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Incumbent innovation and domestic entry

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Abstract This paper analyzes the escape-entry incentive for innovation by incumbent firms. The threat posed by the possibility of leading-edge firms entering the market influences incumbent innovation. To overcome problems of endogeneity, we apply an instrumental variable approach to analyze a rich firm-level dataset (1987–2000) for Germany. We find evidence that domestic entry has a negative effect on incumbent product innovation, which is a strong indication of new entrants' comparative advantage in commercializing new ideas. In contrast, domestic entry has a positive effect on incumbent process innovations, an effect also known as the escape-entry effect.

Keywords Entry · Process innovation · Product innovation

JEL Classifications O3 · L16 · L26 · M13

1 Introduction

New firm entry has a definite impact on incumbent firms. Schumpeter (1912) describes this effect as the process of creative destruction: new replacing old, thereby stimulating change. In line with this view, Aghion et al. (2009) describe a firm's incentive to innovate as an escape-entry strategy, that is, in order to discourage leading-edge competitive entry, an incumbent at the technology frontier will innovate in order to maintain its market position. In their analysis, the authors assume that leading-edge entry is foreign entry, which is then instrumented by exogenous changes in entry regulation. Based on a sample of UK firms, Aghion et al. (2009) find a positive escape-entry effect from foreign entry on domestic incumbents if the incumbents are at the technology frontier. In contrast, when they take domestic entry into consideration in their robustness checks, no significant effect of domestic entry on incumbent innovation is found. However, the authors do note that this could result from their aggregated

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domestic entry data, which does not distinguish between types of domestic entrants.

In this article, we look at domestic entrants and their impact on incumbent innovation. To estimate the effect of domestic entry on incumbent firm performance, we employ an instrumental variable (IV) approach based on theories by Klepper (1996) and Duranton and Puga (2001, 2005). Klepper applies the idea of an industry lifecycle to describe how entry and innovation evolve from the birth of a technologically progressive industry through its maturity. In this process, the number of entrants follows an inverted U-shape through the lifecycle so that during the early stage of the industry, the number of entrants increases, reaches a peak, and then, in maturity, declines. During the period of increasing entry, new firms account for important product innovations. Throughout the industry lifecycle, incumbent firms devote increasing efforts at process innovation instead of product innovations.

Duranton and Puga (2001, 2005) add spatial dimension to the industry lifecycle concept. For our purpose, the most crucial aspect of their argument is that spatial industry concentration increases throughout the industry lifecycle. Duranton and Puga's (2001) first model on process innovation explains the relationship between high entry levels and diverse, specialized cities. These industries are located on the left—i.e., increasing—side of Klepper's inverted U. Duranton and Puga argue that entrepreneurs develop new products in diversified cities where they can try processes borrowed from other activities. However, once a firm finds its ideal process, it switches to mass production and relocates to a specialized city where production costs are lower. Based on their model, Duranton and Puga argue that industries with a high level of innovative entry are more likely to benefit from the advantages offered by diversity and specialization. Accordingly, firms in mature industries have a greater tendency to relocate from diversified to specialized areas, which should result in increasing industry concentration.

Duranton and Puga's second model (2005) on functional specialization explains the relationship between industries dominated by large incumbent firms and diverse, specialized cities. These industries are on the right—i.e. decreasing—side of Klepper's inverted U. Industrial spatial concentration is supported by a functional specialization within incumbent firms. Incumbents choose to separate primary activities, such as management and research and development (R&D), from secondary activities—i.e., actual production—with the end result that management and R&D are located in diverse cities offering complementary services (Ono 2003), while mass production is located in specialized areas.

Duranton and Puga's (2001, 2005) models predict that a sector's geographic concentration is driven by the desire of innovative firms to relocate mass production to locations where production costs are comparatively low due to the availability of inexpensive land or low-cost employees. Thus, a sector's geographic concentration is more driven by pecuniary externalities than it is by intra-sectoral knowledge externalities. Duranton and Puga's prediction is consistent with the empirical findings of Ellison and Glaeser (1999) that at least half of the geographic concentration in U.S. manufacturing industries is driven by natural advantages, where natural advantages are broadly defined and include the availability of inexpensive land or low-cost labor.

