Technological Change and the Make-or-Buy Decision

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Abstract

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 which 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 dataset on Spanish firms and an exogenous proxy for technological change, we provide causal evidence that technological change increases the likelihood of outsourcing.

I. 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 while 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 paper, 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 involves 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 time over which the technology will be used.

[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.

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 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]

Using a panel dataset 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 of this dataset, approximately 1800 firms were asked about their outsourcing activities as well as information on a variety of other firm attributes. The dataset permits us to observe changes within firms over a long time period.

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

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[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 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."

patents granted by the U.S. 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 U.S. 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.

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 non-technology variables that have been studied in the prior literature on

[4] The mapping procedure is described in Section III.

outsourcing, such as firm size, labor costs, market volatility, and capacity utilization.[5] Unlike our results for the patents variable, we find that the relationships between the non-technology variables and outsourcing are not robust to the inclusion of firm-level fixed effects.

Part II provides a conceptual framework that explains why the decision to outsource production should be related to the probability of technological change. Part III discusses the data and empirical specifications used to test this prediction. Results are presented in Part IV. Part V concludes.

II. 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, 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, i.e., we assume that they cannot themselves outsource to other specialized suppliers.

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

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

buy". [6]

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.[7] 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 example, to the loss of control over product design and production.[8] If these additional costs differ across firms then only firms with low enough costs will find it optimal to outsource.[9]

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.[10] 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

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[6] 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).

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

[8] 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 reduces the adjustment and monitoring costs associated with outsourcing.

[9] 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.

[10] Computer numerically controlled (CNC) machines have replaced numerically controlled machines which had previously replaced manual machines. See Bartel, Ichniowski and Shaw (2007) for a discussion of the impact of these new technologies on productivity in the valve-making industry.

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 differences in 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.[11]

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

[11] 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, not outsourcing of training.

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, i.e. the ability to take advantage of economies of scale in production.

A similar argument applies in a dynamic context when firms expect changes in 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 non-adopting firms increases with the pace at which new technologies are expected to arrive in the future. For these non-adopting 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. Because the technology is specific, this demand would consist mostly of the vendors since 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, while 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) that discusses the link between industry size and vertical integration.[12] 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 while 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.

[12]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.

III. Data and Empirical Specification

A. Outsourcing Data

We use data for 1990-2002 from the Encuesta sobre Estrategias Empresariales (ESEE, or Survey on Business Strategies), a survey of 3,195 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 to 100 percent 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.[13]

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 non-customized 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

[13] This dataset 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, Kuzmina and Thomas (2012) who study the impact of foreign direct investment on innovation.

finished products, parts or components that the firm bought from third parties divided by the sum of expenditures on: (1) the cost of external services (R&D, advertising, public relations and other), (2) raw materials and other consumables, (3) purchases of goods for sale in the same condition in which they were acquired, and (4) work carried out by subcontractors. The items in (2), (3) and (4) 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.[14] On average, 43% of 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 percent during this time period; for firms that did outsource production, the mean value of outsourced production as a percentage of total costs is 16 percent, with a minimum value of 1.4 percent (man-made fibers) and a maximum value of 29.7 percent (agricultural and forestry machinery).

[14] Firms that appeared in only one year in the dataset are eliminated from Table 1 and from all of the regressions.

B. 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,[15] 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 reserve causation.[16] Thus, although our dataset contains firm level information on variables that are likely to be 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 U.S. Patent and Trademark Office and mapped to the Spanish industry in which the patents are used. The conceptual framework

[15] 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.
[16] 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.

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developed in Section II 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 firms operating in that industry. The implicit assumption is that a larger number of such patents implies a higher probability of technological change in the future.[17]

The U.S. patent data are available through 2006 from the NBER Patent Citations Data File.[18] In this dataset, each patent is assigned a U.S. 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 International Patent Classification (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)

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[17] 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.

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

linked the Canadian SIC codes to U.S. 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 U.S. SIC codes.[19] Finally, for his study of international technology diffusion, Kerr (2008) linked the U.S. SIC codes to their corresponding ISIC classifications. We applied the probabilities developed by Silverman (1999) and updated by Kerr (2008) to the U.S. 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.[20]

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 A-1, we provide two examples of the concordance 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 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 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

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

[20] 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.

measurement error is of the "classical" type, it will attenuate the effect of patents on outsourcing towards zero. Finding a significant coefficient would therefore be strong evidence of a meaningful relationship between technological change and outsourcing.

