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discussion papers

**Are Product Innovation and Flexible
Technology Complements?**

Astrid Jung

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Are Product Innovation and Flexible Technology Complements?

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February 2003

Abstract

This paper analyzes the interdependence between the firms' technology choice and innovation. Previous literature argues that product flexibility and product innovation are complements, because flexible machines handle a large variety of product designs with low changeover times. In a model where technology is chosen before uncertain demand is realized, we show that long-run technology, by imposing constraints on short-run production, does not only affect the cost of innovating but also its payoff. The results coincide with the literature in that the cost of product innovation is always reduced by flexibility, but we find that the operational profits from product innovation might be decreasing in flexibility. Consequently, flexibility does not necessarily complement product innovation. Empirical evidence from the German mechanical engineering industry supports the complementarity conjecture, since random shocks tend to trigger adjustments of both decision variables in the same direction.

Keywords: Supermodularity, flexible technology, product innovation, multi-product firms, demand uncertainty, capacity constraints, multivariate probit

JEL Classification: C25, D21, D92, L23

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1 Introduction

During the past decades massive advances in information technology (IT) have revolutionized the firm at a shop-floor level. Beyond increasing speed and quality of production, IT is capable of handling a greater variety of product designs with low changeover times thereby decreasing the cost for introducing new products. The apparent cost advantage, which flexible, IT intense equipment offers in innovating, seems to suggest that the two decision variables, flexible technology and product innovation, complement each other.¹

The presence of complementarity simplifies the prediction of mutual adjustments considerably: Any change in the optimal level of one decision, say flexibility, will tend to shift its complement, say product innovation, in the same direction and vice versa. This explains why the concept of complementarity became an important tool in the economic analysis of multidimensional choices. From a policy point of view, given complementarity, the efficiency of measures aimed at promoting product innovation might be substantially enhanced by decreasing impediments to the adoption of flexible technology. Moreover, product innovation could be stimulated indirectly by giving incentives to invest in complementary technologies. This might be a promising approach in practice because product innovation is not precisely defined and therefore difficult to target.

The above argument, which infers complementarity between flexible technology and product innovation from the observation that the former decreases the cost of the latter, focuses entirely on the fixed costs of production. In this paper we take a well-established property of flexible machinery into account, which has not yet been thoroughly related to product innovation: Flexibility provides a hedge against uncertain future conditions. That is, by investing in flexibility today, a firm increases its discretion in later periods when additional information is available. As an example, consider a company with a

¹For example, Chrysler, the US arm of the carmaker Daimler-Chrysler, announced in the beginning of 2002 that it would move towards a more flexible manufacturing in an attempt to reduce huge operating losses and to cut down expenses on new product development by up to 25 per cent.

fixed number of products whose prices are announced in a catalogue. Such a catalogue is printed without information on what quantities costumers will eventually order and hence production has to be adjusted according to incoming requests. Since capacity is costly and usually fixed in the short run, firms are typically not prepared to produce all possible quantity realizations. However, by adopting flexible, multi-tasking technology, which can be used to fabricate a wide range of products instead of machines specialized in a few designs, a firm is more likely able to meet its costumers' demand with a given capacity level. On account of hedging against uncertain demand, flexibility has a positive impact on profits, which goes beyond reducing the cost to innovate. Moreover, due to imposing technology specific capacity constraints on production, the level of flexibility affects the probability that additional orders stimulated by product innovation can actually be complied with. This reasoning reveals an important channel of interdependence between the decision to innovate and the technological setting of a firm, which, to the best of our knowledge, has not yet been covered in the literature.

To formalize the above argument, we build a two-period optimization model. First the multi-product firm decides on whether technology should be dedicated or flexible, what capacity the machines shall accommodate, the level of product innovation and a price. At this stage, only the distribution of demand conditional on price and innovation is known and we assume that flexible technology reduces the cost of incremental product improvement. In the second period demand is realized and actual production is conducted subject to demand and capacity constraints. In order to separate the insurance effect of flexibility as clearly as possible from other factors, we restrict the analysis to product markets with identical characteristics and marginal costs that are constant, equal across products, and independent of technology. The only characteristic that distinguishes our multivariate setting from the notion of a single-product firm is the fact that stochastic demand shocks are allowed to be imperfectly correlated across products.

Our results are as follows. First, we replicate that production will on average be higher if technology is flexible, because then the capacity constraint applies to total

production, whereas dedicated technology imposes one capacity constraint for every single product.

Second, we show that flexibility reinforces the positive effect of incremental product innovation on expected operational profits (sales minus variable costs) only for a limited range of capacity. This ambiguity is driven by the fact that the probability of additional demand being within the firm's production capabilities is not necessarily greater for flexible technology. Hence, concerning the production stage, flexibility and product innovation may be complements or substitutes. Without further and possibly unrealistic assumptions about the size of the effects we cannot rule out that a potentially negative interaction in expected operational profits might dominate bilateral fixed costs savings. Only in the limiting case of the model, where the demand distribution is degenerate (i.e., there is no uncertainty), complementarity in the fixed costs ensures complementarity in overall profits and leads to unambiguous comparative statics results.

As the theoretical model in this paper leads to equivocal predictions, we empirically investigate the interdependence between flexible technology and product innovation using data from 593 plants of the German mechanical engineering industry for the years 1992 and 1994. If complementarity stemming from bilateral fixed cost savings dominates, then any shift in one of the two variables would trigger an adjustment pressure on the other in the same direction. The levels of product innovation and flexibility would thus be expected to be associated in practice. This paper measures the association between the two practices in three subsequent steps: unconditionally, conditioned on observed characteristics of the firms, and, finally, conditioned on observed and unobserved heterogeneity. Controlling for observed and unobserved heterogeneity is necessary in order to wipe out the effects of other factors, which might bias the inference about the direct relationship between technology and innovation. The data reveals that highly flexible firms do tend to adopt significantly more product improvements than others. This effect does not vanish after controlling for heterogeneity.

Our theoretical contribution sheds new light on the discussion of what Milgrom

and Roberts (1990² and 1995a) labeled "modern manufacturing". These authors argue that a paradigm shift in the organization and strategy of the firm replaced traditional mass production of that type as it characterized manufacturing during the first half of the twentieth century. They assume that many features of production, for instance high skills, worker involvement, frequent product improvement and flexible machines, complement each other. Consequently, monotone shifts in complementary exogenous variables, such as the diminishing costs of flexibility and communication during the IT revolution, have not only been favoring investments in high capability technology but have also stimulated monotone adjustments of the entire system of complementary choices. In their arguments Milgrom and Roberts focus on fixed costs effects and on properties of the deterministic demand function while ignoring uncertainty beyond additive random terms.

This applies also to an article by Athey and Schmutzler (1995) who show that complementarity between product and process innovation in the short run induces complementarity between long-run product and process flexibility, if each type of flexibility diminishes the cost of the respective kind of innovation. They allow for a random return to flexibility, which affects the profitability of the short-run variables, but which does not impose restrictions on the decision about these variables. Furthermore, in their model the distribution of the random shock is independent of the long-run decision. In contrast, in our model the probability distribution of uncertain events is affected by the firms' decisions and, moreover, the realized random variable imposes constraints on the set of feasible production choices.³

We model gains from flexibility as a hedge against uncertainty following Fine and Freund (1990) who give necessary and sufficient conditions for adopting flexible machines based on imperfect correlation between the demands for different products. Van Mieghem (1998) shows that flexibility might pay even when products are perfectly

²Note the comments on this article by Bushnell/Shepard (1995), Topkis (1995), and the reply by Milgrom/Roberts (1995b) .

³We exclude a discussion of process flexibility and process innovation, because neither randomness of demand nor randomness of marginal costs would qualitatively change results derived from fixed costs only.

correlated, since it enables the firm to exploit differences between products in profit margins. Epstein (1980) and also He and Pindyck (1992) discuss technology decisions in a framework where uncertainty is resolved piecewise. Jones and Ostroy (1984) formalize the intuition of a flexible option being more valuable as uncertainty aggravates.⁴ DeGroote (1994) generalizes this view by covering the notions of multidimensional flexibility and diversity.⁵

In this paper, flexibility will be exclusively defined as the capability of a production technology to support a variety of products and designs. Aspects resulting from differences in variable costs are ignored, since they would not add to our main point.⁶

The notion of complementary variables is formalized by using the concept of supermodular objective functions on lattices, a generalization of differentiable functions with positive cross partial derivatives.⁷ Monotone changes in a parameter vector, whose elements are all complementary to every decision variable, lead to monotone shifts of the set of maximizers of a supermodular function as established by Topkis (1978) and generalized by Milgrom and Shannon (1994). This property suggests that given such a nicely behaved parameter vector, complementarity between decision variables can be detected by their empirical association. The limits of this approach are discussed by Holmstrom and Milgrom (1994), Arora (1996), and also Athey and Stern (1998).

This paper also contributes to the empirical assessment of modern manufacturing. Although many studies test implications and find support for several aspects of Milgrom and Robert's idea,⁸ to our knowledge, none has explored whether the adoption of

⁴In an oligopoly context Vives (1989) shows that more uncertainty resulting from more variable beliefs may decrease the value of flexibility due to interaction in the market. Novshek and Thoman (1999) find that even for a monopoly optimal flexibility might be decreasing in uncertainty. In contrast to most of the literature however, they define uncertainty as a random support of consumers' taste distribution.

⁵Papers that investigate the impact of endogenizing flexibility on equilibria in oligopoly games include Vives (1986) and (1989), Röller and Tombak (1990), Eaton and Schmitt (1994), Norman and Thisse (1999).

⁶For technology dependent variable costs see Stigler (1939) and Vives (1989). Carlsson (1989) and Gerwin (1993) survey different definitions of flexibility.

⁷For a comprehensive overview see the book by Topkis (1998) and the citations therein.

⁸Examples for studies that assess human resource practices attributed to modern manufacturing are Pil/MacDuffie (1996), Ichniowski/Shaw/Prennushi (1997) and Patibandla/Chandra (1998). Bresnahan/Brynjolfsson/Hitt (2001) and Parthasarthy/Sethi (1993) devote special attention to the

flexible technology favors product innovation.

The paper proceeds as follows. In section 2 we introduce a reference model where price announcements are followed by the markets' deterministic reactions, which make subsequent quantity adjustments unnecessary. This model replicates results from previous literature stating that fixed costs savings from the joint adoption of practices in conjunction with a supermodular demand function lead to a profit function that is supermodular in all decision variables. We then extend this model to situations where demand is uncertain and quantity adjustments follow earlier price announcements. Section 3 is devoted to empirical evidence from adoption decisions in manufacturing. Section 4 concludes.