In summary, we argue that an industry's spatial concentration, as measured by the Ellison–Glaeser (1997) Index, increases along the industry lifecycle. Therefore, by looking at spatial concentration, an industry's position along the lifecycle can be determined and, by extension, the industry's entry potential based on the demonstrated inverted U-shaped relationship. This logic leads to a potential instrument for endogenous domestic entry in Aghion et al.'s (2009) entry threat model and manages to allay several concerns at the same time. For example, we are not worried about problems of simultaneity between entry and an industry's spatial concentration, as Duranton and Puga's (2001) model predicts that an industry's spatial concentration of an industry is only driven by the relocation decisions of past entrants. Further, we are not worried that an industry's spatial concentration will have a direct effect on incumbent innovation, as Duranton and Puga's (2005) model predicts that incumbents choose specialized areas for mass production—and not for innovation. This clearly suggests that these industries benefit from pecuniary externalities in goods production and not from an intra-industry knowledge externalities in R&D.

In our empirical analyses, we make use of a rich firm-level dataset (1987–2000) for West Germany. Exploiting variation between industries within a single country has the advantage of a uniform framework of common laws and institutional settings. Furthermore, West Germany seems particularly suitable for our analysis, as it is characterized by a pronounced coexistence of diversified and specialized areas, probably due to its stable innovation system (compare Audretsch et al. 2009). By means of our IV approach, we find evidence that domestic entrants have a positive effect on incumbents' process innovation, indicating that entry threat motivates incumbents to secure their existing market position; however, we do find a negative effect on incumbents' product innovation. Perhaps the advantage that new entrants enjoy in the commercialization of new and heterodox ideas discourages incumbent firms from putting too much effort into product innovation. This result probably extends what Cohen and Klepper's (1996a, b) model of firm size and the nature of innovation would predict.

The remainder of the paper is organized as follows. Section 2 introduces our data on firm entry and incumbent innovation. In Sect. 3, we discuss our empirical method and present results showing the impact of domestic entry on incumbent innovation. Section 4 summarizes the results and concludes with some implications of our analysis.

2 Data on incumbent innovation and entrepreneurship for West German manufacturing industries

To investigate the effect of endogenous domestic entry on the incumbent's incentive to innovate, we combine West German incumbent innovation data with data on firm entry. We broadly define 11 manufacturing industries for the period 1987–2000 and conduct our analysis at the firm level after sorting the firms into the 11 industries. Concentrating on a single country is advantageous in that basic institutions, such as regulation or administrative barriers, and mentalities, such as entrepreneurial spirit, will be the same throughout the country. Therefore, the analysis should not be hampered by unobserved country-specific characteristics as might be the case in a cross-country analysis. Nevertheless, there is still enough variation between industries within a single country to make it possible to identify the impact of entry on the incumbent's incentive to innovate.

Industry-specific innovation activities of incumbent firms are derived from the Ifo Innovation Survey (for a description of the dataset, see Lachenmaier 2007). More than 1,000 surveyed firms report annually on whether or not they have introduced an innovation, i.e., a product or process innovation. The surveyed firms are a subsample of firms that are surveyed monthly for business cycle research. Therefore, there is no special focus on young firms or startups in the subsample. Furthermore, all surveyed firms have at least 20 employees. These specifics make it possible to derive information on incumbent innovation behavior from the Ifo Innovation Survey (compare Falck 2009).

We construct different outcome measures to capture as accurately as possible those innovations that were introduced as a result of increased competition due to entry. We start with the most general measure of innovation, which is simply a binary variable equaling 1 if a firm introduced an innovation in the year preceding the survey. This variable is then deconstructed to distinguish between product and process innovations. Product and process innovations are subsequently augmented with any additional information that firms provide about the innovation process. When answering questions about their innovation behavior, firms are given a wide selection of motivations to choose from in explaining where the impulse for the innovation process originated. We use the answer "from a competitor" to construct an innovation measure that is again binary and equals 1 if a firm introduced a product or process innovation based on an impulse that came from a competitor. In our opinion, this measure is the best way to capture those incumbent innovations that were motivated by fear of competition.