Table 2 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 four years. Note that there are two groups of industries: Energy machinery, non-specific-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 3-digit ISIC classifications to the corresponding Spanish field was often ambiguous. For these industries we therefore used 2-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 three years and assigned this value to each Spanish firm based on its industrial sector. The three period lag is used instead of the contemporaneous value of patents for two reasons. First, year to year variations in patents are volatile and using information over a three year period smooths the data.[21] Second, given the time lag between patent application and patent granting, using the average of patent counts over the prior three years, rather than a three year period which encompasses the current year

[21]We tried shorter and longer time horizons and our results were unchanged. See Section IV.C.

plus the prior two 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 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.

C. 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 Part II, 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 information on the sample coverage by industry by firm size category reported in the ESEE, and then summing up the reweighted sales values.[22] In addition, because 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.[23] Summary statistics on all of these variables are shown in Appendix Table A-2.

IV. Results

We use two dependent variables: an indicator of whether the firm is engaged in outsourcing production and the value of the firm's outsourced production as a percentage

[22] The ESEE reports the percentage of firms in each industry in five size categories (less than 20 employees, 21 to 50, 51 to 100, 101 to 200, and more than 200) in the Spanish Social Security Census which are represented in the survey.
[23] 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.

of total costs. Results for the two dependent variables are presented in Tables 3 and 4 respectively. The equation we wish to estimate has the following form:

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

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, Year is a year effect, θ_i is a firm fixed effect and u_{it} is the error term.

As discussed in Part III, 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.[24]

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

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

Note that by using a proxy for unobserved technological change we can only

[24] The key assumption is that the other regressors in equation (1), x_{it}, do not provide information on technological change given patents, i.e., 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 paper this assumption is not restrictive.

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 by industry.

In Part III 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 $\text{Tech Change}_{j(i)t} = \delta_0 + \delta_1 \text{R\&}D_{it} + \delta_2 \text{Process}_{it} + r^1_{j(i)t}$. Then, for patents to be a valid instrument, they should be uncorrelated with $r^1_{j(i)t}$. This, 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 in the outsourcing incidence variable is 0.319 (recall from Table 1 that the overall standard deviation is 0.495) while the within-firm standard deviation in the value of outsourcing divided by total costs is 0.091 (compared to the overall standard deviation 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 non-zero (i.e., the firm changed from outsourcing to not outsourcing, or vice versa). Hence, we have considerable within-firm variation in the dependent variable. By contrast, the within-firm standard deviation in the patents variable is considerably smaller than the overall standard deviation (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.

A. Technological Change

Table 3 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 percent in the number of patents granted increases the probability of outsourcing by 1.7 percentage points.[25] This effect is not unreasonable in light of the fact that, in our dataset, the fraction of firms outsourcing is, on average, 43 percent (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.[26] Given the exogeneity

[25] Recall from our discussion in Section IIIC 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 but in results not reported here, the interaction term was negative but insignificant. This result could be due to the fixed transactions costs or search costs associated with outsourcing.

[26] 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 has a positive and significant coefficient on outsourcing. The only interaction terms that were

of the patents variable, we interpret the results 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 three year moving average series on patents measured at the industry level, our approach identifies the effects of technological change by exploiting long differences in patents. In column (4), we collapse the data to the industry level and again find a positive and significant effect of patents.[27]

The results in Table 3 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.[28] We found that the industries with the greatest "influence" are (1) Electronic components, (2) Electric distribution, (3) Pharmaceuticals, (4) Domestic appliances, and (5) Optical instruments. The industries that most poorly fit our model are (1) Furniture, (2) Electric motors, (3) Rubber and plastics products, (4) Other transport equipment and (5) Tobacco products.

Table 4 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

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

[27] We re-estimated the regression in column (2) of Table 3 using first differences and found that the point estimate on the patents variable was very similar to the fixed effects parameter, but was less precisely estimated.

[28] 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.

work carried out by subcontractors.[29] 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 4 are the marginal effects of the exogenous variables on the ratio of outsourcing costs to total costs, conditional on positive outsourcing; the coefficients and standard errors on the time averages of the exogenous variables are not included in the table.