2 A Model of the Firm

2.1 A Model with Deterministic Demand

For later comparisons we will present a non-stochastic version of our model, which involves the decision on flexibility of machinery $f \in \{0, 1\}$, product innovation $i \in R^+$, capacity $k \in R^+$ and price $p \in R^+$. Throughout this paper f is assumed to be binary, a value equal to 1 indicating the adoption of flexible technology. Some of the definitions and results, which are used in the following, are listed in appendix A.

Consider a 2-product firm acting as a monopolist. For simplicity, assume that the marginal cost of production are constant, equal across products, and independent of technology such that it can be normalized to zero.⁹ Further, let the product markets be identical in their demand characteristics. Due to these simplifications, optimal prices as well as optimal capacities must be the same for both products.¹⁰ Consequently,

adoption decisions of high performance – and thus flexible – technology. Gal-Or (2002) studies the relationship between aspects of the internal structure of the firm and scale flexibility. Evidence on what are complementary competences to innovation and whether product and process innovation are complementary can be found in Leiponen (2000) and Miravete/Pernias (2000) respectively.

⁹Treating marginal costs as a function of technology would complicate the analysis by making firms' flexibility decision more complex. This extension would however, not alter the main point of this paper, which focuses on the effect of product innovation on the optimal technology choice.

¹⁰For a discussion of the deterministic demand model, we could (without loss) treat the two products

the firm's price and capacity choices can be fully described by scalars p and k . Let innovation be an activity that keeps the number of products constant and equally improves the quality of both products. Consumers' demand for each product $j = 1, 2$ is denoted by $D_j = D_j(i, p)$. Assume that D_j is supermodular in (i, p) and differentiable in i and p with $\partial D_j / \partial p \leq 0$ and $\partial D_j / \partial i \geq 0$.¹¹

Supermodularity of D_j implies that a price increase will diminish the demanded quantity weakly less if a firm innovates. Supermodularity in conjunction with the above assumption regarding first derivatives implies that the price elasticity, $(-\frac{\partial D_j}{\partial p} \frac{p}{D_j})$, is decreasing in innovation.¹² Hence, the more a firm improves its products, the less sensitive consumers will be to price changes. Total demand for the firm's products is denoted by $D := D(i, p) = 2D_j(i, p)$. This leads to the operational profit function

$$\tilde{\Pi}(i, p) = p D(i, p). \quad (1)$$

Total profits Π equal the operational profits minus fixed costs. Let the fixed costs consist of three components: the cost of capacity γk with $\gamma \geq 0$ fixed and independent of technology, the cost of flexibility $F \geq 0$, and the cost of product innovation $I \geq 0$.

In this paper, a firm is said to be flexible if it is able to operate all products on a single device. With dedicated technology, on the other hand, the firm has to install one machine for every product. If a firm invests in flexibility, it will incur a cost $F = F(f, \omega)$, which depends on a vector of exogenous variables ω and is zero for $f = 0$. In this setting it is never optimal for firms to acquire both types of equipment.¹³

The assumptions about the cost of technology are motivated by the fact that IT, as one. A distinction between two products is made only for the sake of consistency with the stochastic version of the model.

¹¹Although neither differentiability nor the cardinal concept of complementarity are necessary to assess comparative statics, we use the first for its intuitive appeal and the latter because it is easier to verify in the context of the stochastic version of our model. But even under these more restrictive assumptions, the stochastic version of the model will be shown to fail the monotonicity property.

¹²A price elasticity that is decreasing in i is equivalent to the log of the demand function being supermodular, or in other words, the demand function being log-supermodular. This property is sufficient for monotone comparative statics of $p D_j(i, p)$ and less demanding than D_j being supermodular and increasing in i but more difficult to handle once demand is stochastic.

¹³VanMieghem (1998) allows marginal capacity costs to vary with technology and discusses conditions that lead to optimal investment in both technologies.

which makes machines flexible, has become relatively cheap. Thus, most of the cost difference between flexible and dedicated equipment can be attributed to the relatively more expensive adoption of the former (e.g. coordination costs, specific training, the need for high skilled operators).

Let the cost of product innovation I depend on the decision variables i and f and on a parameter vector ω . Product improvements are less costly if they do not require extensive reconfiguration of the production process or extra machinery, i.e. if technology is flexible enough to easily accommodate changes. Based on this observation, Milgrom and Roberts (1995a) suggest that i and f are complements with respect to $(-I)$ and hence, $(-I)$ is supermodular in (i, f) .

Summarizing the preceding paragraphs, the firm's profit can be written as

$$\Pi := \Pi(i, f, k, p, \omega) = p D(i, p) - \gamma k - F(f, \omega) - I(i, f, \omega). \quad (2)$$

The following proposition derives interactions among the decision variables in the overall profit function from their interactions in either demand or fixed costs.

Proposition 1 *Consider the profit function in (2) with $(i, f, k, p)^T \in R^+ \times \{0, 1\} \times R^+ \times R^+$. Let ω be an element of the partially ordered set Ω . Suppose that $D_j(i, p)$ for $j = 1, 2$ is differentiable and supermodular in (i, p) and increasing in i ; $-I(i, f, \omega)$ is supermodular in (i, f) and has increasing differences in $((i, f), \omega)$; and $-F(f, \omega)$ has increasing differences in (f, ω) . Then*

(i) Π is supermodular in (i, f, k, p) .

(ii) $\arg \max_{i, f, k, p} \Pi$ is increasing in ω .

Proof. See appendix B. ■

Monotonicity implies that firms adjust to changes in parameters which complement all endogenous variables in a coherent fashion, that is, by either increasing or decreasing the level of all decisions. As a consequence of proposition 1, we should observe a clustering in the choice of i, f, k and p given the components of ω are associated (i.e.

shifts in ω are monotone) and the fixed parameter γ as well as other individual heterogeneity are controlled for. This implies that innovative firms tend to adopt flexible technology and charge high prices. Note, that supermodularity in k is only weak and neither a strictly positive nor a strictly negative association between k and any other decision variable is predicted.¹⁴

A complementary parameter to the decision problem above could be the skills of potential employees, because high skill levels can be assumed to reduce the cost of adopting flexible technology and make product innovation easier. Another example might be the negative of the cost of IT: Low IT costs make it more attractive to switch production to the flexible, IT controlled mode (computer aided manufacturing – CAM) and decrease the cost of experimenting with design changes (computer aided design – CAD).

Proposition 1 will serve as a point of reference when discussing the impact that the introduction of demand uncertainty has on complementarity.¹⁵

2.2 A Two-period Model of the Firm with Stochastic Demand

The key feature of the elaborate version of our model¹⁶ is that, given price and innovation, we allow for two demand realizations for each product $j = 1, 2$:

$$D_j := D_j(i, p) = \begin{cases} \underline{D} := \underline{D}(i, p) \\ \overline{D} := \overline{D}(i, p) \end{cases} \quad j = 1, 2,$$

where $0 \leq \underline{D} \leq \overline{D}$ for any i and p . The joint density function of identically distributed random variables D_1 and D_2 is fully determined by four parameters: the probability δ_0 that demand, conditional on i and p , equals the lower value \underline{D} ; the expectation and standard deviation of the marginal distributions $\mu := E[D_j]$ and $\sigma := \text{var}[D_j]$; and the correlation coefficient ρ . In order to separate changes in profits due to a variation in μ

¹⁴The reason why we have included capacity choice in the model is that doing so will be natural in the context of the stochastic model below.

¹⁵It should be pointed out that, so far, there is no reason to assume a differentiable demand function. Limiting the variability of i and p to discrete changes would affect the proof but none of the implications of proposition 1 (see Topkis (1998) theorem 3.3.3.).

¹⁶In order to save notation, in the current model functions are named in the same way as in section 2.

from those caused by variance shifts, we assume that expected demand is a function of price and innovation, $\mu = \mu(i, p)$, whereas the uncertainty parameter σ is not affected by these variables. This implies that the marginal effect of price and innovation on \underline{D} equals that on \overline{D} . As a result, changes in price or the level of product innovation shift the probability function along the horizontal axis while maintaining its shape.

Imposing random realizations instead of deterministic demand allows us to analyze a key property of flexible technology, namely its capability to shift capacity among products.¹⁷ In the absence of uncertainty such multifunctional equipment can hardly be an advantage compared to dedicated technology: total capacity would then be chosen to equal the demand for all products. In a stochastic world, however, flexibility might payoff since it enables firms to adjust production according to the realization of demand. This suggests splitting the firm's decision into two periods as has been done by VanMieghem (1998): In the first period the firm decides on the level of i , f , k , and p only knowing the distribution of D_j . Then demand is realized and the actual production level, $y = (y_1 y_2)^T$, is chosen. Note that, a priori, we do not restrict the correlation between the demand shocks of the two products, thus incorporating situations where their interdependence is mostly influenced by macro shocks (e.g. income shifts of the whole economy) as well as settings where such macro trends are dominated by omitted factors hitting the two markets conversely.

Given these amendments to the deterministic model of section 2.1, a risk neutral firm now maximizes expected profits in the first period,

$$\begin{aligned} E\Pi & : = E\tilde{\Pi} - I(i, f, \omega) - \gamma k - F(f, \omega) \\ & = 2p E_{ip} [y_j^*(f, k, D_j)] - I(i, f, \omega) - \gamma k - F(f, \omega), \end{aligned} \quad (4)$$

with respect to i , f , k , and p foreseeing optimal quantity choices y_j^* , $j = 1, 2$, in second period. In equation (4) $E\tilde{\Pi}$ denotes expected operational profits, whereby γ , δ_0 , σ , and ρ are exogenous factors and ω represents a vector of omitted exogenous

¹⁷Throughout the paper we will ignore the quantitative dimension of flexibility treating the capacity as a generally binding constraint to production. We assume that marginal cost of production are infinite above the capacity level.

variables. The subindices i and p emphasize the fact that the expectation of the optimal quantity depends on innovation and price due to the effect these variables have on the distribution of D_j .