Information on firm entry in an industry is derived from the German Social Insurance Statistics (for a description of the dataset, see Brixy and Fritsch 2004). The German Social Insurance Statistics requires every employer to report certain information, such as qualifications, about every employee subject to obligatory social insurance. The information collected can be transformed into an establishment file that provides longitudinal information about the establishments and their employees. As each establishment with at least one employee subject to social security has a permanent individual code number, the appearance of a new code number can be interpreted as an entry. The unit of measurement is the establishment, not the firm. The empirical data thus derived include two categories of entities: firm headquarters and subsidiaries. Because several studies have documented that "de novo" entries tend to be small, new establishments with more than 20 employees in the first year of their existence are excluded from our sample, resulting in a considerable number of new subsidiaries of large firms contained in the database not being counted as real entries. These new subsidiaries are probably the result of a functional specialization within large incumbent firms that, eventually, drives an industry's geographic concentration.

Industry geographic concentration is measured by an index proposed by Ellison and Glaeser (1997):

$$EG = \frac{G - \left(1 - \sum_{r=1}^{M} x_r^2\right)H}{\left(1 - \sum_{r=1}^{M} x_r^2\right)(1 - H)} \tag{1}$$

Employment data from the establishment file of the German Social Insurance Statistics are used to calculate the Ellison–Glaeser index, where G is the Gini coefficient of concentration and x_r is the industry's share of overall manufacturing employment in region r. The regions are 75 West German planning regions. The $\left(1 - \sum_{r=1}^{M} x_r^2\right)$ term is included so that the index has the property $E(EG) = 0$ when neither agglomerative spillovers nor natural advantage are present. H is the Herfindahl index of the industry's establishment size distribution. The Herfindahl index is calculated according to the method proposed by Schmalensee (1977). As industries are defined very broadly, it is not surprising that the Ellison–Glaeser index is relatively small for each of the 11 industries. Nevertheless, for all industries, the Ellison–Glaeser index is larger than zero, which implies excess concentration (see Table 1 for descriptive statistics).

Table 1 sets out descriptive statistics at the industry level. Electrical apparatus, radio, TV, communication, office machinery, and computers have both the highest incumbent innovation rate (63.9%) and the highest entry rate (7.3%).[1] In contrast, food and tobacco has the smallest entry rate (3.6%) and also a fairly small innovation rate (36.7%). These descriptive statistics alone provide some evidence of how the threat of entry influences incumbent innovation.

3 Estimation and results

3.1 The strategy

To assess the effect of domestic entry on the incumbent's incentive to innovate, we are interested in estimating the following innovation production function:

$$\Pr\left(Inno_{fit} = 1 | Entry, X\right) = \alpha + \beta_1 \log(Entry_{it}) + X_{fit}\beta_2 + X_{it}\beta_3 + \varepsilon_{fit} \tag{2}$$

$\Pr(\cdot)$ is the conditional probability of an incumbent having introduced an innovation. Thereby, $Inno_{fit}$ is the binary variable indicating whether firm f in industry i $(i = 1,\ldots,11)$ introduced an innovation (product or process) in year t $(t = 1987,\ldots,2000)$. $Entry_{it}$ is the number of entries in industry i at time t. β_1, the coefficient of interest, is a measure of the impact of entry on the incumbent's incentive to innovate. X_{fit} is a set of firm-level control variables, including firm size (in terms of employment), firm location (a dummy for the federal state), and innovation inputs measured as expenditures committed to innovation activities to control for an individual firm's input in the innovation process. This is the sum of different possible expenditures that foster innovation, such as, expenditures for R&D, construction and design, patents, and investment made in preparation for innovation. Additionally, the innovation expenditures' share of a firm's revenues is included to scale the expenditures according to the financial size of the establishment. Unfortunately, at least one of the latter two variables is missing for 5,197 observations. After checking for the randomness of the missing values, we drop these observations. Our final sample contains 10,351 observations (compare Table 1). We use these observations as

[1] The innovation rate is defined as the number of firms that have reported an innovation (process or product innovation) over the number of all firms of the respective industry that have participated in the Ifo Innovation Survey. The entry rate is the number of entries out of the number of establishments in the respective industry as derived from the establishment file of the Social Insurance Statistics.