In all specifications in Table 4, the patents variable is positive, but weakly significant. Referring to column (2), we find that conditional on positive outsourcing, a 10 percent 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 percent. 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 3 and 4 indicates that the effect of technological change on outsourcing is largely at the extensive margin.

B. Robustness Checks

In Table 5, we consider whether the positive relationship between the patents variable and the incidence of outsourcing is robust to different specifications of the

[29] The number of observations in Table 4 is less than that in Table 3 because some firms that reported positive outsourcing did not report the value of the outsourcing.

patents variable and to the inclusion of dynamics in the equation. For these robustness checks, we use the specification in Column (2) of Table 3. 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 two years while Column (3) replaces it with the average of the number of patents used over the previous four years. Column (4) 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-value = 0.0072). Using a two-period lag or a four-period lag on patent, or using logit does not affect the prior conclusion that the patents variable has a positive and significant impact on the likelihood of outsourcing.[30] In column (5) 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 5.

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 while the second created eight sectors.[31] For each firm i, we

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[30] These results also hold when we use a five-period lag.

[31] The first approach created three sectors defined as (1) Industries 1-5, (2) Industries 6 to 20 and 21-27, and (3) Industries 28 to 44. The eight sectors used in the second method are: (1) Industries 1-2; (2)

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 3 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 3 are indeed causal.

C. 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 non-verifiable ex post and hence non-contractible 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

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Industries 3,4 5; (3)Industries 6, 17, 18, 44; (4) Industries 7, 8; (5) Industries 9-16; (6) Industries 19-27; (7) Industries 28-41; and (8) Industries 42-43. For industry numbers, see Table 2.

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 for 1997 only 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 3 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 estimated effects are likely to be biased because of 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 6, demonstrate that the patent variable remains positive and significant but the coefficient is much smaller than the patent coefficient in column (2) of Table 3 where we controlled for firm fixed effects. More importantly, the estimated coefficient is essentially not affected by the inclusion of the Nunn variable.[32] Note also that the effect of the differentiated inputs variable is positive and significant.[33]

[32] The Nunn variable is positively correlated with the patent measure we use for 1997 (i.e. the mean over 1994-1996) as well as with the mean number of patents over the 1990-2002 time period (.268 and .243, respectively, but the significance levels are only 9 percent and 13 percent, respectively.)
[33] 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

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, i.e. 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 the coefficient on relationship-specific inputs is smaller than it was for the entire sample, it is still positive and significant in this subsample of industries. 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).[34]

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.

D. Non-Technology Variables

Although the focus of this paper is the impact of technological change on outsourcing, our analysis also provides evidence on the impact of non-technology variables that have been studied in the prior empirical literature. In the previous literature

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the version of the property rights theory described 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 6 are based on random effects, not fixed effects, regressions.

[34] We also estimated the regressions in Table 6 restricting the sample to 1997 and found very similar coefficients to those shown in Table 6, with slightly smaller significance levels.

on the non-technology determinants of outsourcing, firm fixed effects have not been included in the regressions. In column (1) of Table 3, 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 while average labor cost has the predicted positive sign but is insignificant. The sign on firm sales in these regressions is consistent with the findings of Ono (2007) and Holl (2008) indicating the relevance of Ono's argument that outsourcing may require some fixed transactions costs or search costs. [35] However, when we add firm fixed effects in column (2), none of the non-technology variables are significant which highlights the importance of including firm fixed effects in properly estimating the impacts of the non-technology variables.

V. 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 problem and argue that the propensity for rapid 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

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

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 dataset 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, i.e. the number of patents granted by the U.S. 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 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 non-technology 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.

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Table 1
Outsourcing by Industry (1990-2002)