After demand is realized the firm chooses optimal production, y^* :

$$\begin{aligned} \max_y \quad & p \sum y_j \\ \text{s.t.} \quad & y_j \leq \frac{1}{2}k \quad \text{if } f = 0, \\ & \sum y_j \leq k \quad \text{if } f = 1, \\ & y_j \leq D_j. \end{aligned} \tag{5}$$

Apparently, the capacity constraint in (5) is less restrictive with flexible technology, because only then is every unit of k multifunctional. Optimal production is in either case straightforward: If technology is dedicated ($f = 0$), then the optimization is done for every product independently. For each $j = 1, 2$ the firm produces the minimum of demand D_j and capacity $\frac{1}{2}k$. When $f = 1$, profit maximization involves choosing output levels simultaneously for both products. Total production will then equal the minimum of total demand $\sum D_j$ and total capacity k . Expected operational profits including second period maximization are thus

$$E\tilde{\Pi}_y^* := E \max_y \tilde{\Pi} = \begin{cases} 2p E \min(D_j, \frac{1}{2}k) & \text{if } f = 0 \\ p E \min(\sum D_j, k) & \text{if } f = 1 \end{cases}. \tag{6}$$

In this model the optimal quantity vector is fully determined by f , k , D_1 , and D_2 . Therefore, the expected payoff from specific combinations of i , f , k , and p will be studied in a profit function where quantity is already maximized for.

Equation (6) can be rewritten as

$$E\tilde{\Pi}_y^* = \begin{cases} p \{2E[D_j|\Xi_0] \Pr(\Xi_0) + k[1 - \Pr(\Xi_0)]\} & \text{if } f = 0 \\ p \{2E[D_j|\Xi_1] \Pr(\Xi_1) + k[1 - \Pr(\Xi_1)]\} & \text{if } f = 1 \end{cases}, \tag{7}$$

where Ξ_0 and Ξ_1 denote the events of having demand as the only binding constraint, that is, $D_j < \frac{1}{2}k$ and $\sum D_j < k$, respectively.

At this point it is worthwhile to note the potential implication of uncertainty as modeled above to proposition 1. Random demand itself does not necessarily matter.

Let, for instance, demand be a function $D(i, p, r)$, where r is a random variable with a distribution which is independent of i , f , k , and p . Expected demand would then be the sum of all potential demand realizations times an exogenous probability. Using the fact that supermodularity is preserved by multiplying factors and by summation, proposition 1 would still hold for expected profits. In this paper we do, however, allow the firm to adjust its production according to new information within the limits set by prior decisions. In fact, since $\tilde{\Pi}$ is strictly increasing in y_j such that at either capacity, demand, or both are binding constraints in (5), prior decisions are always effective limits to production. As a result, the probability function of y_j^* depends on i , f , k , and p by more than an additive shift. For supermodularity to hold in $E\Pi$, supermodularity of $E_{ip} [y_j^*(f, k, D_j)]$ must be established.

Equation (7) does not yet involve any distributional assumption. The second line includes the expectation of the two random variables contingent on their sum. Since there are no general results concerning the distribution of the sum of correlated random variables even if they are identically distributed, we stick to the simplest possible model of randomness.¹⁸ Namely, we assume that the demand for each product is either low (\underline{D}) or high (\overline{D}) and that the probability of the lower outcome, $\Pr(D_j = \underline{D})$, is the same for both products and equal to δ_0 . Computing the joint and conditional marginal distributions and identifying regions in which differentiability with respect to the choice variables is ensured is then straightforward.

Table 2 in appendix D displays the probability that demand is binding ($\Pr(\Xi_0)$ and $\Pr(\Xi_1)$) and, given that it is binding, the expected demand for either technology type ($E[D_j|\Xi_0]$ and $E[D_j|\Xi_1]$).

¹⁸In general, it is even difficult to derive whether the marginal distribution of D_j conditional on Ξ_1 behaves nicely, namely, whether it has an expectation. Furthermore, although we can give an explicit formula for the probability of Ξ_1 , it is in general not differentiable in i and p even if distributions are continuous: For two continuous random variables D_1 and D_2 with joint density h on support $[\underline{D}(i, p), \overline{D}(i, p)]^2$ we have

$$\Pr[x + y \leq k] = \int_{\underline{D}}^x \int_{\underline{D}}^y h(D_1, D_2) dD_1 dD_2$$

with $x = \min(k - \underline{D}, \overline{D})$ and $y = \max(\underline{D}, \min(k - D_2, \overline{D}))$.

Plugging the results from table 2 into equation (7) leads to

$$\begin{aligned}
E\tilde{\Pi}_y^*(f=0) &= \begin{cases} pk & k \leq 2\underline{D} \\ p [2\delta_0 \underline{D} + (1 - \delta_0) k] & \text{if } 2\underline{D} < k \leq 2\overline{D} \\ p2\mu & 2\overline{D} < k \end{cases} , \\
E\tilde{\Pi}_y^*(f=1) &= \begin{cases} pk & k \leq 2\underline{D} \\ p [2\delta_{00} \underline{D} + (1 - \delta_{00}) k] & \text{if } 2\underline{D} < k \leq \underline{D} + \overline{D} \\ p [2(\delta_{00} \underline{D} + \delta_{10} (\underline{D} + \overline{D})) + \delta_{11} k] & \underline{D} + \overline{D} < k \leq 2\overline{D} \\ p2\mu & 2\overline{D} < k \end{cases} , \quad (8)
\end{aligned}$$

where $\delta_{00} = \Pr(D_1, D_2 = \underline{D})$, $\delta_{11} = \Pr(D_1, D_2 = \overline{D})$, $\delta_{10} = \Pr(D_1 = \overline{D}, D_2 = \underline{D})$. Although the function $E\tilde{\Pi}_y^*$ is not differentiable over its entire range, it is continuous as can be seen by inserting the case boundary conditions into (8).

Note that as long as capacity and product improvements are costly, profit maximization implies that the optimal value of k lies within $[2\underline{D}, 2\overline{D}]$, the support of ΣD_j and $2D_j$. If $k < 2\underline{D}$, then the firm could decrease its product improvement efforts or increase the price of the products without affecting production, because capacity is a binding constraint on production with probability one. Similarly, $2\overline{D} < k$ cannot be optimal, as the firm could save capacity costs without decreasing revenues. For this reason we will focus on the intermediate cases for further discussion, although all statements that will appear in the following chapter do apply — at least in a qualitative sense — to the entire range.¹⁹

2.3 Analysis of the Extended Model

In this paragraph we analyze the linkages of the choice variables in the above 2-period model where demand is stochastic. The key question is how the presence of technology dependent constraints on production in the second period alters the first-period incentives to invest in additional capacity and product innovation. From section 2.1 we maintain the assumption of $(-I)$ being supermodular in (i, f) . In contrast to the deterministic model, supermodularity of demand now applies to its expectation, $\partial^2 \mu / \partial i \partial p \geq 0$.

¹⁹The case $k = 2\underline{D}$ should, of course, not be excluded. For the sake of calculating $E\tilde{\Pi}_y^*$ it can be incorporated into the case $2\underline{D} < k \leq \underline{D} + \overline{D}$ because $E\tilde{\Pi}_y^*$ is continuous.

To derive whether the decision variables i , f , k , and p are complements we investigate their interactions in each addend of the profit function (4) and then use the summation property of supermodular functions. To those addends that reflect the fixed cost the same assumptions apply as in the deterministic model. Hence, what remains to show is whether i , f , k , and p are complements with respect to operational profits. Because in this paper the set of feasible actions is a finite product of chains, it suffices to prove pairwise complementarity in order to establish supermodularity: the profit function would be supermodular if and only if it is supermodular in any subset of decision variables.

For a comprehensive exposition of the modeling assumptions the analysis starts by discussing the first order effects of the endogenous variables and of uncertainty on operational profits. This procedure aims at emphasizing the modeling assumptions and at providing the ground for understanding the main results.

Denoting $\Delta_f E\tilde{\Pi}_y^* = E\tilde{\Pi}_y^*(f = 1) - E\tilde{\Pi}_y^*(f = 0)$ and using that $\delta_{11} = \delta_{00} + 1 - 2\delta_0$ and $\delta_{10} = \delta_{01} = \delta_0 - \delta_{00}$ the expected gain from flexible versus dedicated machines in operational profits is the difference

$$\Delta_f E\tilde{\Pi}_y^* = \begin{cases} p(\delta_0 - \delta_{00})(k - 2\underline{D}) & \text{if } 2\underline{D} < k \leq \underline{D} + \overline{D} \\ -p(\delta_0 - \delta_{00})(k - 2\overline{D}) & \text{if } \underline{D} + \overline{D} < k \leq 2\overline{D} \\ 0 & \text{otherwise} \end{cases} . \quad (9)$$

Retrieving that the joint probability δ_{00} cannot be greater than the marginal probability δ_0 and taking the case boundaries of equation (9) into account, it can easily be seen that $\Delta_f E\tilde{\Pi}_y^* \geq 0$. This leads to our first lemma:

Lemma 1 *Using flexible instead of dedicated technology cannot lead to lower profits in the production period.*

Proof. In text. ■

The superiority of flexible technology results from modeling flexibility as a hedge against risky demand. We would also expect that the expected gain from flexibility increases as the uncertainty about demand (i.e., the standard deviation σ) rises. Furthermore, the more positively correlated demands of the two products are, the scarcer

should be situations, in which flexible firms can shift capacity between the products. From lemma 2 both conjectures can be seen to hold in the current context.

Lemma 2 *The gain from flexibility is nondecreasing in demand risk and nonincreasing in demand correlation.*

Proof. See appendix B. ■

Lemma 3 summarizes the results on the first-order effects of i , k , and p :

Lemma 3 *Expected operational profits ($E\tilde{\Pi}_y^*$) are nondecreasing in product innovation and capacity and increasing or decreasing or non-monotone in price.*

Proof. See appendix B. ■

Intuitively, product innovation or enhanced capacity shift expected production upwards. This is true irrespective of the relative size of demand compared to capacity. In a qualitative sense, a price increase acts like a downward shift of innovative activities: it reduces expected demand. But higher prices also boost operational profits from every item that is finally sold. Without further assumptions on the magnitude of this demand effect or on the size of σ and ρ , the price effect is not determined in sign.

To verify whether $E\tilde{\Pi}_y^*$ exhibits complementarity in f , i , k , and p we will now discuss how each of these variables alters the operational profit of increasing the remaining choice variables.

Lemma 4 characterizes the bilateral interdependence of i , k , and p :

Lemma 4 *Product innovation and capacity as well as price and product innovation are complements with regard to $E\tilde{\Pi}_y^*$. The effect of a price increase on the expected operational gain from additional capacity is undetermined.*

Proof. See appendix B. ■

Complementarity between i and k stems from their marginal effects being dependent on the excess of capacity over expected demand, $(k - 2\mu)$. The intuition for this is that more slack capacity better accommodates additional demand and, hence, the increase

in expected production due to innovation is greater in magnitude for high values of $(k - 2\mu)$. Accordingly, the operational gain from additional capacity is decreasing in $(k - 2\mu)$, because capacity is then less often needed to comply with demand.

