Relationship-Specificity, Spatial Clustering and Production to Order Choice *

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Abstract

We study the determinants of the firm-level choice to produce following an order placed by a downstream firm (production to order) or to produce in advance. We rationalize this choice through a simple theoretical model and apply it to a firm-level empirical analysis. Relying on a large dataset of Italian manufacturing firms, we show that two main variables affect this choice: the extent of spatial clustering of the industry, and the degree of product complexity and relationship-specificity of the goods that are traded. The sign of the impact of clustering on the choice of producing to order crucially depends on product complexity. If product complexity is high, production to order prevails when firms are clustered together. On the contrary, clustering is associated to production in advance for sectors where goods are standardized.

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1 Introduction

Despite a large literature studying what favors or hinders vertical integration between intermediate inputs' sellers and final goods' producers, in order to fully characterize the production process of an input it is not sufficient to state whether it is integrated or not with the downstream assembly phase, since there are many other facets attached to inputs' production that are worth considering. In order to add to the knowledge about firms' organizational strategies, in this paper we concentrate on the determinants of the choice to produce a good under production to order. In production to order the supplier waits for a specific order by a downstream buyer describing the specifications of the good to be produced, and production takes place only after the order is received. This way of organizing production is the opposite of production for stock (which we also call production in advance) where products are stored as inventory, and then just shipped at the orders' arrival.

Arm's-length trade through production to order differs from arm's-length trade through production in advance. In production to order the seller knows exactly who the buyer is, and viceversa. This allows the supplier to customize (at least to some extent) the component exactly towards the needs of the buyer. The second peculiar feature of production to order is that, once the product is customized for a specific buyer, the value of the component outside that relationship is considerably decreased. This opens the way for an opportunistic behavior by the buyer. Finally, we identify a third source of difference between the two production modes. This stems from the presence of particularly intense design and marketing activities in production for stock. In this case, since the final recipient of the good is unknown at the production stage, the supplier works out what are the most common and most valuable product specifications required by the generality of downstream firms. In doing so, he raises the effectiveness of the component for each downstream firm, incurring at the same time design and marketing costs.

Our analysis of the production to order choice starts from some facts that we derive from a survey of Italian manufacturing firms.[1] The first general remark is that, even within narrowly defined industries (4-digit NACE), there is lots of variation in the share of firms producing to order in each industry. In Figure 1 we plot a kernel density estimation of the share of firms producing to order in 4-digit NACE industries with at least 5 firms in our dataset.[2]

[Insert Figure 1 about here]

The empirical density function shows that in the bulk of industries the share of firms producing to order is high. In our dataset, only in one 4-digit industry there are no firms producing to order. We then conclude that this mode of supplying the market is a very important feature of manufacturing activity.

[1] The survey that we use is described in detail in Appendix 6.1.

[2] The shape of the density function does not change including also sectors with less than 5 firms.

The other important piece of evidence that we provide concerns the positive correlation, for each industry, between the share of firms that rely on production to order and the average degree of product differentiation of the goods produced.[3] For each industry, we compute a measure of product differentiation through a procedure that draws on the classification by Rauch (1999).[4] In Table 1 we show the results of two related sets of regressions. In the first two columns we regress the number of firms in each industry that produce at least 50% of their output following a specific order on the industry's degree of product differentiation, using two alternative measures of product complexity. In the last two columns we regress the average firm-level share of production to order intensity in each industry (production to order intensity is defined as the value of output produced to order divided by the value of total output) on the same measures of product differentiation.

[Insert Table 1 about here]

The correlation between product differentiation and production to order is strong. The OLS estimated relationship tells us that in industries where products are poorly differentiated, the share of firms producing to order is small. The opposite pattern is observed in industries where product differentiation is high. In this case, the production to order share of firms is high as well. Similar results are derived when the dependent variable is production to order intensity. Hence data show that the likelihood of production to order in each industry is positively related to the degree of product differentiation.

Finally, one may wonder if there is any relationship between the likelihood of production to order and the degree of spatial clustering of an industry. As proved in Table 2, in a simple OLS regression of production to order (either share or intensity) on the Maurel-Sédillot (MS) index based on plant counts,[5] the coefficients are not significantly different from zero.

[Insert Table 2 about here]

At the aggregate industry level, the degree of spatial clustering is not correlated to the likelihood of production to order. This means that both in highly geographically concentrated industries and in poorly geographically concentrated industries there are high and low shares of production to order. However, if one wants to assess whether spatial clustering alleviates opportunistic behavior, it can be misleading to look just at the degree of spatial clustering of an industry. As we will argue below, a crucial variable to

[3] In the paper we use equivalently the terms product differentiation and product complexity.

[4] The degree of product complexity of each industry is obtained computing the share of goods that are not sold on an organized exchange market. In section 4 we provide more details on this procedure.

[5] Data on plant counts for the computation of the MS index are from the Italian Census of manufacturing firms for 2001. The spatial unit of analysis are the 686 local labor systems, while the industry classification is based on 77 industries (see Appendix 6.2), which shrink to 73 in the regressions because we have no observations for 4 industries. We choose the Maurel and Sédillot (1999) index, instead of the employment-based Ellison and Glaeser (1997) index, because we are chiefly interested in the role played by the number of possible buyers located close to suppliers. However, the raw evidence we are going to present does not change ranking industries according to the Ellison-Glaeser index.

be taken into account is the industry's degree of product complexity and relationship-specificity, since agglomeration is expected to be beneficial especially for highly differentiated products.

Summing up, we observe the following. First, there is considerable variability among industries in terms of the share of firms relying on production to order, but in general this share is considerably high. Second, there exists a strong positive correlation among the degree of product differentiation of the industry and the likelihood of production to order. Finally, the correlation among the degree of spatial clustering of the industry and production to order is weak.

In the paper, we also refine our empirical analysis estimating linear models for the production to order choice.[6] Estimates show that, when industries are characterized by high product differentiation, the likelihood of production to order is increased if firms are spatially clustered. On the contrary, spatial clustering makes less likely that the supplier is connected to buyers through production to order when industries are homogeneous. The picture we get is that the role of spatial clustering on production to order crucially hinges on the degree of product differentiation. Then, our view is that, consistently with the raw correlations discussed above, a crucial reason explaining the increase in the share of production to order for industries with strong product differentiation operates through the surge of production to order among firms that are geographically concentrated. Put concisely, strong product differentiation spurs the spatial clustering channel of production to order.

In order to rationalize the empirical evidence, we build a simple model where spatial clustering has two opposite effects on the decision regarding production modes: on the one side it reduces hold-up, thus favoring production to order, on the other it reduces design and marketing costs, thus promoting production in advance. A priori then, the impact of spatial clustering is ambiguous. A crucial element in production to order is the co-operative effort between the supplier and buyer in order to tailor towards the buyer's needs the good. Co-operation, which amounts to sharing customization costs, is assumed to be an effective strategy, and this is implemented in the model through a quadratic cost function for customization. However, we show that only when industries are characterized by high product differentiation, that is only when the potential gain by sharing the adjustment of the good is large, spatial clustering spurs production to order, and also allows a larger relationship-specific investment in equilibrium. On the contrary, when industries are poorly differentiated, there is little gain from co-operation among the supplier and the buyer in the customization of the good. In this case, spatially clustered markets are conducive of production for stock, due to low design and marketing costs.

Apart from the mitigation of transaction costs due to agglomeration, we can think of other reasons that explain the increase in the likelihood to produce to order if firms are spatially clustered. A wide literature stresses the relevance of communication and information flows among firms located within clusters. The literature describing this process, especially for Italy, is really vast. See, among many other papers, Maskell and Malmberg (1999), Capello and Faggian (2005), Lazerson and Lorenzoni

[6] Results are unaffected estimating a probit model.

(1999), Giuliani (2007). Firms in a district can take advantage of information and experiences gained by others. In our case, the relevant information concerns other firms' contractual experience with specific buyers. We label this effect as the "spillover" effect. This effect is arguably more important in the supply of differentiated goods, whose contracts are relatively more complex, because it allows the firm to reduce the costs of the search for the right partner. Therefore, the spillover effect provides another reason for expecting that agglomeration of differentiated industries fosters production to order.

The paper is organized as follows. In section 2 we review the relevant literature, while in section 3 we present a simple model that explains the choice of producing to order or producing in advance. Section 4 presents empirical evidence supporting our ideas. Section 5 concludes.

2 Related literature

Our point of departure is one of the theories reviewed in Duranton and Puga (2004): spatial clustering might mitigate hold-up problems between buyers and sellers. If a large number of potential buyers is located around, it is likely that the hold-up problem is less severe for suppliers. This may be the case in big cities as opposed to smaller urban areas, or in spatial clusters of small and medium-sized firms, as in the case of Italian industrial districts. Matouschek and Robert-Nicoud (2005) formally develop this line of reasoning in a slightly different context. They concentrate on relationship-specific investments made by workers. But by substituting the term "intermediate inputs' suppliers" to the term "workers" their reasoning can be easily generalized. Interpreted in this manner, their paper proves that co-location of firms can induce more efficient (industry-specific) investments.