Table 1 Descriptive statistics

Industry	*n*	Innovation rate		Entry rate		Ellison–Glaeser index	
		SD	Mean	SD	Mean	SD	Mean
Food and tobacco	700	0.114	0.367	0.002	0.036	0.00018	0.0023
Textiles, apparel, and leather	879	0.095	0.358	0.007	0.064	0.00015	0.0116
Wood products, furniture, paper, and pulp	1,912	0.071	0.300	0.006	0.059	0.00029	0.0063
Publishing and printing	933	0.075	0.202	0.006	0.063	0.0001	0.0017
Chemicals	155	0.158	0.568	0.009	0.048	0.00137	0.0182
Rubber and plastics	755	0.109	0.401	0.009	0.059	0.00018	0.0024
Non-metallic mineral products	796	0.115	0.396	0.004	0.043	0.00127	0.0095
Metals and fabricated metal products	1,182	0.112	0.351	0.006	0.067	0.00113	0.0087
Machinery	1,597	0.112	0.548	0.005	0.060	0.00013	0.0012
Electrical apparatus, radio, TV, communication, office machinery, and computers	1,238	0.101	0.639	0.006	0.073	0.00047	0.0038
Motor vehicles and other transport equipment	204	0.159	0.632	0.004	0.056	0.00074	0.0068
Total	10,351	0.167	0.411	0.011	0.059	0.00379	0.0054

SD, Standard deviation

repeated cross-sections, including dummies for survey year as controls.

X_{it} is a set of industry-level control variables, including the size of the industry (in terms of employment), annual industry employment change to control for industry-specific business cycles, and the share of employees with a degree in engineering or natural science. Engineers and natural scientists are most likely to be employed in R&D. We therefore use the share of employees with a degree in engineering or natural science in an industry as a control for the knowledge intensity of an industry. Both variables are derived from the Social Insurance Statistics.

Entry is expected to be endogenous on its own merits and depends on incumbent innovation. Therefore, we use an IV approach to instrument entry in the first stage. Our IV approach is based on Klepper's (1996) observation of an inverted U-shaped relationship between the industry's position in the lifecycle and domestic entry. To this we add Duranton and Puga's (2001, 2005) insight into the spatial dimension of the industry lifecycle, which is that an industry's spatial concentration increases with age. The result is expected to be an inverted U-shaped relationship between entry in an industry and that industry's spatial concentration as measured by the Ellison–Glaeser Index and, indeed, this effect is observed in our data (compare Table 1). For example, the "young" computer industry has one of the smallest values of the Ellison–Glaeser Index, whereas the mature chemical industry has by far the largest. Equation 3 reflects the assumed relationship between entry in an industry and spatial concentration of that industry:

$$\log(Entry_{it}) = \alpha + \beta_1 EG_{it} - \beta_2 EG_{it}^2 + X_{fit}\beta_3 + X_{it}\beta_4 + \varepsilon_{fit} \quad (3)$$

We use only the predicted value of this first-stage model in our second-stage model (compare Eq. 2). The first-stage model does not include industry dummies due to the fact that geographic industry concentration is very persistent over time. Persistency means that there is very little time series within-industry variation that can be exploited. This persistence of the Ellison–Glaeser Index basically signifies that the period 1987–2000 can be viewed as a mere snapshot taken at one point in time of the long-run industry evolution.

However, we are looking at variation of the Ellison–Glaeser Index *across* industries as well as *within* them. As the latter is rather small due to the above-mentioned persistence effect, we are mostly interested in the entry variation in industries that is driven by the actual state of the industry lifecycle and the resulting geographic concentration. This part of the variation is not driven by current innovation activity and can, therefore, be considered exogenous