Product innovation and price are complements in $E\tilde{\Pi}_y^*$, as an increase in price always boosts the demand gain from product improvement (μ is supermodular in i and p) and also increases (at the case boundaries) the probability that the additional demand is within the firm's production capability and, eventually, the net profit from selling an item.

The undetermined connection between capacity and price can be interpreted as follows: a higher price lowers demand thereby decreasing the probability that additional capacity will be used in production once the case boundaries are passed. However, there is also a potential for p interacting positively with k , because, whenever additional capacity is used, it pays more when prices are high. Without further assumptions the net effect of price on marginal changes of capacity is ambiguous.

We argued earlier that, as long as product demands are not perfectly positively correlated, there is a potential gain from the ability to shift capacity among the products, i.e., $\Delta_f E\tilde{\Pi}_y^*$ cannot be negative. Lemma 5 states how the expected operational gain from flexibility is influenced by product innovation.

Lemma 5 *Product innovation and flexibility are substitutes (complements) with respect to expected operational profits for low (high) values of slack capacity $(k - 2\mu)$.*

Proof. See appendix B. ■

The intuition for the result that flexibility and product innovation are not always complements is best seen by comparing the marginal effect of innovation across technology schemes. Remember that the marginal gain in expected operational profits from product innovation equals its expected demand shift times the probability that this additional demand can actually be produced (that is, demand does not exceed capacity) times the per unit profit (p). Thus, the difference between dedicated and flexible technology with regard to gains from innovation arises only because the probability that

demand is a binding constraint on production, $\Pr(\Xi_f)$, depends on technology. $\Pr(\Xi_f)$ is greater for dedicated technology when capacity is relatively small ($2\underline{D} < k \leq \underline{D} + \overline{D}$) and greater for flexible technology when capacity is large ($\underline{D} + \overline{D} < k \leq 2\overline{D}$).²⁰ This is due to the virtual capacity shifting among the two products which is possible with flexible technology: the relevant probability function is then that of the average demand and not that of demand for the individual product. Naturally, averaging leads to a probability function which gives less weight to extreme values than the marginal probability function. Thus, at low values of the capacity constraint the probability that demand is a binding constraint (i.e., the probability to the left of $\frac{1}{2}k$) is smaller in the distribution of the average compared to that of the individual demand. With a large capacity on the other hand, the probability that demand is constraining production is higher when the average is relevant, since the average is less likely to be even larger than capacity.

Note from the discussion above that the result from lemma 5 is not due to the specific distributional assumption we made. Instead the argument is founded on a general property of random variables, namely that their marginal probability (or density) function has fatter tails than the probability (or density) function of the average of equally distributed random variables. Lemma 6 formalizes this point.

Lemma 6 *For any number of products n , whose demand, conditional on price and innovation, is a random draw from the same discrete distribution, we have that, with regard to $E\tilde{\Pi}_y^*$, flexibility and product innovation are substitutes (complements) at sufficiently low (high) values of $(\frac{1}{n}k - \mu)$.*

Proof. See appendix B. ■

The following lemma characterizes the effect that flexibility has on gains from capacity or price shifts.

²⁰This can be seen from table 2: $\Pr(\Xi_1) - \Pr(\Xi_0)$ is equal to $\delta_{00} - \delta_0$, when $2\underline{D} < k \leq \underline{D} + \overline{D}$; and to $1 - \delta_{11} - \delta_0$ when $\underline{D} + \overline{D} < k \leq 2\overline{D}$. By definition the first of these differences cannot exceed zero. To evaluate the latter note that $1 - \delta_{11} \geq 1 - (1 - \delta_0)$ and thus $1 - \delta_{11} - \delta_0 \geq 1 - (1 - \delta_0) - \delta_0 = 0$.

Lemma 7 *Regarding $E\tilde{\Pi}_y^*$ capacity and flexibility are complements (substitutes) for low (high) values of slack capacity. Price and flexibility are complements for low values of $(k - 2\mu)$. Otherwise their interrelation is undetermined.*

Proof. See appendix B. ■

The linkage of capacity and flexibility merely reflects the relationship between flexibility and innovation, since additional capacity is only used when capacity is the binding constraint. This occurs with a probability equal to one minus the probability that demand is constraining production. For this reason, whenever flexibility increases the returns (in terms of $E\tilde{\Pi}_y^*$) from higher innovation, it must decrease the gains from extra capacity and vice versa. Analogously to lemma 6 there is a straightforward generalization of lemma 7 to arbitrary discrete distributions and to any number of products.

As a higher price decreases expected demand, the price effect on the flexibility gain is opposite to that of innovation. On the other hand, the per unit value of flexible technology is strictly increasing in price. The overall effect leads to f and p being complements with regard to $E\tilde{\Pi}_y^*$, when capacity is small compared to μ .²¹

Table 1 informally summarizes the results concerning the interdependence of the choice variables in the function $E\tilde{\Pi}_y^*$. The signs "+" and "-" denote respectively a nonnegative and a nonpositive relationship of two decision variables with respect to $E\tilde{\Pi}_y^*$, while the question mark stands for ambiguous interactions. In cases where one sign does not apply to the whole range of the support the upper value is valid for $\underline{D} + \overline{D} \geq k$ and the lower for $\underline{D} + \overline{D} \leq k$. It is evident from the table that $E\tilde{\Pi}_y^*$ is not supermodular in (i, f, k, p) , because irrespective of assumptions about the undetermined bilateral linkages and about the optimal values of k , \underline{D} , and \overline{D} , the interrelations have no unique direction.

²¹Note that the discussion about the interaction of i , k , and p with f reveals the advantage of assuming differentiability of expected operational profits in i , p and k : Allowing for discrete changes in these variables would lead to the possibility of switching between the cases of equation (9) and hence, further complicate the discussion. In a qualitative sense, however, the results would remain unchanged.

\backslash	i	p	k	f
i	\backslash	$+$	$+$	$-$ $+$
p		\backslash	$?$	$+$ $?$
k			\backslash	$+$ $-$

Table 1: Bilateral interactions in $E\tilde{\Pi}_y^*$.

In order to evaluate the relation between the different aspects of the firms' choice in the overall profit function (4), note that, given linear capacity costs as we have assumed so far, there is no interaction of f and k in the fixed costs which could outweigh their potential negative linkage in the expected operational profits, $E\tilde{\Pi}_y^*$. Taking the fixed costs into account will also not help to overcome those ambiguities from table 1 that involve price. A potential negative interdependence between innovation and flexibility, however, might be overcompensated by fixed cost savings of their joint adoption.

Proposition 2 summarizes the results from the discussion of the stochastic model.

Proposition 2 *Consider the function of expected profits $E\Pi$ in (4) and the second period optimization problem (5) with $(i, f, k, p)^T \in R^+ \times \{0, 1\} \times R^+ \times R^+$. Suppose that $D_j(i, p)$ for $j = 1, 2$ is differentiable and supermodular in (i, p) and increasing in i ; $-I(i, f, \omega)$ is supermodular in (i, f) . Then the following holds with respect to the function $E\Pi$:*

- (i) i and p are complements.
- (ii) i and k are complements.
- (iii) f and k are neither complements nor substitutes.
- (iv) i and f , f and p as well as k and p might be complements or substitutes or neither.
- (v) i and f are complements if their complementarity with respect to $-I(i, f, \omega)$ is sufficiently strong.

Proof. The proof follows directly from lemmas (3)-(5), lemma (7), and the summation property. ■

The analysis in this paragraph illustrates that introducing demand uncertainty into the model does have a substantial impact on complementarity, even though uncertainty was set up in such a way that the conditions for optimality in the extended model converge to those of the basic model in section 2.1 for sufficiently small uncertainty.²² Thus, the limiting case of the stochastic model indeed leads to a supermodular overall profit function as proposed by existing literature. However, the slightest demand uncertainty destroys the system of complementary decision variables.²³

This means for example that, even though price and innovation interact positively, their values might move to opposite directions following monotonic parameter shifts. To see this, consider an example where for the optimal decision of firm 1 we have $\underline{D} + \overline{D} > k$ and $f = 1$. Another firm faces lower product improvement costs and might therefore opt to engage in innovation more than firm 1. This will in turn make higher prices more profitable for the second firm than it will for firm 1, but additionally shrinks the expected gain from flexible technology. If, as a result, $f = 0$, a lower price compared to firm 1 might be optimal.

For an economic interpretation of the relationship between innovation and flexibility imagine extra capacity is sufficiently cheap but not without cost (i.e. γ is small but greater than zero), such that in optimum a firm installs a high capacity compared to expected demand. Such a firm will rarely face situations where demand cannot be met due to capacity restrictions. Then a change in exogenous variables that promotes the adoption of flexible technology will also unambiguously shift the optimal level of prod-

²²To derive this recall that any optimally chosen capacity, price and innovation effort must ensure $k \in [2\underline{D}, 2\overline{D}]$. If the risk approaches zero ($\overline{D} - \underline{D} \rightarrow 0$) we must have $k \rightarrow 2\mu$ for optimality. Or, in words, maximizing behavior under certainty allows for slack neither in capacity nor in demand.

²³Although the decision variables of our model fail to be complements, they could still meet the conditions required by the Monotonicity Theorem based on quasisupermodularity. Quasisupermodularity is more demanding to check (see Milgrom and Shannon (1994) for details). However, with differentiability we can investigate whether, as a direct consequence of the monotonicity property, all first order conditions are nondecreasing in all other decision variables. This is done by plugging in as many FOCs into a given cross partial of the profit function as necessary for sign determination. In our model this procedure does not lead to any new information.

uct innovation upwards, because at a sufficiently large k relative to μ the probability that additionally generated demand can be complied with is larger for flexible than for dedicated technology. On the other hand, high values of γ might induce the capacity constraint to be frequently binding and therefore lead to the case where a negative interdependence between product innovation and flexible technology at the production stage outweighs their fixed costs complementarity. Note however: if γ converges to zero, the incentive to invest into the more expensive flexible technology vanishes, as the firm can then afford to buy a lot of dedicated machines — although it will almost never fully employ them — and therefore cannot gain from the capacity shifting as flexible technology would allow for.