Another theoretical paper in this vein is Helsley and Strange (2007). They analyze a linear space where buyers are equally spaced. If there are transaction costs, they show that proximity between buyers and sellers lowers transaction costs and favors disintegration of production (outsourcing). Moreover, they also show that, as input demanders become closer to each other, their profits go up as well. This happens because agglomeration in space mitigates hold-up risk, thus fostering a more efficient investment by inputs' suppliers. This is named by them a "Williamsonian" agglomeration force. It is well understood since Hotelling (1929) at least that "distance [...] is only a figurative term for a great congeries of qualities".[7] In other terms, it is just a matter of how one interprets the linear space, since it may stand for physical space as well as characteristics' space. So, Helsley and Strange (2007) results also show that product homogeneity (i.e., similarity in the needs of buyers which corresponds to proximity in the linear space) favors disintegration of production and the establishment of trade in intermediate inputs between suppliers and buyers. Under this approach, product differentiation in physical space and product differentiation in the characteristics' space are just two alternative (and mutually exclusive) ways of interpreting the model. Our paper is useful also in disentangling the role

[7] Quotation is from Hotelling original paper.

played by physical space and characteristics' space upon the way of organizing production. We show that it is crucial to consider the interaction among these two dimensions, since product differentiation in downstream markets affects the sign (either positive or negative) of the effect of spatial clustering on production decisions.

Another relevant area for us of research in urban economics is the assessment of the link between geographical concentration of industries and vertical disintegration of production. Holmes (1999) for the U.S. and Li and Lu (2009) for China show that there is indeed a positive correlation between geographical concentration of industries and purchased input intensity (the value of purchased inputs divided by the value of total output). This is in line with Helsley and Strange (2007) theoretical results. As already discussed in the introduction, instead of assessing the degree of vertical disintegration, our paper concentrates on the determinants of the firms' mode of organizing arm's-length trade, to assess whether it is carried out through production to order or through production in advance. From a methodological point of view, our research question is quite similar to Holmes (1999), because we end up regressing production to order intensity (the value of output produced to order divided by the value of total output) on a measure of the geographic concentration of the industry. However, while Holmes (1999) is interested in assessing if spatial clustering raises the extent to which a downstream firm buys from upstream suppliers located nearby, we want to assess if spatial clustering raises the extent to which an upstream firm supplies the downstream buyers located around through production to order.

Our paper relies on Rauch (1999) for the measurement of industries' product differentiation at a very fine level of disaggregation. In that paper, it is shown that proximity[8] is more important for differentiated products than for homogeneous products in fostering trade in a gravity model. The second result is that differentiated products tend to be less traded than more homogenous products. Following his work, some papers have also investigated how contract enforcement affects trade according the complexity of the goods that are exchanged (see Berkowitz et al., 2006, and Ranjan and Lee, 2007). Finally, Nunn (2007) employs Rauch classification to measure product differentiation in upstream industries, his focus being the relationship-specificity of upstream intermediate inputs. He finds that countries' ability to enforce contracts is a source of comparative advantage, since countries with good contract enforcement specialize in the production of goods for which relationship-specific investments are most important.

Differently from this line of research, our approach, more than being focused on the determinants of aggregate volumes of trade, concentrates on the firm-level determinants of production decisions made by individual firms. However, broadly speaking and in accordance with this line of research, also our approach deals with the way in which product complexity and relationship-specificity affect production decisions.

[8]Proximity is defined both in a geographical sense and in a cultural sense, the latter being proxied by language or colonial ties.

3 A simple model

3.1 Setup

We model the decision concerning how to organize production by a supplier who produces one unit of a component for downstream firms. We imagine that each supplier is embedded in a given market. To simplify the analysis, each supplier and the corresponding downstream market are isolated from other suppliers/markets.

In each downstream market buyers bid a price to secure the component produced by the supplier. The traded good can be customized in two different, though not mutually exclusive, manners: towards the needs of a specific buyer and towards a market as a whole. Customization towards a specific buyer is always needed since downstream firms differ from each other, and so they require specialized inputs. It can be carried out by the supplier alone, by the buyer alone, or by both of them in co-operation.

Customization towards a market is an activity which can be performed only by the supplier, but it is not always implemented. We assume that customization for the downstream market entails a design and marketing activity whose aim is to produce the component according to the best-valued product specifications common to all potential customers. The benefits of customization for the market consist in raising the marginal value of the component, A, for each downstream firm by a constant amount equal to u. In formal terms we have:

$$A = \begin{cases} \overline{A} & \text{under production to order} \\ \overline{A} + u & \text{under production for stock} \end{cases} \tag{1}$$

where $\overline{A}$ is the basic value of the component, and u is a measure of the effectiveness of design and market research in raising that value.[9]

We also assume that the possible production modes are two, production to order and production in advance (also called for stock). These production modes differ in terms of the customization activities that are performed. Under production to order, *there is no* customization for the market, while the supplier may share with the buyer the effort of customizing the component towards the buyer's needs. As we argue below, this makes production to order more efficient with respect to production for stock, though it opens the way to opportunistic behavior. Under production for stock, the component is of higher value thanks to customization for the market, but after production takes place the buyer is left alone in adapting the product towards her needs.[10] Table 3 represents the options the supplier has in

[9] Assuming that the marginal product of marketing activity for the supplier, u, is positive is strictly related to similar assumptions formulated in advertising models, as Dorfman and Steiner (1954), where the firm is able to increase gross revenues through advertising. See also, in a dynamic setting, the notion of *advertising goodwill* introduced by Nerlove and Arrow (1962). However, our notion of customization for the market also encompasses the design of the good, and so it is somewhat different from the strict notion of advertising activity, since it does not involve adding new buyers for an existing product, but rather finding the best suited specifications of a product for a range of potential buyers.

[10] It is important to stress that this is a highly stylized framework, since we assume that design and marketing activities

terms of production modes, and the implications for customization activities that are performed.

[Insert Table 3 about here]

The sequence of choices regarding the supplier is modelled as a two-stage process: in the first stage (organization stage) he decides whether to produce to order or produce for the stock. In the second stage (production stage) firms who chose to produce to order decide for which buyer to customize, and the amount of effort to be spent for her, while firms who chose to produce in advance simply bear the design and marketing cost.

3.2 Production stage

3.2.1 Production to order

Similarly to Grossman and Helpman (2002), we imagine the space of characteristics of the component as a circle of radius R, with K buyers located around the circumference and equally spaced at an angle measuring $\theta \equiv 2\pi/K$ at the center of the circle. Each circle represents a separate market and is served by a single supplier. The center of the circle corresponds to a component which is not customized for any particular buyer. Hence, the scope for the specialization of the input is proxied by the dimension of the circle. When $R = 0$, the circle reduces to a single point, there is no room for specialization, and we have many buyers with identical needs. If $R > 0$, the component needs to be specialized, and the higher it is R the bigger it is the scope for specialization. In what follows we always assume that $R > 0$.

As already put forward in the literature (Matouschek and Robert-Nicoud, 2005; Duranton and Puga, 2004; Helsley and Strange, 2007) spatial clustering improves outside options when the supplier-buyer interaction is affected by hold-up. This is precisely the scenario of production to order. Since we assume that the buyer and the supplier cannot contract over prices prior to input production, the buyer for whom the product was customized offers a price to the supplier only when supplier's customization costs are sunk. In doing so, the buyer tries to extract the highest possible surplus from the transaction. Competition among buyers to secure the component leads her to offer what the buyer with the second highest valuation is actually willing to pay. The bidding mechanism we imagine resembles that in Helsley and Strange (2007). The expectation about this conduct leads to an inefficient relationship-specific investment by the supplier. However, downstream buyers' opportunistic behavior can be mitigated by their degree of spatial clustering, to the extent that this raises the willingness to pay of the buyer with the second highest valuation. Assuming that the downstream market (our circle) is spatially bounded with respect to the supplier's location, the degree of clustering coincides with the number K of buyers that are located around the circumference. When K is high, the downstream market is populated by

are carried out under production for stock only. Although we cannot rule out that also under production to order some preliminary design and marketing activity is performed, we prefer to stick to a simplified framework where the traded good under production to order is of lower intrinsic value, but where co-operation in customization for the specific buyer guarantees a certain appeal to this production mode, at the cost of some inefficiencies due to opportunism.

many buyers, so that, given a buyer 1 for whom a component was originally designed, there is another buyer 2 with similar needs, which is willing to offer pretty much the same price for the good produced by the supplier.

