of Ono's argument that outsourcing may require some fixed

in Gibbons (2005) in the case of supplier investments dominating the relationship. But, as Whinston (2003) points out, it is extremely difficult to construct an accurate empirical test of the property rights theory. Furthermore, it is difficult to make definitive conclusions about either the transactions cost theory or the property rights theory because the results in Table 5 are based on random effects, not fixed effects, regressions.

36. We also estimated the regressions in Table 5 restricting the sample to 1997 and found very similar coefficients to those shown in Table 5, with slightly smaller significance levels. In addition, for the complete sample, we included an interaction term between patents and the Nunn variable and obtained a coefficient of −0.1280 that was significant at 10% level, the patents variable was significant at the 5% level, and the Nunn variable was significant at the 1% level. At the mean of the Nunn variable, the marginal effect of patents is 0.0662.

37. In Lafontaine and Slade's (2007) survey of the empirical evidence on firm boundaries, they show that the majority of the papers written on this topic are based on cross-sectional data.

transactions costs or search costs.[38] However, when we add firm fixed effects in column (2), none of the nontechnology variables are significant, which highlights the importance of including firm fixed effects in properly estimating the impacts of the nontechnology variables.

5. Conclusions

A large literature has focused on how characteristics such as asset specificity and contractual incompleteness influence the firm's decision to produce in-house or outsource production of some of its products or their components. We contribute to this research agenda by proposing a complementary approach that sheds light on the outsourcing decision and argue that the rate of technological change in production will influence the make-or-buy decision.

The pace at which new technologies appear affects the decision to outsource by determining the length of time over which the investment in the new technology can be harvested. When new production technologies are more likely to appear in the future, firms will be more reluctant to adopt the new technology today and produce in-house because these technologies will soon be obsolete. Specialized suppliers find it easier to amortize the sunk costs because of the larger markets they face. Therefore, outsourcing enables their customers to partake of the latest technologies while avoiding these sunk costs.

We test the prediction that outsourcing will increase with the pace of technological change by using a panel data set on Spanish firms for the time period 1990 through 2002. Our econometric analysis controls for unobserved fixed characteristics of the firms and, most importantly, uses a plausibly exogenous measure of technological change, that is, the number of patents granted by the US patents office and mapped to the Spanish industrial sectors in which the patents are used. The empirical results support the prediction that outsourcing of finished products, parts, or components increases with the pace of technological change. The patent variable that we use enables us to conclude that this relationship is causal; no prior study has been able to provide such causal evidence.

Our results are robust to various specifications as well as the inclusion of a variable that measures the proportion of each industry's inputs that are "specific." Furthermore, while the existing literature has found evidence that a number of nontechnology variables, such as labor costs, capacity utilization, and sales volatility play a role in the decision to outsource, we find limited evidence of this when accounting for firms' fixed effects. Rather our results imply that in an environment characterized by technological change, outsourcing of production is attractive.

38. Holl (2008) suggested that large firms may be more likely to outsource because they have greater capacity to establish and manage subcontracting relationships.

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Table A1. Examples of Probabilistic Concordance Between Patents and Industries of Use[a]

1. US Patent Class 334 (tuners)
SIC365: Radio and television receiving, except communication, $p = 0.535$
SIC366: Communication equipment, $p = 0.205$
SIC367: Electronic components and accessories, $p = 0.123$
2. US Patent Class 708 (electrical computers: arithmetic processing and calculating)
SIC357: Office, computing, and accounting machines, $p = 0.480$
SIC359: Misc. machinery, except electrical, $p = 0.154$
SIC358: Refrigeration and service industry machinery, $p = 0.084$

[a]Each patent is linked to many SICs of use, sometimes numbering in the hundreds. This table lists the SICs with the three largest probabilities for each of the two patents.

Table A2. US Patents Assigned to Spanish Industry of Use[a]