3 Empirical Evidence

3.1 Methodology

The literature on testing for complementarity follows two main directions. First, a theoretically straightforward procedure is to estimate the decision maker's objective function.²⁴ If the decision variables are indeed complements, then their interaction terms in the objective function should be positive and significant. Beyond that, the coefficients' size measures the strength of the complementarity among the endogenous variables. However, this approach assumes knowledge about what decision makers maximize and which constraints limit their choice. Plant managers, for example, might be maximizing firms profits, plant profits, a mixture of both or neither of the two. Even taking their behavior for granted, it might turn out to be very difficult or impossible to get data on the objective.

Second, an alternative method applied in the literature²⁵ builds on implications of Topkis' (1978) Monotonicity Theorem: Given a system of complements and a vector of complementary exogenous variables, monotone shifts in the predetermined vector imply

²⁴Parametric examples include Bresnahan/Brynjolfsson/Hitt (2001), Ichniowski/Shaw/Prennushi (1997), Leiponen (2000), Parthasarthy/Sethi (1993) and Patibandla/Chandra (1998). Beresteanu (2000) introduces nonparametric techniques for the estimation of supermodular objective functions.

²⁵Arora/Gambardella (1990) and Miravete/Pernias (2000) are examples for this approach.

monotone reactions of the endogenous variables. Empirically, monotone shifts imply correlation, or, more generally, association among variables (Holmstrom and Milgrom 1994).²⁶ Thus, complementary practices are expected to be associated (unconditional association). Of course, in real life problems, exogenous variables might not vary monotonically and often relevant exogenous variables are not complementary to all endogenous variables. In these cases, the test for complementary dependence applies to the residuals of regressions in which potentially troublesome variables have been controlled for (conditional association).

The association approach comes along with the obvious advantage that no information is necessary about the objective and what functional form approximates it well. The cost for the less demanding data requirements is that the estimation will not give indications of the decision variables' direct effect on the objective. Further, a strong positive association between decision variables may not be interpreted as particularly strong complementarity, since part of it may be due to association in the driving exogenous variables that were not controlled for. We might even find positive association between the decision variables when they are in fact not complementary. However, Athey and Stern (1998) show that the tendency to overestimate complementarity, if unobserved exogenous variables are associated, is also a problem when the objective function is estimated.

One attempt to deal with unobserved heterogeneity is proposed by Miravete and Pernias (2000) who estimate a system of decision variables with random effects using panel data. They consider the association between the purely random components of the reduced-form residuals (error term minus the idiosyncratic component) as the relevant indicator of complementarity.²⁷ Athey and Stern (1998) propose a method to

²⁶ Association is preserved by monotone transformations of the random variables whereas correlation is not.

²⁷ The authors point out a possibly important limitation of their approach: if decisions are state dependent (e.g. a firm that uses a given technology today is likely to continue to do so in the near future) and this cannot be explicitly modeled because the panel is too short, the random firm effect in the adoption equation will contain some of the state dependence. Hence, excluding the part of random variation that is idiosyncratic to the firm causes a tendency to overestimate unobserved heterogeneity and thereby biasing the estimated complementarity.

overcome the unobserved-heterogeneity problem in the context of cross-sectional data. It relies on the estimation of the objective function and requires extremely rich data.

In this paper we apply the association approach on the basis of reduced-form adoption equations for flexible technology and product innovation. As suggested by Miravete and Pernias (2000), we estimate both equations as a system in order to disentangle association between the unobserved individual effects from pure error association.

3.2 Data

For the empirical investigation this paper analyzes a balanced panel of 593 German mechanical engineering plants for 1992 and 1994.²⁸ The data summarized in tables 3 and 4 in appendix D includes information on both the formal and the informal organization of the plant.

Product innovation is measured as a binary variable INNOVATION, which equals one whenever the plant introduced new products and zero otherwise. The variable FLEXIBILITY equals zero if the plant adopted conventional, numerically controlled (NC) or computer-numerically controlled (CNC) machines but no more integrated technologies and it is equal to one if machining centers, flexible manufacturing cells (FMC) or flexible machine systems (FMS) were installed.²⁹ The difference between the two categories is an ordering with respect to the flexibility of a single machine as well as with respect to the flexibility of the entire shop floor.

Table 5 in appendix D shows that in 1992 roughly 47% of the firms adopted the more flexible technologies, whereas in 1994 this figure increased to 51%. On the other hand, the share of firms reported to engage in product innovation decreased from 78%

²⁸We would like to thank Ulrich Widmaier, University of Bochum, for his permission to use this data, which is a subset of the original panel NIFA (Neue Informationstechnologien und Flexible Arbeitssysteme). It is available for the period 1990-1997 but various items of interest to this study were not included in the questionnaires of all waves.

²⁹NCs and CNCs are single-task machines with decentralized numerical control, i.e. there is no coordination between the machines. Machining centers are also stand-alone devices but they perform a variety of tasks. Very often they include automatic tool changing. FMC/S denote systems of a few (FMC) or many (FMS) machines that are connected by automatic material handling and controlled by a single, central device. See Gurisatti et al. (1997) for the definitions.

to 66% during the same period. While the apparent raise in flexibility might reflect a general trend towards high capability systems, the time pattern of innovation is likely to be the result of the recession following the reunification boom in Germany shortly after 1990. Firms, which had adopted flexible technology in 1992, were considerably more often flexible than others in 1994, too. The same, though less accentuated, holds for the tendency to innovate in 1994 conditional on innovation in 1992. The apparent inertia in both practices indicates that either sunk costs are involved in the adoption of flexible technology and in the innovative process or time-invariant characteristics of firms influence their decisions.

As the panel covers only two years, time effects are captured by the dummy YEAR94 equal to one in 1994 and zero otherwise. The log of the total number of employees working in a plant (LOGSIZE)³⁰ is expected to have an effect on technology choice and innovation due to many reasons, like economies of scale, size dependent coordination costs, and so forth.

The dummy FIRMLEVEL equals one if technological or organizational issues were reported to be on the firm-level agenda. Because the firm-level influence might not always be directly perceived by plant managers but still be significant, we also include the variable MULTIPLANT, which equals one if the plant belongs to a multi-plant firm.³¹

A high share of products, which can be either modified from a basic design or completely specified by customers (CUSTOMIZE), supposably increases gains from flexibility, whereas there is no such clear-cut intuition for its effect on product innovation. The variable HIERARCHY proxies communication costs, which might hinder all sorts of changes and especially product innovation. It takes the value one if managers reported the number of hierarchical levels on their plants to be average or more. Information on hierarchy is only available for 1992. Since this organizational characteristic is typically a long-run choice, we also control for HIERARCHY in the 1994 regressions.

³⁰We use the logarithm because the original size variable is extremely skewed: Most firms have less than 100 employees and only very few reach very large numbers such as several thousands.

³¹The correlation between FIRMLEVEL and MULTIPLANT is surprisingly low (0.32).

Worker’s skills, which typically cannot be freely determined in the short run, might play a crucial role in the decision whether new products are introduced into the market and on the complexity of machines a firm wants to install. We capture this effect by the share of skilled workers, foremen, and engineers in production (EDUCATION).

The theoretical part of this paper argued that the gain from flexibility tends to increase with the level of demand uncertainty that the firm faces. The bivariate variable RISK is a proxy for uncertainty indicating whether a crucial part of revenues is assured by long term contracts or not. In the former case RISK is equal to zero (one otherwise).

3.3 Estimation and Results

This paper assesses complementarity between product innovation and flexible technology based on the association between these variables. Starting with observations about the joint occurrence of the original variables, we investigate to what extent the dependence is driven by the plants’ observed and unobserved characteristics.

Unconditional association between FLEXIBILITY and INNOVATION is measured by Kendall’s tau (τ) as defined in appendix C, which, unlike the standard Pearson correlation coefficient, captures nonlinear interdependence. Ignoring any effect of exogenous variables, we find a small positive but significant dependence ($\tau = 0.144$). Table 6 shows that this number is effectively equivalent for both years. As discussed above, interpreting the positive unconditional association as evidence for complementarity between flexible machines and product innovation requires very restrictive assumptions on the exogenous variables. To avoid such restraints we estimate the reduced form adoption equations for FLEXIBILITY and INNOVATION:

$$\begin{aligned} y_{git}^* &= x_{it}\beta_g + e_{git} \\ \text{with } e_{git} &= u_{gi} + \varepsilon_{git} \\ \text{and } u_{gi} &\sim N(0, \sigma_{u_g}^2), \quad \varepsilon_{git} \sim N(0, \sigma_{\varepsilon_g}^2), \end{aligned}$$

where y_{git}^* denotes the latent endogenous variable $g = 1, 2$ of individual $i = 1, \dots, 593$ at time $t = 1, 2$, x_{it} is a vector of exogenous variables used to control for observed hetero-

geneity in both equations, β_g is a parameter vector, and e_{git} is a normally distributed random shock. In order to take unobserved heterogeneity between the plants into account, the equation error is additively separated into a time independent individual component (u_{gi}) and a pure random term (ε_{git}). We assume that the variance of the disturbances has the simple form $\sigma_{e_g}^2 = \sigma_{u_g}^2 + \sigma_{\varepsilon_g}^2$, i.e., u_{gi} and ε_{git} are uncorrelated. Since the tendency to innovate or to be flexible, y_{git}^* , is not observed, a probit model of the actual choices subject to the usual variance restriction $\sigma_{e_g}^2 = 1$ is estimated.³² It is then possible to test for complementarity based on the empirical association between ε_{1it} and ε_{2it} . Yet, given that only the distributional parameters σ_{gu}^2 and not the individual effects itself are estimated, the dependence between e_{1it} and e_{2it} cannot be decomposed into the correlation stemming from the individual effects and the pure error correlation. As a consequence, the inference about complementarity would be biased by unobserved heterogeneity. Everything else being equal, the presence of a strictly positively affiliated³³ vector of unobserved characteristics tends to overestimate complementarity from residual dependence. If, on the other hand, unobserved characteristics are strictly negatively affiliated, the residuals of effectively complementary decision variables might actually be negatively associated. Athey and Stern (1998) give examples for such misbehavior and demonstrate that even if unobservable factors are independent, omission reduces the testing power.

Correlation of the pure errors can be separated from linkages of the individual effects when both adoption equations are estimated as a system. Because our panel is too short, we abstract from time series effects in the pure error terms. Furthermore, we let all individual effects be independent from all pure errors ($cov(u_{git}, \varepsilon_{kit}) = 0$) and assume that all plants are independent from each other. Then, the nonzero system

³²The equally popular logit model is less suited to multivariate settings and for the incorporation of random effects due to the less flexible correlation pattern of the multivariate logistic distribution.