Let us consider a simple picture to explain the model. In Figure 2 we depict a space with $K = 6$ buyers. The supplier customizes the product up to a length equal to i, where $0 \leq i \leq R$. The supplier's effort is not directed towards a specific customer, but instead goes along the dashed line in a direction that is a compromise between buyer 1's and buyer 2's needs. To this purpose, we introduce a parameter, γ, where $\gamma \in [1/2, 1]$, measuring how much the supplier is deviating from the ideal direction of customization for buyer 1. Specifically, $\tau_{o,1}$ is buyer 1's willingness to pay for the component, where

$$\tau_{o,1} = \overline{A} - \beta \left(i^2 + R^2 - 2Ri\cos\left((1-\gamma)\theta\right)\right) \tag{2}$$

The right hand side in (2) is equal to the difference between the basic marginal value of the input and the adjustment cost to be paid by buyer 1. The latter is proportional to the square of the customization distance buyer 1 has to fill in on her own, after the supplier has customized the characteristics of the component up to a measure equal to i along a certain direction γ. For $\gamma = 1$ the component is customized exactly towards buyer 1, while for $\gamma = 1/2$ the component is equally suitable for buyer 1 and buyer 2, provided that the same customization cost has to be paid by buyer 1 and buyer 2 in order to make the component fit their needs. The cost proportionality parameter is β, and it will turn to be a key determinant of the equilibrium production mode. We provide further interpretation for it below. Obviously, when there is no customization by the supplier (i=0), the willingness to pay of the buyer is the lowest possible one.

[Insert Figure 2 about here]

After the component has been produced, buyer 1, entering in a contractual relationship with the supplier, adopts an opportunistic behavior. As a result, the supplier having customized the product for buyer 1 is offered as a price for the component only what buyer 2 is willing to pay, $\tau_{o,2}$, equal to

$$\tau_{o,2} = \overline{A} - \beta \left(i^2 + R^2 - 2Ri\cos(\gamma\theta)\right)$$

where the second term on the right-hand side represents the adjustment cost that buyer 2 has to incur.

Generally speaking, when the supplier produces to order he knows that he will be offered only what the second closest buyer is willing to pay. In Figure 2, the supplier customizes (although partially) the product more towards the needs of buyer 1, and so the distance that has to be filled by buyer 2 (the second closest buyer) is $\sqrt{i^2 + R^2 - 2Ri\cos(\gamma\theta)}$, a function of θ, the exogenous distance among two consecutive buyers around the circumference, and γ, the chosen direction of customization.

The supplier's profits under production to order thus depend on two endogenous variables: the relationship-specific investment, i, and the direction of customization between two consecutive buyers,

γ. We indicate supplier's profits through the symbol $\phi_o(i,\gamma)$, so that we can write

$$\phi_o(i,\gamma) = \tau_{o,2} - i^2 = \overline{A} - \beta \left(i^2 + R^2 - 2Ri\cos(\gamma\theta) \right) - i^2 \quad (3)$$

In (3) we assume that the supplier's customization costs are, similarly to those encountered by the buyer, proportional to the square of the specialization distance filled, i. By an appropriate choice of units, we normalize the proportionality parameter for the supplier's customization costs to 1. Therefore, β measures the relative buyer's customization cost compared to that of the supplier. When β is close to zero the buyer's cost of adjusting the product is negligible, while, as β goes up, the cost for the buyer increases with respect to the one afforded by the supplier. In a sense, when β is small it does not really matter for whom the product was initially designed, since a buyer can very easily use an input that was designed for someone else, or she can use an input even not specialized at all ($i = 0$). As β increases, the buyer's customization activity becomes more and more costly. Hence, in our framework, β captures the intensity of the loss in the value of the component *due to imperfect specialization.* As β goes up, it becomes increasingly more important that the component is strongly specialized by the supplier at the production stage, since it is more costly to change or adapt product specifications afterwards.

The optimal relationship-specific investment, i^*, that maximizes the supplier's profits, taking for the moment as given a certain direction of customization, γ, then solves the problem

$$\begin{cases} \max\limits_{i} \quad \phi_o(i,\gamma) = \bar{A} - \beta \left(i^2 + R^2 - 2Ri\cos(\gamma\theta) \right) - i^2 \\ \text{s.t.} \quad i \geq 0 \end{cases}$$

and the solution is

$$\begin{cases} i^* = R\cos(2\pi\gamma/K)\dfrac{\beta}{1+\beta}, & \text{if } K > 4 \\ i^* = 0, & \text{if } K \leq 4 \end{cases}$$

Proposition 1. *The optimal level of relationship-specific investment i^* is non-decreasing in: market thickness, K, the radius of the circumference, R, and the relative cost of adjustment, β. No relationship-specific investment is undertaken if the number of buyers is small (equal or less than 4). Moreover, the supplier always performs only partial customization ($i^* < R$).*

Focusing on the role played by β, our simple modelling of the production to order stage gives rise to the following results:

1. When $\beta = 0$, there is no relationship-specific investment ($i^* = 0$), independently of the thickness of the downstream market;

2. When $\beta > 0$, there is relationship-specific investment ($i^* > 0$) only if $K > 4$.

The intuition for the corner solution when $\beta = 0$ is that there is no rationale for the supplier's effort, since it only brings in an extra cost provided that the buyer can adjust the component for free. Since the loss in imperfect customization is nil, the component's value is the same for each buyer ($\bar{A}$), and is independent of i and γ. In such a case, without undertaking previously any design and marketing activity, the supplier will sell the product to some buyer, but he will not customize the product for her.

For $\beta > 0$, in order to have some customization activity from the supplier, a sufficiently dense downstream industry is required. If $K \leq 4$, it is better not to customize at all the product for any particular customer, because, once the supplier enters a production to order relationship with a buyer, the outside option is unattractive. Finally, notice that i^* is strictly increasing in the cost parameter β for $K > 4$. The interpretation of this result is that, when β goes up, the supplier finds optimal to increase the specialization effort i^*, in order to reduce buyers' customization cost, and, ultimately, to increase the revenue he will get from the sale of the component. It is interesting to note that also i^*/R is increasing in β. This means that, also relatively to the total distance R that has to be filled, the supplier increases his investment when β goes up. So, a higher intensity in the loss due to imperfect customization motivates a higher relationship-specific investment.

Going backwards, the supplier, as a first step, makes also a decision concerning the optimal direction of customization γ, provided that $\beta > 0$, and $K > 4$. The maximization problem is solved substituting back into the profit function the optimal relationship specific investment, i^*, which is a function of γ itself, so that the problem becomes

$$\begin{cases} \max\limits_{\gamma} \quad \phi_o(i^*, \gamma) = \overline{A} - \beta\left(i^{*2} + R^2 - 2Ri^*\cos(\gamma\theta)\right) - i^{*2} \\ \text{s.t.} \quad 1/2 \leq \gamma \leq 1 \end{cases}$$

The derivative of the profit function $\phi_o(i^*, \gamma)$ with respect to γ turns to be always negative if $K > 4$. Then, the solution of the problem corresponds to the corner solution $\gamma^* = 1/2$. The choice of the supplier is to make buyer 1 and buyer 2 equally willing to pay for the component, so to maximize the price received. Hence, the ideal direction of customization is the one equally distant from two consecutive buyers, and is associated to a relationship-specific investment equal to $i^* = R\cos(\pi/K)\beta/(1+\beta)$.[11]

Proposition 2. *The optimal direction of customization is the one equally distant from two consecutive buyers around the circle,* $\gamma^* = 1/2$.

3.2.2 Production for stock

Under production for stock, there is no customization towards a specific customer, and consequently no relationship-specific investments. Through design and marketing activities, the supplier raises every

[11] For β going to infinity, the limit of i^* is

$$\lim_{\beta \to \infty} i^* = R\cos\left(\frac{\pi}{K}\right)$$

which is equal to one of the legs of a right triangle, where the hypotenuse is the radius, and the other leg is the distance filled by the buyer. Actually, when β is too high the customization activity becomes too costly for the buyer, and so the component will not be traded. However, computing this limit is noteworthy since it allows us to state that, conditionally on production to order being chosen, the customization distance filled by the buyer is always decreasing in β.

buyer's willingness to pay by an amount equal to u. Design and marketing are assumed to be costly activities. However, the magnitude of these costs differ according to the number of buyers in the downstream market. We assume that design and marketing are cheap where there are many potential buyers around, and expensive for markets with few customers. The idea is that, when only a few buyers populate the market, it is very costly to search for them and interview them to learn what is the most valuable product for them. Hence, a difference in terms of the number of potential buyers translates into a difference in the cost of customization for the market. Through this line of reasoning, a large number of potential buyers K, associated to a high degree of spatial clustering, reduces design and marketing costs. In formal terms, we indicate them as $m(K)$, with $\partial m(\cdot)/\partial K < 0$.[12] As a result, profits under production for stock are:

$$\phi_a = \overline{A} + u - \beta R^2 - m(K) \tag{4}$$

As (4) makes clear, also under production for stock the component needs to be customized, but the whole specialization effort has to be carried out by the buyer. Through this channel, the parameter β, which represents product complexity, affects profits also under production in advance. *Ceteris paribus*, a lower β increases supplier's profits, because the component produced for the stock can be easily adapted by the buyers and this increases their willingness to pay for it. On the other side, a large β provokes a significant profit's loss.