Industry	Incidence of Outsourcing Mean	Std Dev	N	Value of Outsourcing ÷ Total Costs All	If > 0
Food, beverages	0.210	0.407	3,387	0.022	0.108
Tobacco products	0.567	0.499	67	0.034	0.067
Textile	0.451	0.498	1,107	0.056	0.125
Wearing apparel	0.548	0.498	1,333	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, printing	0.584	0.493	1,148	0.119	0.208
Petroleum products, nuclear fuel	0.444	0.527	9	0.088	0.236
Basic chemical	0.245	0.430	364	0.017	0.071
Paints, varnishes	0.179	0.385	223	0.007	0.039
Pharmaceuticals	0.595	0.491	588	0.049	0.085
Soaps, detergents, 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	1,159	0.058	0.122
Non-metallic mineral products	0.270	0.444	1,559	0.032	0.120
Basic metals	0.302	0.459	703	0.030	0.108
Fabricated metal products	0.484	0.500	1,949	0.075	0.157
Energy machinery	0.507	0.501	225	0.076	0.154
Non-specific 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, transformers	0.644	0.481	118	0.066	0.112
Electric distribution, control, wire	0.632	0.483	277	0.081	0.125
Accumulators, 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, telecommunication	0.727	0.447	132	0.089	0.127
TV & radio receivers, 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
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	1,025	0.099	0.188
Other transport equipment	0.676	0.469	447	0.147	0.223
Furniture and Other Mfg.	0.378	0.485	1,070	0.062	0.165
Year					
1990	0.364	0.481	1,633	0.061	0.169
1991	0.477	0.500	1,810	0.063	0.145
1992	0.442	0.497	1,763	0.069	0.163
1993	0.423	0.494	1,659	0.067	0.164
1994	0.410	0.492	1,682	0.062	0.153
1995	0.417	0.493	1,552	0.064	0.156
1996	0.423	0.494	1,553	0.068	0.164
1997	0.448	0.497	1,725	0.074	0.167
1998	0.465	0.499	1,653	0.076	0.164
1999	0.431	0.495	1,628	0.075	0.177
2000	0.447	0.497	1,731	0.069	0.157
2001	0.430	0.495	1,598	0.067	0.159
2002	0.426	0.495	1,595	0.067	0.156
All Observations	0.432	0.495	21,582	0.068	0.161