³³Affiliation is defined as association conditional on any feasible choice of endogenous variables, assuming the latter are sublattices. See Milgrom and Weber (1982) for details.

covariances are:

$$cov(e_{1it}, e_{2it}) = cov(u_{1i}, u_{2i}) + cov(\varepsilon_{1it}, \varepsilon_{2it}), \quad (10)$$

$$cov(e_{1it}, e_{2is}) = cov(u_{1i}, u_{2i}), \quad \forall s \neq t. \quad (11)$$

Equations (10) and (11) allow us to decompose the contemporaneous dependence between FLEXIBILITY and INNOVATION in (10) according to its sources: the covariance between the firm effects, $cov(u_{1i}, u_{2i})$, and the pure error covariance, $cov(\varepsilon_{1it}, \varepsilon_{2it})$. Because we exclude time series effects, the noncontemporary covariance between the unexplained parts of FLEXIBILITY and INNOVATION, $cov(e_{1it}, e_{2is})$, in equation (11) stems entirely from the covariation of the individual effects, $cov(u_{1i}, u_{2i})$.

Table 7 presents the single equation and the system estimates for the random-effects probit model. While both procedures are consistent, the latter is more efficient. The results differ only slightly in significance between the two specifications.

The year 1994 (YEAR94) has a significant impact on the decision to innovate and also on the adoption of flexible technology. As discussed above, the sign of this coefficient may be interpreted as a business cycle effect on innovation and as a positive time trend for the adoption of flexible technology. Plant size (LOGSIZE) is significantly positively related to both product innovation and flexibility. The single equation results suggest that being part of a company with multiple plants (MULTIPLANT=1) increases the tendency to innovate and to be flexible, whereas no such effect is found in the system estimation. Decision making at the firm level instead of the plant level (FIRMLEVEL=1) is not found to have any significant impact.

Plants offering to customize a large part of their product line (CUSTOMIZE=1) are less likely to introduce new products into the market. Presumably, the term "new" will be interpreted in different ways by the firms: With perfectly standardized products small changes in design might be interpreted as a new product. A customizing supplier, on the other hand, will probably define product innovation by abstracting from minor changes in design, if these are within the usual variety and even if a given combination of features had never been created before. Surprisingly, customization has no significant

effect on flexibility.

Risky business perspectives (RISK=1) and highly skilled employees (EDUCATION=1) seem to favor product innovation but these results were found only in one of the two specifications. Very hierarchical structures (HIERARCHY=1) prove to be obstacles to innovation.

Conditional on observed characteristics, both endogenous variables are strongly related over time as indicated by the size of $cov(e_{git}, e_{gis})$. This suggests that unobserved heterogeneity is indeed a serious issue in this study. One potential source for the high magnitude of correlation is, of course, the inertia to switch technology and innovation modes, which we could not estimate separately due to the two-period limitation of our data. If this inertia plays the role that intuition suggests, then the extent of individual heterogeneity in our model may be substantially overestimated.

To assess how controlling for observed heterogeneity changed the empirical interdependence between product innovation and flexible technology, we compute Kendall's tau based on the generalized residuals (as defined in appendix C) from the single equation estimation. Compared to the unconditional dependence, the association decreased substantially to only 0.043 (see table 6) implying that part of the joint occurrence of flexibility and innovation is driven by the observed exogenous variables.

From the system of INNOVATION and FLEXIBILITY the total error correlation is estimated as 0.1052 (see table 8).³⁴ The estimated covariance of the individual effects is equal to 0.0395, suggesting that around 38% of the total error covariance can be attributed to unobserved heterogeneity between the plants in our sample. The remaining 62% are attributed to pure error interrelation. However, the estimate of $cov(u_{1i}, u_{2i})$ does not significantly differ from zero. Hence, the decomposition of the total error covariance is not significant either.

As an alternative test of the variance composition we reestimate the model under the restriction that the total error covariance is only due to covariation of the unobserved

³⁴Because of the variance standardization $\sigma_{e_g}^2 = 1$, $\widehat{cov}(e_{1it}, e_{2it}) = \widehat{corr}(e_{1it}, e_{2it})$. This correlation is not directly comparable to Kendall's tau calculated from generalized residuals.

individual effects, $cov(e_{1it}, e_{2it}) = cov(u_{1i}, u_{2i})$. Based on a likelihood-ratio test this restriction is not rejected in favor of the more flexible model. Hence, in our sample the effect of unobservable individual approaches towards innovation and flexibility on the apparent association of these variables could neither be clearly isolated nor shown to be different from zero.

4 Conclusion

This paper reconsiders the firm's decision on technology and innovative activities. An optimization model with stochastic demand is introduced, which takes into account gains from flexibility due to a wider set of future production possibilities. Because product innovation affects demand while the degree of flexibility sets constraints on production, the interaction between both variables is shown to be more than just a fixed cost issue. Our results point out that the gain from incremental innovation might be lowered by flexibility even though the fixed costs of introducing a new product to the market are decreased by flexible machines.

Since the theoretical predictions are ambiguous, we empirically investigate whether complementarity in the fixed costs is strong enough to compensate potentially adverse effects in operational profits using data from the German mechanical engineering sector. We find that firms which adopt a highly flexible production technology tend to have a higher rate of product innovation and vice versa. This association is also observed after controlling for exogenous variation which might overlap with the direct relation between flexibility and innovation. Unobserved heterogeneity is estimated to have inflated but did not entirely cause this association. The latter finding was, however, not statistically precise enough for a clear inference. In sum, the empirical evidence provided in this paper supports the view that flexible technology and innovation are complements, although the general methodological constraints for the measurement of complementarity suggest that this should not be interpreted as an ultimate proof.

The theoretical finding does, however, raise general concerns about applications of

the theory of technological complementarity, which derive their results exclusively from fixed cost considerations ignoring uncertainty and optimization over time. Their findings are robust to the introduction of randomness only if uncertainty enters the model in a purely additive way, such that indeed the summation property of supermodular functions holds. Additive uncertainty is, as this paper argues, not always realistic, especially when decision makers adapt to the realization of stochastic variables. Investigating the implications of information revelation over time in conjunction with the possibility that decision makers adapt to it, is not only important for assessing the interdependence of product innovation and flexible technology. It might, in general, lead to new insights about whether the complementarity and monotonicity predictions based on fixed costs considerations really hold for overall profits.

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A Complementarity and Supermodular Functions

This appendix provides the definition of a supermodular function and points out some of its properties, which are used in the main part of the paper. For details see Topkis (1998).

Definition 1 *Suppose that $f(x)$ is a real-valued function on a lattice X . If $f(x') + f(x'') \leq f(x' \vee x'') + f(x' \wedge x'')$ for all x' and x'' in X , then $f(x)$ is supermodular in x on X . Supermodularity is strict if the inequality holds strictly. For the definition of (strict) submodularity reverse the inequality symbol.*

If, as in this paper, X is a sublattice of some n -dimensional product of chains, then supermodularity is equivalent to complementarity. Supermodularity on any finite product of chains is equivalent to supermodularity on the product of each pair of chains and thus can be checked pairwise in these cases.

Supermodularity is preserved by summation, multiplication with a factor and partial maximization. The latter property ensures that qualitative results gained from the inspection of a subsystem of complementary decision variables will still hold once the whole system is considered. As supermodularity is a cardinal property, it is not preserved by arbitrary increasing transformations.

Exogenous variables are parameters of the decision making process and may be included in the vector x of the definition above. However, to address effects of monotone changes in exogenous variables it is sufficient to assume that they are complementary to the endogenous variables but not necessarily complements among themselves. This property is formalized by the notion of increasing differences:

Definition 2 *Let X and Ω be partially ordered sets and $f(x, \omega)$ be a real-valued function on a subset S of $X \times \Omega$. For $\omega \in \Omega$. Let S_ω denote the section of S at ω . If $f(x, \omega'') - f(x, \omega')$ is (strictly) increasing in x on $S_{\omega''} \cap S_{\omega'}$ for all $\omega' \prec \omega''$ in Ω , then $f(x, \omega)$ has (strictly) increasing differences in (x, ω) on S . Analogously, if the differ-*

ence $f(x, \omega'') - f(x, \omega')$ is (strictly) decreasing, then $f(x, \omega)$ has (strictly) decreasing differences.

Increasing differences in (x, ω) is equivalent to stating that all parameters are complements to all decision variables. Twice differentiable functions exhibit increasing differences, if and only if all cross-partial derivatives of the objective with respect to any combination of decision variables and parameters are nonnegative.

Supermodularity and increasing differences in conjunction with a feasible set, which is increasing in the parameter are sufficient conditions for monotone comparative statics:

Theorem 1 (Topkis 1978) *If X is a lattice, Ω is a partially ordered set, the section S_ω is a subset of X for each ω in Ω , S_ω is increasing in ω on Ω , the function $f(x, \omega)$ is supermodular in x on X for each ω in Ω , and $f(x, \omega)$ has increasing differences in (x, ω) on $X \times \Omega$, then $\arg \max_{x \in S_\omega} f(x, \omega)$ is increasing in ω on $\{\omega : \omega \in \Omega, \arg \max_{x \in S_\omega} f(x, \omega) \text{ is nonempty}\}$.*

Milgrom and Shannon (1994) generalized theorem 1 by showing that it also holds for the ordinal concepts of quasisupermodularity and single crossing (ordinal complementarity). Thus, the conditions of the theorem hold whenever all decision variables are ordinal complements and all components of the parameter vector ω are ordinal complements to the vector x . The components of ω need not be ordinal complements.

B Proofs

This appendix proofs the propositions and lemmas stated in the main text.

Proof of proposition 1. $-F(f, \omega)$ and $-\gamma k$ are trivially supermodular in f and k respectively. As supermodularity is preserved under summation, we have that $-I(i, f, \omega) - \gamma k - F(f, \omega)$ is supermodular in (i, f, k) .

The cross partial derivative of $[p D_j(i, p)]$ with respect to i and p exists and is positive, because differentiability and supermodularity of $D_j(i, p)$ imply $\partial^2 D_j / \partial i \partial p \geq 0$ and $\partial D_j / \partial i \geq 0$. Thus $[p D_j(i, p)]$ and $2[p D_j(i, p)]$ are supermodular in (i, p) . Applying the summation property again gives the first statement of the proposition.