3.3 Organization stage

In the first stage the upstream firm chooses the production mode. After the substitution of the equilibrium values of i^* and γ^*, the supplier's production to order profits are

$$\phi_o(i^*, \gamma^*) = \overline{A} + \frac{R^2\beta^2\cos^2(\pi/K)}{1+\beta} - \beta R^2 \tag{5}$$

The supplier compares these profits with the profits he could get by producing in advance. Therefore, the supplier decides to produce to order, and the indicator variable for production to order Ord equals 1, if the latent variable, ϕ^*, defined as the difference in profits under the two production modes, is positive:

$$Ord = 1 \Leftrightarrow \phi^* \equiv \phi_o(i^*, \gamma^*) - \phi_a \geq 0 \tag{6}$$

If $K > 4$, the latent variable can be written as:

$$\phi^* = \frac{R^2\beta^2\cos^2(\pi/K)}{1+\beta} - u + m(K) \tag{7}$$

[12]Another possible assumption would be that the benefits of design and marketing are increasing in the number of potential buyers, $u'(K) > 0$, keeping at the same time the associated costs, m, to be fixed and independent from K. The qualitative nature of our results would not change.

The first term on the right-hand side is always positive, it is increasing in β and K, and pushes towards production to order. It represents the surplus in the relationship deriving from the fact that under production to order the supplier and the buyer share the specialization effort and its associated costs. Under production to order, the buyer bears only a part of the total specialization required, R. The supplier performs a specialization effort corresponding to i^*, while the remaining part, corresponding to the distance $\sqrt{i^{*2} + R^2 - 2Ri^* \cos(\pi/K)}$, is borne by the buyer. Specialization costs turn out to be smaller if the two parties separately bear a fraction of them. This is straightforward for the case $\beta \geq 1$, but it turns out to be true also when $0 < \beta < 1$. Actually, as β shrinks below 1, customization carried out by the supplier, i^*, becomes more expensive than customization by the buyer, but this effect is offset by the simultaneous decrease in the equilibrium level of i^*: in other terms, as β shrinks, the supplier's relationship-specific investment i^* decreases rapidly enough in order to guarantee that, overall, the cost for customizing the component is always less if the two parties co-operate in the customization activity. However, as β goes down, this term decreases since it is monotone in β and, in the limit, it approaches zero when β does.

The first term also goes up as the number of downstream firms, K, increases.[13] This occurs because an increase in the market thickness reduces the scope for opportunistic behavior, and raises the optimal relationship investment of the supplier, i^*, which is beneficial to the cost effectiveness of production to order with respect to production for stock.

The second term, u, is the marginal benefit of design and marketing, while the third one, $m(K)$, represents the associated costs. For the model to be meaningful, we need to assume that $u > m(K)$. The higher the design and marketing benefits are with respect to costs, the more likely it is that the supplier will choose production in advance. The costs $m(k)$ are assumed to be decreasing in K. This part of the latent variable depends again on the mass of potential customers in the downstream market. When the degree of clustering is high, design and marketing costs are low, and this comes up against production to order.

Summing up, the mass of firms K (our proxy for the degree of spatial clustering) has opposite effects in (7). On the one side, it makes hold-up less severe and production to order more likely, on the other it decreases design and marketing costs, in so fostering production for stock. A higher K makes production to order more desirable only in sectors where customization activities performed by the buyers are expensive enough relative to customization undertaken by the supplier; that is, only is sectors where β is large enough.

[13]Differentiating the first term in (7) with respect to K we get

$$\frac{2\pi R^2 \beta^2 \sin(\pi/K)\cos(\pi/K)}{K^2(1+\beta)} > 0.$$

4 Relationship-specificity, spatial clustering and production to order choice: Further evidence from Italian data

Through (7), the parameters β and K impact on the equilibrium production mode. We already discussed that β parameterizes the cost borne by the buyer due to imperfect customization performed by the supplier. As such, this feature is industry-specific, and common to each good belonging to the same industry. Looking for real word counterparts of β, we think that the best way to capture it is through the complexity of products. When traded components are complex we have a large β, signalling the difficulty in the adjustment of the component after it has been produced. A buyer will be forced to work hard to adapt the characteristics to her own needs, if customization has not been completed during the production stage of the component. Even worse, in some cases it could be simply impossible to adapt to the buyer's needs a component. On the contrary, when complexity is low, the loss due to imperfect specialization is negligible (β is small), since the required product specifications are not very sophisticated. In our empirical applications, the complexity of a product is captured indirectly through the existence or not of an organized exchange market where the product is traded, following the classification proposed by Rauch (1999). When an organized exchange market exists, the product's complexity is necessarily low.

There is another determinant of the equilibrium production mode: suppliers differ from each other according to the degree of spatial clustering of potential buyers in the downstream market they serve. In our simple model, clustering is exogenous, and captured by the parameter K.

The qualitative implications of our model can be condensed in Table 4, where we provide a taxonomy for the equilibrium production mode chosen by the supplier, according to the level of product differentiation in the industry (capturing β), and to the spatial clustering of buyers in the market (capturing K).

[Insert Table 4 about here]

4.1 Estimation strategy

This section presents our strategy to measure the impact of clustering and product complexity on the production to order choice by the firms.[14]

In order to identify whether a firm produces to order or for the stock, and the share of each production mode relative to total output, we employ question E2 in the UniCredit surveys.[15] We also

[14] As discussed above, from a methodological point of view, our baseline regressions are related to the approach pioneered by Holmes (1999), where it is established whether spatial clustering raises the extent to which a downstream firm buys from upstream suppliers located nearby. But differently from Holmes (1999) we want to assess if spatial clustering raises the extent to which an upstream firm supplies the downstream buyers located around through production to order. We include a detailed description of the dataset, the dependent variable and the controls in the Appendix 6.1.

[15] See again the Appendix 6.1.

have information on whether the supplier is selling its product to other firms, to retailers or to final consumers. This information is retrieved through the question E1. By looking at this question, we can infer if the firm produces predominantly an intermediate input (direct sales to other firms), or if the firm sells predominantly final goods (sales to families or retailers shops). We restrict our empirical analysis to the sample of firms that sell at least 30% of their output to other firms; that is, we select those firms for which the sum of shares in questions E1.9 and E1.10 is at least 30%. We also use as an alternative sample selection criterion a share of sales to other firms that equals at least 50%.

The baseline dependent variable is POI_{ij}^{g}, measuring production to order intensity (the value of output produced to order divided by the value of total output) of firm i in industry j in geographic unit g. We also consider another specification where the dependent variable is a dummy, Ord_{ij}^{g}, which takes value one if firm i in industry j in local area g reports to have produced following an order at least 30% (alternatively 50%) of the output. In other terms, Ord_{ij}^{g} is a dummy indicating that POI is at least 30% (alternatively 50%).

The variable we use in our regressions to capture geographic concentration of the industry is a dummy, $Clust_{j}^{g}$, which is equal to 1 if industry j in the geographic unit g is spatially clustered, and zero otherwise. To compute such a dummy we use the so-called location quotient (see, for example, Freedman, 2008) capturing the degree of agglomeration of a particular industry in a certain geographic unit. In our case, the geographic units are local labor system (LLS hereafter).[16] For each firm, the location quotient (LQ hereafter) is computed comparing the concentration of industry j at the level of the LLS g where the establishment is located to that of the industry at the corresponding regional level.[17] In formal terms, the LQ for a firm belonging to industry j and LLS g is equal to

$$LQ_{j}^{g} = \frac{E_{j}^{g}/E_{g}}{E_{j}/E} = \frac{E_{j}^{g}/E_{j}}{E_{g}/E},$$

where E_{j}^{g} is the number of establishments in industry j in the LLS g where the firm is located, E_g is the number of establishments in all manufacturing industries in the LLS g, E_j is the number of establishments in industry j in the region where the firm is located, E is the total number of manufacturing plants in the region. The variable LQ_{j}^{g} is larger than one when the concentration of industry j in the LLS is higher than the concentration at the regional level. It is less than one in the opposite case. Another interpretation is that LQ_{j}^{g} is greater than one when the LLS's share of industry j's establishments with respect to the total number of j establishments at the regional level is greater than the corresponding share for total manufacturing establishments. Our spatial clustering dummy $Clust_{j}^{g}$ takes value one if LQ_{j}^{g} is greater than a certain threshold and zero otherwise. We use as thresholds three different values: the median of the distribution of non-zero location quotients, the 75th percentile of the distribution of non-zero location quotients, and the value 1. Data about establishments by geographic units (LLS and

[16] Italy is divided in 686 local labor systems. Local labor systems are defined by the Italian Statistical Institute using workers' patterns for daily commuting and residential location.