	Industry	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	Total
1	Food and beverages	2087	2091	2205	2233	2464	2797	2684	3097	2989	3315	3344	3201	2744	35,252
2	Tobacco products	184	183	151	145	177	178	181	202	191	186	188	178	178	2320
3	Textile	911	871	898	923	1022	1160	1155	1299	1259	1304	1325	1349	1188	14,665
4	Wearing apparel	638	610	606	647	691	779	810	915	910	938	971	1005	906	10,426
5	Leather articles	254	261	233	312	309	338	355	403	388	396	373	395	375	4392
6	Wood products	646	650	657	684	743	813	822	955	924	961	1000	1027	940	10,822
7	Paper	2276	2303	2376	2451	2679	3062	3000	3490	3315	3463	3567	3652	3196	38,829
8	Publishing and printing	1367	1369	1511	1463	1632	1803	1908	2070	2010	2016	2175	2201	2031	23,554
9	Petroleum products and nuclear fuel	825	807	825	803	843	911	812	971	890	908	976	989	811	11,370
10	Basic chemical	1300	1307	1334	1304	1409	1683	1434	1641	1533	1649	1753	1771	1519	19,636
12	Paints and varnishes	407	410	429	427	448	538	468	536	481	517	532	559	462	6214
13	Pharmaceuticals	2772	2778	3160	3430	4258	5998	4168	5258	5167	5778	5904	5892	4801	59,364
14	Soaps, detergents, and toilet preparation	654	653	665	727	819	995	927	1052	996	1098	1151	1131	964	11,832
15	Other chemicals	1358	1360	1381	1367	1481	1744	1543	1765	1660	1758	1872	1883	1607	20,779
16	Man-made fibers	24	23	24	25	28	31	30	34	32	34	35	35	31	384
17	Rubber and plastics products	5687	5574	5653	5785	6078	7288	6639	7613	7132	7506	7785	8144	7145	88,029
18	Nonmetallic mineral products	1933	1958	1939	1956	2109	2336	2338	2716	2529	2705	2927	2998	2545	30,987
19	Basic metals	1537	1541	1578	1574	1703	1835	1853	2106	2090	2233	2477	2728	2475	25,728
20	Fabricated metal products	3685	3648	3682	3775	4069	4489	4556	5133	4990	5267	5618	5797	5296	60,004
21	Energy machinery	9273	9191	9329	9332	9888	10,666	11,112	12,440	12,363	12,967	13,723	14,464	13,508	148,257
22	Nonspecific purpose machinery	9273	9191	9329	9332	9888	10,666	11,112	12,440	12,363	12,967	13,723	14,464	13,508	148,257
23	Agricultural and forestry machinery	9273	9191	9329	9332	9888	10,666	11,112	12,440	12,363	12,967	13,723	14,464	13,508	148,257

(continued)

Table A2. Continued

Industry	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	Total
24 Machine tools	9273	9191	9329	9332	9888	10,666	11,112	12,440	12,363	12,967	13,723	14,464	13,508	148,257
25 Special purpose machinery	9273	9191	9329	9332	9888	10,666	11,112	12,440	12,363	12,967	13,723	14,464	13,508	148,257
26 Weapons and ammunition	9273	9191	9329	9332	9888	10,666	11,112	12,440	12,363	12,967	13,723	14,464	13,508	148,257
27 Domestic appliances	9273	9191	9329	9332	9888	10,666	11,112	12,440	12,363	12,967	13,723	14,464	13,508	148,257
28 Office machinery and computers	4535	4852	5147	5581	7228	9193	10,419	12,697	12,636	13,436	14,633	14,015	11,976	126,349
29 Electric motors, generators, and transformers	4151	4228	4404	4608	5354	6117	6706	7950	8181	8816	9687	10,078	9036	89,315
30 Electric distribution, control, and wire	4151	4228	4404	4608	5354	6117	6706	7950	8181	8816	9687	10,078	9036	89,315
31 Accumulators and battery	4151	4228	4404	4608	5354	6117	6706	7950	8181	8816	9687	10,078	9036	89,315
32 Lighting equipment	4151	4228	4404	4608	5354	6117	6706	7950	8181	8816	9687	10,078	9036	89,315
33 Other electrical equipment	4151	4228	4404	4608	5354	6117	6706	7950	8181	8816	9687	10,078	9036	89,315
34 Electronic components	3006	3195	3370	3512	4315	5121	5802	7049	7245	7788	8260	8412	7345	74,420
35 Signal transmission and telecommunication	4608	4936	5211	5452	6740	8062	9131	11,156	11,487	12,321	13,047	13,265	11,500	116,916
36 TV and radio receivers and audiovisual electronics	2312	2442	2558	2652	3263	3787	4192	5030	4993	5260	5532	5494	4619	52,132
37 Medical equipment	2503	2513	2668	2758	3233	3926	3578	4232	4171	4503	4805	4987	4474	48,351
38 Measuring instruments	2043	2090	2170	2210	2575	2925	3139	3681	3686	3928	4242	4424	4046	41,159
39 Industrial process control equipment	3970	4124	4278	4483	5377	6454	7120	8492	8451	8934	9654	9479	8385	89,199
40 Optical instruments	512	542	573	615	782	978	1097	1328	1320	1402	1525	1473	1269	13,416
42 Motor vehicles	5655	5507	5448	5564	5893	6554	7045	7894	7814	8247	9135	9753	9321	93,830
43 Other transport equipment	1133	1120	1084	1164	1185	1329	1331	1496	1546	1560	1688	1755	1829	18,219
44 Furniture and other Mfg.	2488	2505	2616	2790	3218	3716	4033	4695	4672	4909	5261	5185	4637	50,727
Total	146,978	147,699	151,749	155,179	172,753	196,071	203,879	235,840	234,948	249,169	266,247	274,818	248,349	2,683,680

[a]See text for procedure used to map US patents to Spanish industries of use.

Table A3. Summary Statistics

Variable	Mean (SD)
Age of firm (years)	25.331 (22.771)
Average labor cost (thousands of Euros)	10.035 (32.489)
Capacity utilization rate	81.270 (15.276)
Herfindahl Index	0.056 (0.085)
Market expanded	0.298 (0.457)
Market declined	0.220 (0.414)
Process innovation	0.344 (0.475)
R&D activities	0.374 (0.484)
Sales in 2002 (thousands of Euros)	59,057 (271,279)
Total industry sales	19.717 (20.955)