To proof part (ii) of the proposition, note that according to the assumptions $-I(i, f, \omega)$ has increasing differences in $((i, f), \omega)$ and $-F(f, \omega)$ has increasing differences in (f, ω) . Because k and p have no effect on I and i , k , and p do not influence F , both $-I$ and $-F$ have increasing differences in $((i, f, k, p), \omega)$. All remaining addends of the profit function have nondecreasing differences in $((i, f, k, p), \omega)$ since none of them depend on ω . As increasing differences are preserved by summation, Π exhibits increasing differences in $((i, f, k, p), \omega)$. Together with the first part of the proposition and the fact that the set of feasible actions does not depend on ω the conditions of the Monotonicity Theorem (see appendix A) are met and the result is established. ■

Proof of lemma 2. Solving the definitions of μ and σ for the upper and lower demand realization and using $\underline{D} \leq \overline{D}$ yields

$$\underline{D} = \mu - \sigma \sqrt{\frac{1 - \delta_0}{\delta_0}} \quad \text{and} \quad \overline{D} = \mu + \sigma \sqrt{\frac{\delta_0}{1 - \delta_0}}. \quad (12)$$

Inserting (12) into (9) it is straightforward to see that $\Delta_f E \tilde{\Pi}_y^*$ is increasing in σ .

For a given marginal probability δ_0 the joint probability δ_{00} is increasing in ρ . Hence, as (9) is decreasing in δ_{00} , it is also decreasing in ρ .

Because neither σ nor ρ affects the fixed costs, their influence on the profitability of flexible technology at the production stage, $\Delta_f E \tilde{\Pi}_y^*$, directly translates to overall profits as stated in the lemma. ■

Proof of lemma 3. The derivative of $E\tilde{\Pi}_y^*$ with respect to innovation is

$$\frac{\partial E\tilde{\Pi}_y^*}{\partial i} = \begin{cases} 0 & k \leq 2\underline{D} \\ 2p\frac{\partial \mu}{\partial i} [\delta_{00}f + \delta_0(1-f)] & \text{if } 2\underline{D} < k \leq \underline{D} + \overline{D} \\ 2p\frac{\partial \mu}{\partial i} [(\delta_{00} + 2\delta_{10})f + \delta_0(1-f)] & \underline{D} + \overline{D} < k \leq 2\overline{D} \\ 2p\frac{\partial \mu}{\partial i} & 2\overline{D} < k \end{cases} \quad (13)$$

Because $\partial \mu / \partial i$ is assumed to be nonnegative, equation (13) is nonnegative irrespective of the relative magnitude of k , \underline{D} , and \overline{D} . Since $E\tilde{\Pi}_y^*$ is continuous, equation (13) captures all first order effects of i . Hence, $E\tilde{\Pi}_y^*$ is nondecreasing in i .

The derivative of $E\tilde{\Pi}_y^*$ with respect to capacity is

$$\frac{\partial E\tilde{\Pi}_y^*}{\partial k} = \begin{cases} p & k \leq 2\underline{D} \\ p[(1-\delta_{00})f + (1-\delta_0)(1-f)] & \text{if } 2\underline{D} < k \leq \underline{D} + \overline{D} \\ p[\delta_{11}f + (1-\delta_0)(1-f)] & \underline{D} + \overline{D} < k \leq 2\overline{D} \\ 0 & 2\overline{D} < k \end{cases} \quad (14)$$

which is easily seen to be nonnegative in all cases. With continuity of $E\tilde{\Pi}_y^*$ this establishes that $E\tilde{\Pi}_y^*$ is nondecreasing in k .

Dropping the term $\partial \mu / \partial i$ in equation (13) yields $\partial E\tilde{\Pi}_y^* / \partial \mu$ which was shown to be nonnegative. Since, by assumption, $\partial \mu / \partial p \leq 0$, $E\tilde{\Pi}_y^* / p$ must be nonincreasing in p . On the other hand, the per unit payoff from every item sold increases in price. Without further assumptions it is not possible to compare these two effects. This accomplishes the proof of lemma 3. ■

Proof of lemma 4. First, we will show how $\partial E\tilde{\Pi}_y^* / \partial k$ and $\partial E\tilde{\Pi}_y^* / \partial i$ depend on $k - 2\mu$. The analysis of the cross partials within the case boundaries completes the proof.

Since \underline{D} and \overline{D} are functions of μ and δ_0 , $\partial E\tilde{\Pi}_y^* / \partial k$ being nonincreasing in $(k - 2\mu)$ would imply a descending order of the lines in (14). This order is easily seen to hold because $1 \geq \delta_0 \geq 0$ and $1 \geq 1 - \delta_{00} = 2\delta_{10} + \delta_{11} \geq \delta_{11} \geq 0$. Note that, within each of the four cases, $\partial E\tilde{\Pi}_y^* / \partial k$ does not depend on either k or μ .

Accordingly, $\partial E\tilde{\Pi}_y^* / \partial i$ being nondecreasing in $(k - 2\mu)$, implies an ascending order of the derivatives in (13). For the case of $f = 0$ this is obviously true as $0 \leq \delta_0 \leq 1$. With flexible technology ($f = 1$) an ascending order requires $0 \leq \delta_{00} \leq \delta_{00} + 2\delta_{10} \leq 1$,

which is true since all probabilities are positive and sum up to one. Thus, $\partial E\tilde{\Pi}_y^*/\partial i$ is nondecreasing in k . Again, within each of the four cases $\partial E\tilde{\Pi}_y^*/\partial i$ neither depends on k nor on μ .

Because $\partial E\tilde{\Pi}_y^*/\partial k$ is nonincreasing in $(k - 2\mu)$ and $\partial\mu/\partial i \geq 0$, $\partial E\tilde{\Pi}_y^*/\partial k$ is nondecreasing in i . Together with $\partial E\tilde{\Pi}_y^*/\partial i$ being nondecreasing in k as shown above, this establishes complementarity between i and k with respect to the function $E\tilde{\Pi}_y^*$.

Since $\partial^2\mu/\partial i\partial p \geq 0$ and $\partial\mu/\partial i \geq 0$, $\partial E\tilde{\Pi}_y^*/\partial i$ in equation (13) is increasing in p within the case boundaries. Furthermore, $\partial\mu/\partial p \leq 0$ implies that a higher price increases $k - 2\mu$ and might thus trigger an upward jump of $\partial E\tilde{\Pi}_y^*/\partial i$. Therefore, the incremental payoff from innovating increases in price. Analogously, within the case boundaries $\partial^2 E\tilde{\Pi}_y^*/\partial i\partial p = \partial^2 E\tilde{\Pi}_y^*/\partial p\partial i$ and, with the same arguments used above to show that $\partial E\tilde{\Pi}_y^*/\partial\mu \partial\mu/\partial i$ is increasing in $(k - 2\mu)$, $\partial E\tilde{\Pi}_y^*/\partial p = E\tilde{\Pi}_y^*/p + \partial E\tilde{\Pi}_y^*/\partial\mu \partial\mu/\partial p$ is increasing in i when case boundaries are passed. Thus, i and p are complements with regard to $E\tilde{\Pi}_y^*$.

The derivative of equation (14) with respect to p is clearly positive. As argued above, at the case boundaries $\partial E\tilde{\Pi}_y^*/\partial k$ is nondecreasing in μ . Because $\partial\mu/\partial p \leq 0$, without further assumptions the effect of price changes on the gain from increasing capacity is undetermined. ■

Proof of lemma 5. Differentiating equation (9) with respect to i leads to

$$\frac{\partial \Delta_f E\tilde{\Pi}_y^*}{\partial i} = \begin{cases} -2p (\delta_0 - \delta_{00}) \frac{\partial\mu}{\partial i} & \text{if } 2\underline{D} < k \leq \underline{D} + \overline{D} \\ 2p (\delta_0 - \delta_{00}) \frac{\partial\mu}{\partial i} & \text{if } \underline{D} + \overline{D} < k \leq 2\overline{D} \\ 0 & \text{otherwise} \end{cases} . \quad (15)$$

Since $\delta_0 \geq \delta_{00}$, the first line of equation (15) is nonpositive and the second must thus be nonnegative. Because (9) is continuous (as can be seen by plugging in the case boundaries), equation (15) captures all effects of i on the gain from flexibility. Equivalently, from equation (13) it is clear that the difference in $\partial E\tilde{\Pi}_y^*/\partial i$ for $f = 1$ and $f = 0$ is nonpositive for $2\underline{D} < k \leq \underline{D} + \overline{D}$ and nonnegative for $\underline{D} + \overline{D} < k \leq 2\overline{D}$ (remember that $\delta_{10} = \delta_0 - \delta_{00}$). As $2\underline{D} < k \leq \underline{D} + \overline{D}$ corresponds to relatively low values of $(k - 2\mu)$ while $\underline{D} + \overline{D} < k \leq 2\overline{D}$ coincides with relatively high values of

$(k - 2\mu)$, i and f are with respect to $E\tilde{\Pi}_y^*$ (weakly) complementary for high values of the capacity slack $(k - 2\mu)$ but (weak) substitutes for low values of $(k - 2\mu)$. ■

Proof of lemma 6. In the general case

$$\frac{\partial E\tilde{\Pi}_y^*}{\partial i} = np \frac{\partial \mu}{\partial i} [\Pr(\Xi_1)f + \Pr(\Xi_0)(1 - f)], \quad (16)$$

where $\Pr(\Xi_0) = \Pr(D_j < \frac{1}{n}k)$ and $\Pr(\Xi_1) = \Pr(\Sigma D_j < k) = \Pr(\frac{1}{n}\Sigma D_j < \frac{1}{n}k)$. Irrespective of the distribution of D_j the random variables D_j and $\frac{1}{n}\Sigma D_j$ are defined on the interval $[\underline{D}, \overline{D}]$, have the same mean, but $\text{var}(D_j) \geq \text{var}(\frac{1}{n}\Sigma D_j)$. Let the distributions of D_j and $\frac{1}{n}\Sigma D_j$ be G and H respectively. For some small value ε we have

$$\begin{aligned} G(\underline{D} + \varepsilon) &\geq H(\underline{D} + \varepsilon) \quad \text{and} \\ G(\overline{D} - \varepsilon) &\leq H(\overline{D} - \varepsilon), \end{aligned}$$

because, for the average to be in the interval $[\underline{D}, \underline{D} + \varepsilon]$, it takes all random variables D_j , $j = 1, \dots, n$, to be realized very close to the lower bound, which cannot happen with greater probability than the event that a single D_j is near \underline{D} . Equivalently, $\frac{1}{n}\Sigma D_j$ will be less frequently close to the upper bound of the support than D_j . Therefore, for sufficiently small values of $(\frac{1}{n}k - \mu)$ we have $\Pr(\Xi_0) \geq \Pr(\Xi_1)$, whereas $\Pr(\Xi_0) \leq \Pr(\Xi_1)$ for sufficiently large values of $(\frac{1}{n}k - \mu)$. As a consequence, for small values of $(\frac{1}{n}k - \mu)$ the decision variables i and f are substitutes with respect to $E\tilde{\Pi}_y^*$, while for large values of $(\frac{1}{n}k - \mu)$ both variables are complements. ■