[17] Italy is divided in 20 regions, so, on average, each region contains 34 LLS.

regions) and industries are retrieved from the Census, and are measured with reference to October 22, 2001.[18] Obviously, the value of the LQ and $Clust$ variables depend on the partitions that are chosen for geographic units and industries. As far as our choice of LLS is concerned, this geographic unit is quite common to measure local phenomena (see, for example, Koenig, 2009). As for the industry partitioning, we use a classification consisting of 77 different manufacturing industries. In Appendix 6.2 we explain the procedure we adopted and the logic underlying it. Additionally, to check the robustness of our results, we also adopt a standard 2-digit NACE classification, which groups the whole manufacturing sector in 22 different industries.

To measure product complexity and relationship-specificity in the transactions that suppliers undertake with buyers, in a way which is quite similar to Nunn (2007), we construct a variable called z_j. In order to construct such a measure, we use the industry classification developed by Rauch (1999). Based on the nature of the transactions of the goods in the industry, each of the 1,189 sectors of the 4-digit SITC Rev. 2 classification is assigned to one of the following three categories: sold on a standardized exchange market; sold with a reference price; neither of the two. Rauch develops two classifications using, respectively, a conservative, and a more liberal criterion for the assignments. Following this distinction, we derive two measures of contractual intensity, a conservative measure, and a liberal measure. We then assign each of the 1,189 SITC industries to one of the 77 sectors, or, alternatively, to one of the 22 2-digit NACE sectors, depending on the level of aggregation we work with. For each of these J industries, where $J = 77$ or $J = 22$, we finally build the variable z_j that captures the fraction of SITC industries in a certain industry j that is *not* traded on an organized exchange market. Clearly, the higher it is z_j, the higher it is average products' complexity and relationship-specificity in industry j, since organized exchange markets are unfit to trade differentiated products. In Table 5 we provide summary statistics for the main variables of interest across all firms included in the sample.[19]

[Insert Table 5 about here]

In the first model that we estimate the conditional expectation of POI is specified as follows:

$$E(POI_{ij}^{g}|Clust_j^g, z_j, Share_g, X_i, \eta_j, \eta_g) = \beta_0 + \beta_1 Clust_j^g + \beta_2 Clust_j^g * z_j + \beta_3 Share_g * z_j + X_i' \overline{\beta}_4 + \eta_j + \eta_g \tag{8}$$

In this linear model, $Clust_j^g$ is interacted with z_j in order to allow the effect of geographical concentration to vary by industry. $Share_g$ is the share of all manufacturing establishments located in LLS g out of the region's total number of manufacturing plants. The higher it is $Share_g$, the higher it is the

[18]As explained with greater detail in Appendix 6.1, we pool observations from two separate waves of the UniCredit Survey, so that each firm-level observation is measured with reference to the year 2000 or the year 2003. The fact that Census data were collected as of mid 2001 is extremely convenient for us, because in this manner the LQ variable is equally suitable to capture geographical concentration in both waves, and on this basis we can pool observations from the 8th and 9th wave of the UniCredit Survey, while still using the same clustering regressor for both of them.

[19]Remember that we restrict our analysis to the sub-sample of firms that sell al least 30% of their output to other firms.

concentration of the overall manufacturing activity in the LLS. The interaction between this variable and z_j, in addition to the fixedeffects at the level of each LLS (η_g), controls for the differential impact by level of industry differentiation of the degree of geographical concentration of the whole manufacturing sector.

X_i is a set of firm level controls, that includes the logs of age, age squared, size, labor productivity,[20] capital intensity, skill intensity, and dummies for whether or not the firm is an exporter or belongs to a business group. In the econometric model, fixed effects at the level of each LLS (η_g), and industry (η_j) are included.

Another set of estimates relies on the following linear probability model:[21]

$$Prob(Ord_{ij}^g = 1|Clust_j^g, z_j, Share_g, X_i, \eta_j, \eta_g) = \beta_0 + \beta_1 Clust_j^g + \beta_2 Clust_j^g * z_j + \beta_3 Share_g * z_j + X_i' \overline{\beta}_4 + \eta_j + \eta_g \quad (9)$$

where the continuous POI measure is replaced by the Ord dummy described above.

On the basis of the predictions derived from the model presented in section 3, we expect the coefficient on the clustering dummy, β_1, to be negative. By contrast, when product complexity and relationship-specificity is high, being located in LLS where the industry is spatially clustered, so that suppliers are surrounded by many buyers, reduces the inefficiencies due to opportunistic behavior if firms choose to produce to order. Thus, we expect the coefficient of the interaction term to have a positive sign, $\beta_2 > 0$.

Our model provides an unbiased estimate of the key coefficients under the assumption that there are no omitted variables that simultaneously affect the location choice and the choice to produce to order. We take several steps to mitigate this potential problem. First, through the inclusion of geographic area and industry fixed effects, we make sure that our key variables are not capturing the effect of other location or sector-level variables. Second, our model controls for many firm's characteristics that might be correlated with production to order propensity. Third, we can conclude that the dependence of production to order on spatial clustering in a given industry does not operate through the concentration of the whole manufacturing sector in a certain LLS: in our approach the effect on production to order of the geographic concentration of manufacturing is netted out by the variable $Share_g * z_j$, and by the spatial fixed effects η_g.

However, we admit that our research strategy does not definitively address the issue of the potential endogeneity of geographic localization of a particular industry in a particular LLS, primarily because it is hard to find a suitable instrumental variable for the location of specific industries in specific areas.[22]

[20]In unreported regressions we also experimented with total factor productivity according to Levinsohn and Petrin (2003) as a control, in place of labor productivity. Results were not affected.

[21]Results discussed with regard to the linear probability model are robust if we use a nonlinear model such as the probit.

[22]In Li and Lu (2009), replicating the empirical strategy of Holmes (1999) for the case of China, the causality issue is addressed instrumenting China's geographic concentration by industry/region in 2002 with the population of China's regions in 1920. We could have adopted a similar instrument for Italian LLS. However, since this instrumental variable varies only by local area, and is constant across industries belonging to the same geographic unit, the fitted values from the first stage do so. Hence, with this IV strategy, we could have provided only evidence for a causal effect of the overall

4.2 Estimation results

Table 6 presents our baseline results.

[Insert Table 6 about here]

The dependent variable is *POI*. In columns from (1) to (3) the clustering dummy takes value one when the *LQ* is greater than the median of the distribution of non-zero location quotients (1.065), in column (4) the threshold is set at the 75th percentile of the distribution of non-zero location quotients (1.803), and in column (5) the threshold equals one. In column (1) we first show that the *Clust* dummy *per se* is not correlated with the propensity to produce to order (we include fixed effects for LLS and industries). This is consistent with the raw evidence we presented regarding the sectoral MS indices, and it is also consistent with our theory, where spatial clustering in the industry has an ambiguous effect on production to order, provided that it crucially depends on the level of the complexity of the intermediates traded in the industry.

Column (2) shows that, in industries where all the transactions occur on organized exchange markets, clustering reduces on average *POI* by 46 percentage points, but raises it by 3 percentage points in sectors where products are never traded on organized exchange markets.[23] This is consistent with our theoretical predictions, $\beta_1 < 0$ and $\beta_2 > 0$. One concern is that some omitted factors might drive the relation between our key explanatory variables and the mode of production. Thus, in column (3) we show that the results of the baseline specification are robust to the inclusion of the set of control variables described above. We notice that production to order is more likely in smaller and less capital intensive firms.

In columns (4) and (5), we run similar regressions with a different clustering dummy, that now takes value one if *LQ* is greater than the 75th percentile of the distribution of non-zero *LQ* (column (4)), and greater than 1 (column (5)). These regressions consistently support our theoretical predictions, and emphasize that the impact of spatial clustering on production to order intensity crucially depends on the degree of product complexity.

4.3 Robustness checks

In Table 7 we perform several robustness checks.

[Insert Table 7 about here]

concentration of economic activity. As noticed in the main text, our focus is not on the impact of the overall concentration of economic activity in a given geographic unit, which is netted out in our estimates, but on the impact of the concentration of a certain industry in a certain geographic unit.

[23] The threshold value of z_j that makes positive the impact of *Clust* is 0.942. In our sample, there are 3,240 firms that belong to industries with a value of z_j that is higher than this threshold, while 275 firms belong to industries characterized by a z_j that is lower than this threshold.