Table 2
U.S. Patents Assigned to Spanish Industry of Use*

	Industry	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	Total
1	Food, beverages	2,087	2,091	2,205	2,233	2,464	2,797	2,684	3,097	2,989	3,315	3,344	3,201	2,744	35,252
2	Tobacco products	184	183	151	145	177	178	181	202	191	186	188	178	178	2,320
3	Textile	911	871	898	923	1,022	1,160	1,155	1,299	1,259	1,304	1,325	1,349	1,188	14,665
4	Wearing apparel	638	610	606	647	691	779	810	915	910	938	971	1,005	906	10,426
5	Leather articles	254	261	233	312	309	338	355	403	388	396	373	395	375	4,392
6	Wood products	646	650	657	684	743	813	822	955	924	961	1,000	1,027	940	10,822
7	Paper	2,276	2,303	2,376	2,451	2,679	3,062	3,000	3,490	3,315	3,463	3,567	3,652	3,196	38,829
8	Publishing, printing	1,367	1,369	1,511	1,463	1,632	1,803	1,908	2,070	2,010	2,016	2,175	2,201	2,031	23,554
9	Petroleum products, nuclear fuel	825	807	825	803	843	911	812	971	890	908	976	989	811	11,370
10	Basic chemical	1,300	1,307	1,334	1,304	1,409	1,683	1,434	1,641	1,533	1,649	1,753	1,771	1,519	19,636
12	Paints, varnishes	407	410	429	427	448	538	468	536	481	517	532	559	462	6,214
13	Pharmaceuticals	2,772	2,778	3,160	3,430	4,258	5,998	4,168	5,258	5,167	5,778	5,904	5,892	4,801	59,364
14	Soaps, detergents, toilet preparation	654	653	665	727	819	995	927	1,052	996	1,098	1,151	1,131	964	11,832
15	Other chemicals	1,358	1,360	1,381	1,367	1,481	1,744	1,543	1,765	1,660	1,758	1,872	1,883	1,607	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	5,687	5,574	5,653	5,785	6,078	7,288	6,639	7,613	7,132	7,506	7,785	8,144	7,145	88,029
18	Non-metallic mineral products	1,933	1,958	1,939	1,956	2,109	2,336	2,338	2,716	2,529	2,705	2,927	2,998	2,545	30,987
19	Basic metals	1,537	1,541	1,578	1,574	1,703	1,835	1,853	2,106	2,090	2,233	2,477	2,728	2,475	25,728
20	Fabricated metal products	3,685	3,648	3,682	3,775	4,069	4,489	4,556	5,133	4,990	5,267	5,618	5,797	5,296	60,004
21	Energy machinery	9,273	9,191	9,329	9,332	9,888	10,666	11,112	12,440	12,363	12,967	13,723	14,464	13,508	148,257
22	Non-specific purpose machinery	9,273	9,191	9,329	9,332	9,888	10,666	11,112	12,440	12,363	12,967	13,723	14,464	13,508	148,257
23	Agricultural and forestry machinery	9,273	9,191	9,329	9,332	9,888	10,666	11,112	12,440	12,363	12,967	13,723	14,464	13,508	148,257
24	Machine-tools	9,273	9,191	9,329	9,332	9,888	10,666	11,112	12,440	12,363	12,967	13,723	14,464	13,508	148,257
25	Special purpose machinery	9,273	9,191	9,329	9,332	9,888	10,666	11,112	12,440	12,363	12,967	13,723	14,464	13,508	148,257
26	Weapons and ammunition	9,273	9,191	9,329	9,332	9,888	10,666	11,112	12,440	12,363	12,967	13,723	14,464	13,508	148,257
27	Domestic appliances	9,273	9,191	9,329	9,332	9,888	10,666	11,112	12,440	12,363	12,967	13,723	14,464	13,508	148,257
28	Office machinery and computers	4,535	4,852	5,147	5,581	7,228	9,193	10,419	12,697	12,636	13,436	14,633	14,015	11,976	126,349
29	Electric motors, generators, transformers	4,151	4,228	4,404	4,608	5,354	6,117	6,706	7,950	8,181	8,816	9,687	10,078	9,036	89,315
30	Electric distribution, control, wire	4,151	4,228	4,404	4,608	5,354	6,117	6,706	7,950	8,181	8,816	9,687	10,078	9,036	89,315
31	Accumulators, battery	4,151	4,228	4,404	4,608	5,354	6,117	6,706	7,950	8,181	8,816	9,687	10,078	9,036	89,315
32	Lighting equipment	4,151	4,228	4,404	4,608	5,354	6,117	6,706	7,950	8,181	8,816	9,687	10,078	9,036	89,315
33	Other electrical equipment	4,151	4,228	4,404	4,608	5,354	6,117	6,706	7,950	8,181	8,816	9,687	10,078	9,036	89,315
34	Electronic components	3,006	3,195	3,370	3,512	4,315	5,121	5,802	7,049	7,245	7,788	8,260	8,412	7,345	74,420
35	Signal transmission, telecommunication	4,608	4,936	5,211	5,452	6,740	8,062	9,131	11,156	11,487	12,321	13,047	13,265	11,500	116,916
36	TV & radio receivers, audiovisual electronics	2,312	2,442	2,558	2,652	3,263	3,787	4,192	5,030	4,993	5,260	5,532	5,494	4,619	52,132
37	Medical equipment	2,503	2,513	2,668	2,758	3,233	3,926	3,578	4,232	4,171	4,503	4,805	4,987	4,474	48,351
38	Measuring instruments	2,043	2,090	2,170	2,210	2,575	2,925	3,139	3,681	3,686	3,928	4,242	4,424	4,046	41,159
39	Industrial process control equipment	3,970	4,124	4,278	4,483	5,377	6,454	7,120	8,492	8,451	8,934	9,654	9,479	8,385	89,199
40	Optical instruments	512	542	573	615	782	978	1,097	1,328	1,320	1,402	1,525	1,473	1,269	13,416
42	Motor vehicles	5,655	5,507	5,448	5,564	5,893	6,554	7,045	7,894	7,814	8,247	9,135	9,753	9,321	93,830
43	Other transport equipment	1,133	1,120	1,084	1,164	1,185	1,329	1,331	1,496	1,546	1,560	1,688	1,755	1,829	18,219
44	Furniture and Other Mfg.	2,488	2,505	2,616	2,790	3,218	3,716	4,033	4,695	4,672	4,909	5,261	5,185	4,637	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

*See text for procedure used to map U.S. patents to Spanish industries of use.

Table 3
Dependent Variable is Incidence of Outsourcing, 1990-2002[a]

	(1)	(2)	(3)	(4)[b]
log(Patents - 3 yr avg)	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	NA
R-squared	0.054	0.008	0.007	0.207
Observations	21582	21582	21582	535

*p<.10 **p<.05 ***p<0.01

[a]Standard errors are clustered by industry. All regressions are estimated using linear probability and include year dummies. Sales are in 000,000s of Euros. Wages are in 00s.