Table 2 Simple probit results

Industry data	Product innovation	Product innovation (impulse from competitor)	Process innovation	Process innovation (impulse from competitor)
Number of entrants (log)	−0.119	−0.123	0.0895	0.0298
	(−0.99)	(−1.25)	(1.12)	(0.93)
Spending on innovation (log)	0.391***	0.333***	0.347***	0.300***
	(30.7)	(33.5)	(17.0)	(19.2)
Spending on innovation (percentage of revenues)	−0.000391***	−0.000328***	−0.0000871	−0.000126**
	(−5.56)	(−4.80)	(−1.23)	(−2.18)
Number of employees (log)	−0.164***	−0.146***	−0.154***	−0.121***
	(−4.75)	(−6.04)	(−4.84)	(−4.72)
Number of employees in industry (log)	0.290	0.250	−0.237	−0.119
	(0.92)	(0.88)	(−1.27)	(−1.35)
Annual change in employment in industry (%)	−0.0358	−0.0246*	0.0264**	0.0191
	(−1.63)	(−1.85)	(2.22)	(1.36)
R&D employment: Percentage of engineers and natural scientists	−0.0705	0.167	1.533	2.214*
	(−0.020)	(0.051)	(0.61)	(1.89)
Constant	−4.091	−4.299	0.570	−1.162
	(−1.22)	(−1.39)	(0.29)	(−1.23)
Observations	9,987	9,987	9,987	9,987
Pseudo-R^2	0.464	0.363	0.379	0.311

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Cluster-robust z-statistics on the industry level are given in parenthesis

Dummies for years and federal states not shown

in our regression framework using incumbent innovation as the outcome.

Since the first stage of our estimation occurs on a higher level of aggregation, i.e., the industry level, and the second stage is estimated at the firm level, we end up with a two-stage estimation framework in a nested sample, as described by Karaca-Mandic and Train (2003). To control for correlation among observations within each industry, we use a robust covariance estimator in the first step (compare Rogers 1993). However, the use of a robust covariance estimator in this setup is appropriate only if there is no error in the first stage (compare Karaca-Mandic and Train 2003, p. 404). Therefore, in a subsequent step, we bootstrap the full instrumental variable regression. Karaca-Mandic and Train (2003) show that the bootstrap procedure leads to more reliable standard errors.

3.2 Results

As our outcome variable is binary, we estimate Eq. 2 with probit models. We also run linear probability models, as suggested by Angrist (2001), and qualitatively obtain the same results as in the probit models. Thus, we report results from the probit models only. Table 2 sets out the results of the simple probit regressions of Eq. 2. The dependent variable is either of the binary variables reporting whether a firm has introduced a product innovation or a process innovation in the preceding year. Both outcome variables are further narrowed down to those innovations motivated in some way by a competitor. This leaves us with four outcome measures.

In all specifications, the domestic entry coefficient is not significantly different from zero, which is in line with Aghion et al.'s findings (2009). However, when instrumenting *Entry* by *EG* and EG^2, the entry coefficient becomes significantly different from zero, suggesting that we have succeeded in isolating leading-edge domestic entry in technologically progressive industries. The results of the instrumental variable approach are summarized in Table 3. In the first stage, the expected inverted U-shaped

Table 3 Instrumental variable probit results

Industry data	Product innovation	Product innovation (impulse from competitor)	Process innovation	Process innovation (impulse from competitor)
Number of entrants (log)	−0.181**	−0.129*	0.116***	0.0879**
	(−2.15)	(−1.81)	(2.66)	(2.24)
Spending on innovation (log)	0.390***	0.333***	0.347***	0.301***
	(31.9)	(34.0)	(17.1)	(19.1)
Spending on innovation (percentage of revenues)	−0.000385***	−0.000327***	−0.0000899	−0.000132**
	(−5.66)	(−4.88)	(−1.27)	(−2.30)
Number of employees (log)	−0.164***	−0.146***	−0.154***	−0.121***
	(−4.76)	(−6.08)	(−4.83)	(−4.73)
Number of employees in industry (log)	0.364	0.256	−0.270*	−0.190*
	(1.57)	(1.14)	(−1.73)	(−1.91)
Annual change in employment in industry (%)	−0.0355	−0.0246*	0.0263**	0.0190
	(−1.62)	(−1.82)	(2.20)	(1.42)
R&D employment: percentage of engineers and natural scientists	−0.974	0.0858	1.938	3.103**
	(−0.29)	(0.028)	(0.79)	(2.09)
Constant	−4.576*	−4.342	0.788	−0.688
	(−1.68)	(−1.62)	(0.43)	(−0.67)
First-stage results				
Ellison-Glaeser (EG) index	196.1***	196.1***	196.1***	196.1***
	(2.61)	(2.61)	(2.61)	(2.62)
Squared EG index	−14,778***	−14,779***	−14,779***	−14,778***
	(−3.50)	(−3.50)	(−3.50)	(−3.50)
χ^2-test of EG = EG2 = 0	22.435***	22.435***	22.457***	22.448***
Observations	9,987	9,987	9,987	9,987

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Cluster-robust z-statistics on the industry level are given in parenthesis

Dummies for years and federal states not shown

relationship between *Entry* and the Ellison-Glaeser index is found across industries.