In columns (1) and (2) we introduce as a dependent variable the *Ord* dummy, which is equal to one if *POI* is at least 30% and 50%. Results are unaffected, since spatial clustering reduces on average the likelihood of production to order by more than 40% if goods belonging to the industry are traded exclusively on organized exchange markets, but raises it by roughly 3% for sectors that are completely differentiated.

In column (3) we check whether results are robust to considering the Rauch liberal classification. Results are qualitatively the same, even if the estimated impact is smaller than in the case of the conservative measure, and the statistical significance of coefficients is lower as well.

An issue that should be kept in mind is that our sample is non-random, since it follows a stratified design.[24] In column (4), in order to account for the stratified nature of the sample, we weight each observation by the square root of the original sampling weight, according to the estimator proposed by, among others, Hausman and Wise (1981).[25]

In column (5) we include in the sample only those firms that sell at least 50% of their output to other firms. This is a more restrictive criterion than the 30% threshold employed throughout the paper, so the number of observations shrinks. Results do not change.

Finally, in Table 8 we prove that our findings are also robust to the industrial classification we employ. In the Table we show the coefficients of a regression of our three dependent variables (*POI* and the two *Ord* dummies, computed at the 30% and 50% thresholds respectively) on *Clust* and on z_j (for both the conservative and the liberal classification), if industries are classified in accordance to 2-digit NACE (for this reason the total number of industries shrinks from 77 to 22). Results are qualitatively the same as before, even if coefficients are smaller in magnitude.[26]

[Insert Table 8 about here]

5 Conclusions

In this paper we discuss the choice of whether to produce after a specific order is placed by a buyer or to produce in advance for the market. First, we describe to what extent production to order is different from production for stock. Second, we single out two important features that affect the choice of the production mode: the first is the degree of spatial clustering, which captures the thickness of the local market where the producer operates, the second is the degree of product complexity and relationship-specificity. We build a simple model and show that the qualitative nature of the impact of spatial

[24]See Appendix 6.1 about the stratification procedure adopted in the UniCredit surveys.

[25]See Wooldrige (2001).

[26]It is important to stress that in the case of 2-digit NACE we are facing a severe aggregation bias. For example, as documented in Table 5, the minimum for z_j equals 0.325 under the 77-industries classification, while it raises to 0.620 for 2-digit NACE. This is clearly the sign that, in the transition from 77 to 22 industries, rather homogeneous industries are being aggregated with more differentiated ones. The estimates under 2-digit NACE should be taken with more caution than our baseline ones.

clustering on the type of production critically depends on the degree of product complexity. In particular, our framework shows that an increase in the degree of spatial clustering pushes toward production to order in sectors where the loss due to imperfect customization is high, and product complexity is strong. We find the opposite effect in relatively homogenous sectors, where it is not valuable for buyers that the supplier undertakes relationship-specific customization activities. The main insight that generates this result is that higher spatial clustering increases supplier's profits in both modes of production, but the positive impact on profits deriving from production to order prevails in sectors where customization activities that have to be performed by the buyers induce a large loss in the component's value, and so it becomes convenient for the supplier to engage in relationship-specific investments to reduce that loss.

We provide empirical support to these results, testing our predictions on a large dataset of Italian manufacturing firms. We proxy spatial clustering with a binary indicator derived from the location quotient of industries in Italian local labor systems, while the degree of product complexity is obtained indirectly looking at whether the products belonging to the industry are traded or not on an organized exchange market. Depending on the specification we use, clustering decreases the probability of producing to order by roughly 40 percentage points for suppliers that sell in industries where all the transactions occur on organized exchange markets, and increases it by 3 percentage points for suppliers selling in industries where no organized exchange market exists.

In conclusion, we have provided the first attempt we are aware of to shed light on the link between the choice of producing to order or in advance and spatial clustering. While we argued that geographic concentration of industries and product complexity are important elements in this decision, we believe that further work will be necessary to improve our understanding on the prevalence of each production mode. In particular, we think that a particularly promising area of research is the study of the link between spatial clustering, design and marketing activities on the one side, and the choice of the production mode on the other. Even if we touched upon these issues in our theoretical section, our empirical part has been rather silent on that, essentially due to the unavailability of relevant data.

6 Appendix

6.1 The dataset

The micro data set we use for this paper comes from pooling together the 8th and 9th waves of "*Indagine sulle imprese manifatturiere*" (Survey on manufacturing firms), which were carried out by Mediocredito Centrale, now incorporated into UniCredit Group, one of the largest Italian banks. The quality and reliability of the dataset is documented by the fact that papers employing this Survey have already been published in peer-reviewed journals (see Angelini and Generale, 2008, and Benfratello et al., 2009). Each wave is representative of the universe of Italian firms in manufacturing. Firms in each wave are sampled with a stratified method: 80 strata are defined, based on geographical area (4 areas in Italy), Pavitt sectoral classification, and 5 size classes. The size of each stratum follows the Neyman sampling procedure. In doing so, each stratum is assigned a weight with respect to the universe. This allows us to run regressions where each observation in the sample is weighted according to its sampling weight as reported in the UniCredit dataset.

About half of the firms in the 8th wave (1998-2000) are dropped in the 9th wave (2001- 2003), with other new firms being added. The choice of firms to be dropped from the 8th wave, and of those to be added in the 9th wave is random, but the stratified nature of the sample is maintained. The original data set contains information for 4,680 firms during 1998-2000 (8th wave) and 4,178 firms during 2001-2003 (9th wave). The number of firms present in both waves is 2,097. Pooling the two datasets, we retrieve observations for some 6,761 different firms (4,178 firms from the 9th wave, plus 2,583 firms from the 8th wave that were not included in the 9th wave). It is important to stress that even if a firm is sampled in both waves, it is counted only as a single observation in our estimates, provided that the other observation is dropped. We end up with a cross-section of roughly 3,500 firms, because out of 6,761 units we keep only those firms that are selling most of their output to other firms.

The survey contains a detailed description of firms' labor force composition, investment and innovation activity, internationalization strategies, production choices, financing choices, etc. In addition, the data set includes balance sheet information for each of the years covered.

We adopt a trimming procedure that consists in flagging observations with an extreme growth rate for any of the following variables: value added, capital, number of white collars (i.e. skilled labor), number of blue collars (i.e. unskilled labor). We do not flag observations with extreme values in the growth rate of intermediates' consumption. In particular, we consider a growth rate as an extreme one if it belongs to the upper (99.5%) and bottom (0.05%) tails of the corresponding distribution across the firms in the panel, for a given couple of years. For example, observations for the years 2002 and 2003 are flagged if the growth rate in value added between 2002 and 2003 belongs to the bottom 0.5% of the distribution, or if it belongs to the upper 99.5% of the distribution. We also consider the following firm-level controls:
Age: Age of the firm in 2000 (8th wave) or 2003 (9th wave).
Exporter: Dummy variable indicating whether the firm is an exporter.
Size: The size measure we use is the total number of employees, including entrepreneurs and management.
Labor productivity: Average value added per employee.
Capital intensity: Total assets divided by size (as defined above).
Skill intensity: The share of white collars over the total number of employees (size variable). White collars are entrepreneurs, managers, and clerks.
Belongs to a group (group): Dummy variable indicating whether the firm belongs to a business group.

6.1.1 Questions employed from the UniCredit Surveys

Here we report the two main questions (E1, E2) regarding distribution channels and production choices that we use from the surveys. The questions here refer to the 9th wave, so the relevant year is 2003. Firms in the 8th wave were asked the same questions, but the reference year was 2000.

E1. Having normalized to 100 the total revenues in the year 2003, state the percentage share for each type of distribution channel:

- E1.1. Modern national distribution channels (including: hypermarkets, department stores, cash & carry, hard discount, specialized retail stores);
- E1.2. Modern foreign distribution channels (including: hypermarkets, department stores, cash & carry, hard discount, specialized retail stores);
- E1.3. Sales to franchising firms;
- E1.4. Intermediaries specialized in goods for households;
- E1.5. Intermediaries specialized in goods for firms;
- E1.6. Small retailers;
- E1.7. Direct sales to households (not through electronic commerce);
- E1.8. Direct sales to households through electronic commerce;

- E1.9. Direct sales to firms (not through electronic commerce);
- E1.10. Direct sales to firms through electronic commerce;
- E1.11. Other customers.

E2. Having normalized to 100 the total revenues in the year 2003, state the percentage share for each type of selling:

- E2.1. Selling of goods produced under an order placed by the buyer;
- E2.2. Selling of goods produced by the firm on its own.

6.2 The industrial classifications

In this paper we use an industrial classification which is based on 77 industries. The concordance between our classification and the NACE Rev. 1 is provided in Table 9.