Proof of lemma 7. Differentiating equation (9) with respect to k leads to

$$\frac{\partial \Delta_f E\tilde{\Pi}_y^*}{\partial k} = \begin{cases} p(\delta_0 - \delta_{00}) & \text{if } 2\underline{D} < k \leq \underline{D} + \overline{D} \\ -p(\delta_0 - \delta_{00}) & \text{if } \underline{D} + \overline{D} < k \leq 2\overline{D} \\ 0 & \text{otherwise} \end{cases} \quad (17)$$

The first line of equation (17) is nonnegative while the second line is nonpositive. All remaining arguments are the same as in the discussion of the interrelation between f and i , except for their reversed signs (see the proof of lemma 5 above). Hence, k and f are (weakly) complementary with respect to $E\tilde{\Pi}_y^*$ for low values of $(k - 2\mu)$ but (weak) substitutes otherwise.

Differentiating equation (9) with respect to p leads to

$$\frac{\partial \Delta_f E \tilde{\Pi}_y^*}{\partial p} = \begin{cases} \frac{\Delta_f E \tilde{\Pi}_y^*}{p} - 2(\delta_0 - \delta_{00}) \frac{\partial \mu}{\partial p} & 2\underline{D} < k \leq \underline{D} + \overline{D} \\ \frac{\Delta_f E \tilde{\Pi}_y^*}{p} + 2(\delta_0 - \delta_{00}) \frac{\partial \mu}{\partial p} & \underline{D} + \overline{D} < k \leq 2\overline{D} \\ 0 & \text{otherwise} \end{cases} . \quad (18)$$

As $\Delta_f E \tilde{\Pi}_y^* \geq 0$ and $\partial \mu / \partial p \leq 0$ the equation (18) is nonnegative when $2\underline{D} < k \leq \underline{D} + \overline{D}$ and undetermined when $\underline{D} + \overline{D} < k \leq 2\overline{D}$. Therefore f and p are complements with regard to $E \tilde{\Pi}_y^*$ for low values of $(k - 2\mu)$, but they might be complements or substitutes elsewhere. ■

C Definitions

Kendall's tau

To calculate Kendall's tau (τ) of two vectors x and y we use the following definition:

$$\tau = \frac{c - d}{\sqrt{(c + d + t_x)(c + d + t_y)}},$$

where c and d are the number of concordant and discordant pairs respectively and t_x (t_y) denotes the number of pairs tied on x (y) but not on y (x). Values of τ lie in the interval $[-1, 1]$, positive (negative) values indicate positive (negative) dependence.

Generalized Residuals

The Pearson residual for a binary response model is defined as

$$r_i = \frac{y_i - \hat{\pi}_i}{\sqrt{\hat{\pi}_i(1 - \hat{\pi}_i)}},$$

where y denotes the endogenous variable that can take values equal to zero or one, i indexes the observation and $\hat{\pi}_i$ is the estimated probability that $y = 1$. Because in such a model $\text{var}(y_i - \hat{\pi}_i) \neq \hat{\pi}_i(1 - \hat{\pi}_i)$ we have that $\text{var}(r_i) \neq 1$. Pregibon (1981) developed the standardized Pearson residual for this case

$$r_i^{st} = \frac{r_i}{\sqrt{(1 - h_i)}},$$

where $h_i = \hat{\pi}_i(1 - \hat{\pi}_i)x_i\widehat{\text{var}}(\hat{\beta})x_i'$ and x_i denotes the row vector of exogenous variables and $\hat{\beta}$ is the estimated parameter vector. In our estimation there is practically no difference between r_i and r_i^{st} but only the latter are used for computation of Kendall's tau.

Condition	Dedicated Technology (f=0)		Flexible Technology (f=1)	
	$\Pr(\Xi_0)$	$\mathbf{E}[D_j \Xi_0]$	$\Pr(\Xi_1)$	$\mathbf{E}[D_j \Xi_1]$
$k \leq 2\underline{D}$	0	/	0	/
$2\underline{D} < k \leq \underline{D} + \overline{D}$	δ_0	\underline{D}	δ_{00}	\underline{D}
$\underline{D} + \overline{D} < k \leq 2\overline{D}$			$1 - \delta_{11}$	$\underline{D} \frac{\delta_{00}}{1 - \delta_{11}} + (\underline{D} + \overline{D}) \frac{\delta_{10}}{1 - \delta_{11}}$
$2\overline{D} < k$	1	μ	1	μ

Table 2: Probability that demand is a binding constraint to production and expected demand given demand is the binding constraint for dedicated and flexible technology. $\delta_{00} = \Pr(D_1, D_2 = \underline{D})$, $\delta_{11} = \Pr(D_1, D_2 = \overline{D})$, $\delta_{10} = \Pr(D_1 = \overline{D}, D_2 = \underline{D})$.

D Tables

Variable	Description
INNOVATION	= 1 if new products were introduced, 0 otherwise
FLEXIBILITY	=1 if the plant adopted machining centers, FMC or FMS, 0 otherwise
YEAR94	=1 for 1994, =0 otherwise
HIERARCHY	=0 if organizational structure is reported to be less hierarchical than average, 1 otherwise (only available for 1992)
RISK	=0 if an essential (for continuation of the business) share of revenues is from long term contracts with costumers, 1 otherwise
FIRMLEVEL	=1 if technological or organizational issues were decided at the firm instead of the plant level, 0 otherwise
MULTIPLANT	=1 if plant belongs to some multi-plant firm, 0 otherwise
CUSTOMIZE	share of products that where not standardized, but the customer could add to a basic design or completely specify the design
LOGSIZE	log of total number of employees (except administrative)
EDUCATION	number of skilled workers, foremen and engineers relative to total number of employees in production

Table 3: Definition of Variables.

Variable	Mean	Std.Dev.
INNOVATION	0.7226	0.4479
FLEXIBILITY	0.4899	0.5001
HIERARCHY	0.7049	0.4563
RISK	0.8137	0.3895
FIRMLEVEL	0.2074	0.4056
MULTIPLANT	0.2985	0.4578
CUSTOMIZE	0.8264	0.2674
LOGSIZE	4.0817	1.0665
EDUCATION	0.7523	0.2348
Observations	1186	

Table 4: Descriptive Statistics.

	Mean	Std.Dev.
INNOVATION		
all	0.7226	0.4479
1992	0.7808	0.4141
1994	0.6644	0.4726
1994 (0 in 1992)	0.3462	0.4776
1994 (1 in 1992)	0.7538	0.4313
FLEXIBILITY		
all	0.4899	0.5001
1992	0.4688	0.4994
1994	0.5110	0.5003
1994 (0 in 1992)	0.1873	0.3908
1994 (1 in 1992)	0.8777	0.3282

Table 5: Yearwise means and conditional means of INNOVATION and FLEXIBILITY.

	Unconditional		Conditional	
	Kendall's tau	P-value	Kendall's tau	P-value
1992	0.122***	0.003	—	—
1994	0.119***	0.004	—	—
all	0.114***	0.000	0.043**	0.027

Table 6: Association between INNOVATION and FLEXIBILITY. Conditional association is based on generalized residuals from single-equation probit estimations. ***, ** represent significance at the 1% and 5% level respectively.

Variable	Single Equations			
	Innovation		Flexibility	
	Coeff.	Std.E.	Coeff.	Std.E.
Constant	0.5610	0.3778	-4.1913***	0.6996
YEAR94	-0.5069***	0.0994	0.3400***	0.1226
HIERARCHY	-0.2444*	0.1425	-0.1617	0.2618
RISK	0.1433	0.1491	-0.2065	0.2199
FIRMLEVEL	0.1759	0.1663	-0.0317	0.1989
MULTIPLANT	0.2820*	0.1592	0.3892*	0.2250
CUSTOMIZE	-1.5693***	0.2523	-0.0653	0.3648
LOGSIZE	0.3409***	0.0644	0.9960***	0.1099
EDUCATION	0.5929**	0.2660	0.1705	0.4698
$\widehat{cov}(e_{git}, e_{gis}), s \neq t$	0.4772***	0.0665	0.8343***	0.0289
$\widehat{cov}(e_{git}, e_{kit}), k \neq g$		—		
$\widehat{cov}(e_{git}, e_{kis}), k \neq g, s \neq t$		—		

Table 7: Estimation results of random effects model . ***, **, * represent significance at the 1%, 5%, 10% level respectively. ML single equation estimates using the Broyden-Fletcher-Goldfarb-Shanno algorithm (BFGS).

Variable	System of Equations			
	Innovation		Flexibility	
	Coeff.	Std.E.	Coeff.	Std.E.
Constant	0.4172	0.2913	-2.2794***	0.3569
YEAR94	-0.3803***	0.0700	0.1251***	0.0476
HIERARCHY	-0.2018*	0.1037	-0.0649	0.1096
RISK	0.2023*	0.1196	0.0145	0.1283
FIRMLEVEL	0.1036	0.1338	-0.0368	0.1313
MULTIPLANT	0.2110	0.1303	0.0038	0.1219
CUSTOMIZE	-1.0101***	0.2117	-0.0103	0.1937
LOGSIZE	0.2270***	0.0486	0.5006***	0.0546
EDUCATION	0.2910	0.2049	0.2793	0.2359
$\widehat{cov}(e_{git}, e_{gis}), s \neq t$	0.4906***	0.0655	0.8501***	0.0280
$\widehat{cov}(e_{git}, e_{kit}), k \neq g$		0.1052* (0.0593)		
$\widehat{cov}(e_{git}, e_{kis}), k \neq g, s \neq t$		0.0395 (0.0581)		

Table 8: Estimation results of random effects model . ***, **, * represent significance at the 1%, 5%, 10% level respectively. ML system estimates using the Broyden-Fletcher-Goldfarb-Shanno algorithm (BFGS).