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

Table 4

Dependent Variable: Outsourcing Costs/Total Costs, 1990-2002[a]
Marginal Effects on Extent of Outsourcing Conditional on Positive Outsourcing

	(1)	(2)	(3)	(4)[b]
log(Patents - 3 yr avg)	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 Random Effect	No	Yes	Yes	NA
R-squared	NA	NA	NA	NA
Observations	21205	21205	21205	534

*p<.10 **p<.05 ***p<0.01

[a]Standard errors 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 000,000s of Euros.

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

Table 5

Robustness Checks[a]

Dependent Variable is Incidence of Outsourcing, 1990-2002

	(1) Add Quadratic Patents	(2) 2-year Moving Average	(3) 4-year Moving Average	(4) Logit Marginal Effects	(5) Dynamic Model
log(Patents - 3 yr avg)	0.1826*			0.2129***	0.0400***
	(0.1001)			(0.0517)	(0.0138)
$(\log(\text{Patents-3 yr avg}))^2$	-0.0035				
	(0.0149)				
log (Patents - 2 yr avg)		0.1570*			
		(0.0844)			
log (Patents - 4 yr avg)			0.1686*		
			(0.0844)		
Outsourcing (t-1)					0.3698***
					(0.0243)
Sales	-0.0446	-0.0450	-0.0448	-0.1017*	0.0834***
	(0.0305)	(0.0307)	(0.0299)	(0.0614)	(0.0292)
% capacity usage	-0.0003	-0.0003	-0.0003	-0.0004	0.0006
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0005)
Average labor cost	0.0000	0.0000	0.0000	0.0008*	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0005)	(0.0000)
Market expanded	0.0099	0.0099	0.0098	0.0132	0.0109
	(0.0069)	(0.0069)	(0.0069)	(0.0104)	(0.0102)
Market declined	0.0074	0.0076	0.0075	0.0078	0.0130
	(0.0087)	(0.0087)	(0.0087)	(0.0116)	(0.0120)
Herfindahl Index	-0.0865	-0.0749	-0.0848	-0.1162	0.3334*
	(0.1324)	(0.1303)	(0.1312)	(0.1566)	(0.1850)
Total Industry Sales	0.0005	0.0005	0.0005	0.0006	-0.0025**
	(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-squared	0.008	0.008	0.008	0.014	NA
Observations	21582	21582	21582	12851	18488

*p<.10 **p<.05 ***p<0.01

[a]Standard errors are clustered by industry. In column (5), standard errors are estimated using bootstraping with 500 replications. All regressions include year dummies. Sales are in 000,000s of Euros. Columns (1) through (4) include fixed effects. Column (5) 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 (4) has a smaller sample size than in columns (1)-(3) because Conditional Logit excludes panels where the dependent variable remains constant. The number of observations in column (5) is smaller than in columns (1)-(3) because we lose the initial observation for each firm to account for the lag structure and because we estimate the equations in first differences.

Table 6
Dependent Variable is Incidence of Outsourcing, 1990-2002[a]
Controlling for Relationship-Specific Inputs

	(1)	(2)	(3)	(4)
	All Industries		Below-Median Relationship-Specific Inputs	
log(Patents - 3 yr avg)	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-squared	0.005	0.006	0.007	0.007
Observations	21582	21332	15466	15216

*p<.10 **p<.05 ***p<0.01

[a]Standard errors are clustered by industry. All regressions are estimated using linear probability random effects and include year dummies. Sales are in 000,000 of Euros. See text for definition of "Relationship Specific Input".

Table A-1

Examples of Probabilistic Concordance Between Patents and Industries of Use*

1.U.S. Patent Class 334 (Tuners)

SIC365 Radio and Television Receiving, Except Communication, Prob =.535

SIC366 Communication Equipment, Prob =.205

SIC367 Electronic Components and Accessories, Prob =.123

2.U.S. Patent Class 708 (Electrical Computers: Arithmetic Processing and Calculating)

SIC357 Office, Computing, and Accounting Machines, Prob=.480

SIC359 Misc Machinery, Except Electrical, Prob=.154

SIC358 Refrigeration and Service Industry Machinery, Prob =.084

*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 A-2
Summary Statistics

Variable	Mean	Std. Dev.
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