[Insert Table 9 about here]

The industrial classification that we adopt is the same employed by the UK Office for National Statistics in the Input-Output tables. The reason for adopting such a classification is the following. Our paper deals with the trade of intermediates occurring within industries, and we need to define an industry partitioning which is broad enough so to encompass a high share of within-industry trade of intermediates, but which is at the same time detailed enough so to allow between-industry variation in relationship-specificity and product complexity. We solved this trade-off relying on the same classification that the UK Office for National Statistics employs in the Input-Output Use tables. For example, according to our classification and the 2002 UK Use tables (Italian Input-Output tables are not publicly available at this level of disaggregation) the average within-industry share of total intermediates' trade amounts to 36.8%. This means that, on average, 36.8% of the value of traded intermediates is taking place among suppliers and buyers belonging to the same industry.

However, in the paper we also use the more standard 2-digit NACE, based on 22 different industries, in order to be sure that our results are robust to the industrial classification employed. In the case of 2-digit NACE, Italian Input-Output Use tables are publicly available. From them we learn that, at this level of disaggregation, for the year 2002 the average within-industry share of total intermediates' consumption amounts to 48.2%. In the case of UK tables, the average within-industry share of intermediates trade for 2002 at 2-digit NACE level amounts to 50.5%. As expected, the higher the aggregation level, the higher the share of within-industry trade that is captured. However, the higher it is the aggregation level, the less precise it is our measure of the industries' degree of relationship-specificity, since homogeneous industries are aggregated with more differentiated ones. See also footnote 26 about this aggregation issue.

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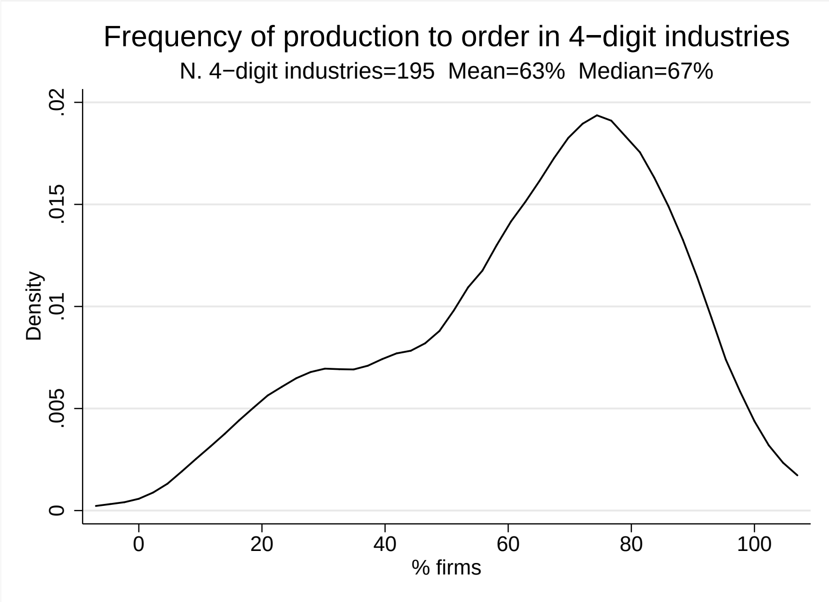

Figure 1: Kernel density estimation of the share of firms producing to order, within 4-digit NACE industries with at least 5 firms in our dataset.

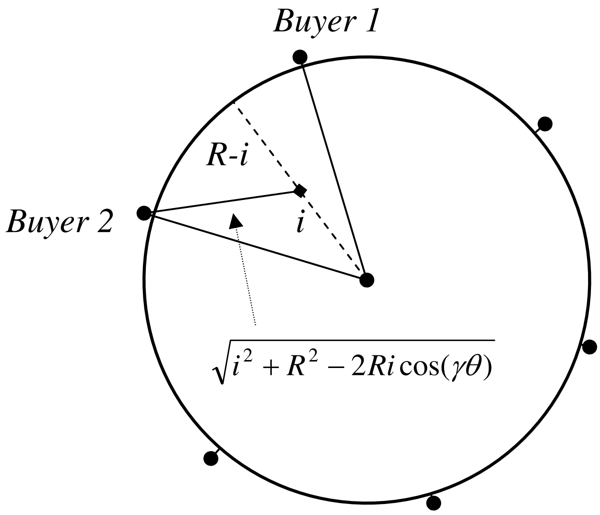

Figure 2: The characteristics' space with 6 downstream buyers, equally spaced with an angle measuring θ at the center, in a circumference of radius R. The supplier is making along the dashed line a relationship-specific investment which is closer to buyer 1's needs than buyer 2's needs ($1/2 < \gamma < 1$), although specialization is incomplete ($i < R$).

Table 1: *Production to order (share and intensity) and product differentiation across industries*

	Product to order share		Production to order intensity	
	$z_{j,con}$	$z_{j,lib}$	$z_{j,con}$	$z_{j,lib}$
Product differentiation	0.533***	0.434***	0.533***	0.426***
	(0.168)	(0.120)	(0.160)	(0.115)
Number of obs.	73	73	73	73
R^2	0.12	0.15	0.14	0.16

Note: In the first two columns the dependent variable is the share of firms producing to order at least 50% of output in each industry. In the last two columns the dependent variable is the average of firms' production to order intensity (value of output produced to order divided by the value of total output) in each industry. We employ as regressor either Rauch's conservative classification ($z_{j,con}$) or Rauch's liberal one ($z_{j,lib}$). *** denotes significance at the 1 per cent level.

Table 2: *Production to order (share and intensity) and spatial concentration across industries*

	Product to order share	Production to order intensity
MS concentr. index	0.284	0.004
	(0.918)	(0.009)
Number of obs.	73	73
R^2	0.00	0.00

Note: In the first column the dependent variable is the share of firms producing to order at least 50% of output in each industry. In the last column the dependent variable is the average of firms' production to order intensity (value of output produced to order divided by the value of total output) in each industry. We employ as regressor the MS concentration index based on plants' counts.

Table 3: *Production modes and customization activities*

	Cust. for a specific buyer	Cust. for the market
Production to Order	POSSIBLE CO-OPERATION BTW. SUPPLIER AND BUYER	ABSENT
Production for Stock	PERFORMED BY THE BUYER IN ISOLATION	PRESENT

Note: The table reports by row the possible production modes and by the column the type of customization activities performed for each production mode.

Table 4: *A taxonomy of production modes*

	Low degree of spatial clustering (low K)	High degree of spatial clustering (high K)
Homogeneous industry (low β)	**PRODUCTION TO ORDER**	PRODUCTION IN ADVANCE
Differentiated industry (high β)	PRODUCTION IN ADVANCE	**PRODUCTION TO ORDER**

Note: The table reports a qualitative taxonomy for the choice of the production mode according to the degree of product differentiation (rows) and the degree of spatial clustering (columns).

Table 5: *Summary statistics for main variables*

	Notation	Obs.	Mean	Std. Dev.	Min.	Max.
Production to order intensity	POI_{ij}^{g}	3,515	.730	.403	0	1
Production to order dummy (30% threshold)	Ord_{ij}^{g}	3,515	.782	.413	0	1
Production to order dummy (50% threshold)	Ord_{ij}^{g}	3,515	.756	.429	0	1
Spatial clustering dummy (median threshold)	$Clust_{j}^{g}$	3,515	.610	.488	0	1
SITC without org. exch. mkt. (cons. class.; $J = 77$)	z_j	3,515	.971	.109	.325	1
SITC without org. exch. mkt. (cons. class.; $J = 22$)	z_j	3,515	.946	.102	.620	1

Note: The table reports some summary statistics across firms for the main variable of interest.

Table 6: *The determinants of production to order: Baseline estimation*

	col1	col2	col3	col4	col5
	(1)	(2)	(3)	(4)	(5)
Clust (median)	0.016	-.463***	-.433***		
	(0.015)	(0.104)	(0.121)		
Clust (75 pct.)				-.309***	
				(0.118)	
Clust (1)					-.351**
					(0.158)
Clust (median) * Cons		0.491***	0.463***		
		(0.108)	(0.125)		
Clust (75 pct.) * Cons				0.325***	
				(0.125)	
Clust (1) * Cons					0.388**
					(0.162)
Share manuf. * Cons			-.242	-.310	-.346
			(0.471)	(0.504)	(0.496)
Age (log)			0.106**	0.107**	0.107**
			(0.053)	(0.052)	(0.053)
Age^2 (log)			-.018**	-.018**	-.018**
			(0.008)	(0.008)	(0.008)
Exporter			-.019	-.020	-.018
			(0.017)	(0.017)	(0.017)
Size (log)			-.040***	-.040***	-.040***
			(0.01)	(0.01)	(0.01)
Labor Productivity (log)			-.026	-.027	-.027
			(0.022)	(0.022)	(0.022)
Capital Intensity (log)			-.039***	-.039***	-.039***
			(0.011)	(0.011)	(0.011)
Skill intensity (log)			-.009	-.009	-.009
			(0.008)	(0.008)	(0.008)
Belongs to Group			-.007	-.008	-.006
			(0.017)	(0.017)	(0.017)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
LLS fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	3,515	3,515	3,438	3,438	3,438
R^2	0.235	0.238	0.267	0.265	0.266

Note: Standard errors clustered by industries are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 per cent level respectively.