The results of the second stage reveal that instrumented entry has a significantly positive impact on process innovation, but a negative influence on product innovation. To confirm the validity of our instruments, we included the Ellison–Glaeser Index directly in the first non-instrumented probit model to see whether it has a direct influence on firm innovation behavior. The coefficient of the Ellison–Glaeser index is not significantly different from zero when controlling for entry in this model. This suggests that the Ellison–Glaeser Index is a valid instrument for entry since it has no direct effect on innovation behavior beyond the indirect effect via the entry variable. The validity of the instruments is further reinforced by the χ^2-test of joint significance of the excluded instruments in the first stage.

Marginal effects are calculated at the sample mean of variables and since the entry variable is coded in logs, the corresponding interpretation is in semi-elasticities (compare Table 4). The computed marginal effects implied by the estimates suggest that a 1% increase in leading-edge domestic entry for an industry leads to a 5.3% point decrease in the probability that the incumbent will introduce a product innovation and a 2.6% point increase in the probability that the incumbent will introduce a process innovation.

As the robust covariance estimator in this setup is valid only under relatively strong assumptions, in a further step we bootstrap the full instrumental variable

Table 4 Marginal effects at the sample mean of the instrumental variable probit

Industry data	Product innovation	Product innovation (impulse from competitor)	Process innovation	Process innovation (impulse from competitor)
Number of entrants (log)	−0.053**	−0.024*	0.026***	0.013**
Spending on innovation (log)	0.115***	0.062***	0.079***	0.043***
Spending on innovation (percentage of revenues)	−0.0001***	−0.00006***	−0.00002	−0.00002**
Number of employees (log)	−0.048***	−0.027***	−0.035***	−0.017***
Number of employees in industry (log)	0.107	0.048	−0.061*	−0.027*
Annual change in employment in industry (%)	−0.01	−0.0046*	0.006**	0.003
R&D employment: percentage of engineers and natural scientists	−0.287	0.016	0.44	0.445**

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5 Comparison of significance levels with different standard errors

Model	Outcome variable	Entry (marginal effect)	Significance level clustered SEs	Significance level bootstrapped SEs
IV probit	Product innovation	−0.053	**	***
IV probit	Product innovation (Impulse from competitor)	−0.024	*	*
IV probit	Process innovation	0.026	***	*
IV probit	Process innovation (Impulse from competitor)	0.013	**	–

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

IV, Instrumental variable; SE, standard error

regression, a process that should result in more reliable standard errors of the coefficients. Point estimates and marginal effects are the same as described previously, since only the standard errors are computed differently. This different method of computing the standard errors results in a decline of the significance levels but, even so, our hypothesis as to the negative influence instrumented entry has on product innovation and its positive influence on process innovation can be maintained (compare Table 5).

4 Conclusions

Our instrumental variable approach confirms Aghion et al.'s (2009) theory that leading-edge entry has an impact on an incumbent's incentive to innovate, an effect that is positive only in regard to process innovations. In contrast to Aghion et al. (2009), our choice of instruments is based on the assumption that leading-edge entry is not foreign entry but, rather, domestic entry in technologically progressive industries. The negative impact of domestic entry on incumbent product innovation can be viewed as further support for Audretsch's (1995) findings that new products are most likely to be introduced by new entrants that have not yet developed routines that inhibit thinking outside the box. The advantage that new entrants enjoy in the commercialization of new and heterodox ideas might discourage incumbent firms from putting too much effort into product innovation. This idea fits with Baumol's (2002) "David–Goliath Symbiosis," which has to do with how the work of innovation is divided between large incumbent firms and small new firms.

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