Table 7: *Robustness checks*

	Ord (30%)	Ord (50%)	Lib. Classif.	Weighted LS	Restrict. sample
	(1)	(2)	(3)	(4)	(5)
Clust (median)	-.400***	-.419***	-.208*	-.394***	-.422***
	(0.107)	(0.136)	(0.109)	(0.109)	(0.141)
Clust (median) * Cons	0.425***	0.443***		0.422***	0.456***
	(0.111)	(0.14)		(0.113)	(0.145)
Clust (median) * Lib			0.239**		
			(0.113)		
Share Manuf. * Cons	0.265	-.252		-.267	-.159
	(0.503)	(0.468)		(0.547)	(0.648)
Share Manuf. * Lib			-.387		
			(0.365)		
Exporter	0.011	0.002	-.019	-.021	-.005
	(0.016)	(0.017)	(0.017)	(0.018)	(0.018)
Age (log)	0.104**	0.115**	0.11**	0.102*	0.097*
	(0.053)	(0.056)	(0.053)	(0.054)	(0.057)
Age^2 (log)	-.019**	-.020**	-.019**	-.017**	-.017**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Size (log)	-.036***	-.036***	-.040***	-.034***	-.040***
	(0.01)	(0.01)	(0.01)	(0.008)	(0.011)
Labor Productivity (log)	-.040**	-.039*	-.027	-.026	-.028
	(0.02)	(0.022)	(0.022)	(0.022)	(0.022)
Capital Intensity (log)	-.035***	-.040***	-.039***	-.039***	-.036***
	(0.01)	(0.011)	(0.011)	(0.01)	(0.01)
Skill Intensity (log)	-.009	-.004	-.009	-.005	-.006
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Belongs to Group	-.011	0.001	-.007	-.002	-.004
	(0.019)	(0.017)	(0.017)	(0.018)	(0.019)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
LLS fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	3,438	3,438	3,438	3,438	3,124
R^2	0.253	0.244	0.266	0.268	0.257

Note: Standard errors clustered by industries are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 per cent level respectively.

Table 8: *Alternative industrial classification: 2-digit NACE*

	POI		Ord (30%)		Ord (50%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Clust (median)	-.207**	-.154**	-.287***	-.208**	-.208**	-.144**
	(0.095)	(0.075)	(0.102)	(0.081)	(0.087)	(0.067)
Clust (median) * Cons	0.256***		0.334***		0.256***	
	(0.098)		(0.105)		(0.09)	
Clust (median) * Lib		0.208***		0.260***		0.195***
		(0.078)		(0.085)		(0.071)
Share manuf. * Cons	-.994		-.818		-.788	
	(0.662)		(0.623)		(0.554)	
Share manuf. * Lib		-.939		-.752		-.751
		(0.577)		(0.55)		(0.484)
Age (log)	0.095	0.096	0.093	0.093	0.105	0.105
	(0.067)	(0.067)	(0.07)	(0.07)	(0.07)	(0.07)
Age^2 (log)	-.017	-.017	-.017	-.017	-.019*	-.019*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Exporter	-.034*	-.034*	-.003	-.003	-.012	-.012
	(0.018)	(0.018)	(0.016)	(0.016)	(0.017)	(0.017)
Size (log)	-.038***	-.038***	-.034***	-.034***	-.035***	-.034***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)
Labor Productivity (log)	-.028	-.028	-.041**	-.041**	-.038*	-.038*
	(0.02)	(0.021)	(0.019)	(0.019)	(0.02)	(0.02)
Capital Intensity (log)	-.040***	-.040***	-.036***	-.036***	-.042***	-.041***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)
Skill Intensity (log)	-.010	-.010	-.010	-.009	-.004	-.004
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Belongs to group	-.010	-.010	-.013	-.013	-.002	-.001
	(0.017)	(0.017)	(0.021)	(0.021)	(0.015)	(0.015)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
LLS fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,438	3,438	3,438	3,438	3,438	3,438
R^2	0.236	0.236	0.220	0.220	0.224	0.224

Note: Standard errors clustered by industries are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 per cent level respectively.

Table 9: *Concordance table of the industrial classification with NACE Rev. 1*

Industrial classification used in the paper	NACE Rev. 1
1 Production, processing and preserving of meat and meat products	15.1
2 Processing and preserving of fish and fish products; fruit and vegetables	15.2 + 15.3
3 Vegetable and animal oils and fats	15.4
4 Dairy products	15.5
5 Grain mill products, starches and starch products	15.6
6 Prepared animal feeds	15.7
7 Bread, rusks and biscuits; pastry goods and cakes	15.81 + 15.82
8 Sugar	15.83
9 Cocoa; chocolate and sugar confectionery	15.84
10 Other food products	15.85 to 15.89
11 Alcoholic beverages - alcohol and malt	15.91 to 15.97
12 Production of mineral waters and soft drinks	15.98
13 Tobacco products	16
14 Preparation and spinning of textile fibres	17.1
15 Textile weaving	17.2
16 Finishing of textiles	17.3
17 Made-up textile articles, except apparel	17.4
18 Carpets and rugs	17.51
19 Other textiles	17.52 to 17.54
20 Knitted and crocheted fabrics and articles	17.6 + 17.7
21 Wearing apparel; dressing and dyeing of fur	18
22 Tanning and dressing of leather; luggage, handbags, saddlery and harness	19.1 + 19.2
23 Footwear	19.3
24 Wood and wood products, except furniture	20
25 Pulp, paper and paperboard	21.1
26 Articles of paper and paperboard	21.2
27 Publishing, printing and reproduction of recorded media	22
28 Coke, refined petroleum products and nuclear fuel	23
29 Industrial gases, dyes and pigments	24.11 + 24.12
30 Other inorganic basic chemicals	24.13
31 Other organic basic chemicals	24.14
32 Fertilisers and nitrogen compounds	24.15
33 Plastics and synthetic rubber in primary forms	24.16 + 24.17
34 Pesticides and other agro-chemical products	24.2
35 Paints, varnishes and similar coatings, printing ink and mastics	24.3
36 Pharmaceuticals, medicinal chemicals and botanical products	24.4
37 Soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations	24.5
38 Other chemical products	24.6
39 Man-made fibres	24.7
40 Rubber products	25.1
41 Plastic products	25.2
42 Glass and glass products	26.1
43 Ceramic goods	26.2 + 26.3
44 Bricks, tiles and construction products in baked clay	26.4
45 Cement, lime and plaster	26.5
46 Articles of concrete, plaster, cement; cutting, shaping, finishing of stone; other non-metallic mineral products	26.6 to 26.8
47 Basic iron and steel and of ferro-alloys; manufacture of tubes and other first processing of iron and steel	27.1 to 27.3
48 Basic precious and non-ferrous metals	27.4
49 Casting of metals	27.5
50 Structural metal products	28.1
51 Tanks, reservoirs and containers of metal; central heating radiators and boilers; steam generators	28.2 + 28.3
52 Forging, pressing, stamping and roll forming of metal; powder metallurgy; treatment and coating of metals	28.4 + 28.5
53 Cutlery, tools and general hardware	28.6
54 Other fabricated metal products	28.7
55 Machinery for the production and use of mechanical power, except aircraft, vehicle and cycle engines	29.1
56 Other general purpose machinery	29.2
57 Agricultural and forestry machinery	29.3
58 Machine tools	29.4
59 Other special purpose machinery	29.5
60 Weapons and ammunition	29.6
61 Domestic appliances not elsewhere classified	29.7
62 Office machinery and computers	30
63 Electric motors, generators and transformers; manufacture of electricity distribution and control apparatus	31.1 + 31.2
64 Insulated wire and cable	31.3
65 Electrical equipment not elsewhere classified	31.4 to 31.6
66 Electronic valves and tubes and other electronic components	32.1
67 Television and radio transmitters and apparatus for line telephony and line telegraphy	32.2
68 Television and radio receivers, sound or video recording or reproducing apparatus and associated goods	32.3
69 Medical, precision and optical instruments, watches and clocks	33
70 Motor vehicles, trailers and semi-trailers	34
71 Building and repairing of ships and boats	35.1
72 Other transport equipment	35.2 + 35.4 + 35.5
73 Aircraft and spacecraft	35.3
74 Furniture	36.1
75 Jewellery and related articles; musical instruments	36.2 + 36.3
76 Sports goods, games and toys	36.4 + 36.5
77 Miscellaneous manufacturing not elsewhere classified; recycling	36.6 + 37

Note: The table provides the concordance between the industrial classification used in the paper and NACE Rev. 1.