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An innovation adoption model of licensing-in for US start-ups

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Abstract

Using the Kauffman panel dataset of US start-ups, we analyse the key determinants of licensing-in adoption. Licensing-in entails an intellectual property contract between the licensor (e.g. upstream established firm) and licensee (e.g. downstream start-up) aiming to bring an innovation to market rapidly. Assuming maximizing of the owner's managerial utility in the start-up years, we explain licensing-in adoption through firm characteristics like size, R&D and capital structure, as well as other IP types, and controls for year and regional fixed effects, using panel probit estimation with adjustments for sample selection bias and endogeneity. We find key determinants of licensing-in to be owners' equity, product (rather than service) sales and R&D spend; and then comment on their policy implications for business incubation.

Keywords: Licensing-in; US start-ups; IP adoption
JEL Classification Codes: M2, L2, L5, O32, O34

1. Introduction

This paper is concerned with enterprise-based knowledge inflows in the form of licensing-in, also called 'in-licensing'. Its focus is the determinants of licensing-in activity by US start-ups. Licensing-in is a type of intellectual property (IP) (Lemley 1999). It typically involves a formal contract, (Anand and Khanna 2000), that puts the responsibility on a small start-up (the licensee) to get an innovative product to market rapidly, in exchange for which an upstream established firm (the licensor) provides the necessary resources, financial and technical, to accelerate product development and reduce the time to product launch (Razgaitis 2003). The current rise of research interest in licensing-in is part of collective disillusion with 'closed innovation' practices and an emerging appetite for 'open innovation', driven by inflows and outflows of knowledge within and between firms, all aiming to generate, and to sell, innovation (Chesbrough 2003; Pereira et al. 2015; Santoro et al. 2018).

Extant research on licensing-in emphasizes its potential benefits. For example, it can

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accelerate innovation, contribute to new product development at lowered cost and risk, diversify a firm's portfolio, and prevent technological obsolescence (Authane-Gima 2003; Laursen et al. 2010; Belingheri and Leone 2017). Studies show licensing-in to have a positive impact on financial performance, innovation, and growth (Hung and Chou 2013; Parida et al. 2012; Pereira et al. 2015). It can also help start-ups to overcome limitations of scale, like under-capacity, by generating indigenous R&D (Tsai and Chang 2008; Belingheri and Leone 2017).

As licensing-in can transform the development of start-ups, it is to the advantage of researchers, practitioners, and policymakers to understand what factors drive licensing-in adoption. This is the research gap that this article aims to fill. Recent research around licensing-in offers insight into its potential determinants. Consistent with the absorptive capacity approach of Cohen and Levinthal (1990), more recent research suggests that higher internal R&D capabilities are positively linked to licensing-in activity by large firms (Cassiman and Veguelers 2006; Tsai and Chang 2008; Wang and Li-Ying 2014), including international licensing-in, Dohse et al. (2019). However, for the specific case of licensing-in within small start-ups, there has been little evidence to corroborate this. Both Sikimic et al. (2015) and Pereira et al. (2015) confirm the synergies between licensing-in and licensing-out activities for large firms, but this has not been explored for small start-ups in the context of licensing-in new technologies. Turning to industry characteristics, increased technological turbulence, high levels of competition, and manufacturing or supplier-dominated industries have been found to be linked to higher levels of licensing-in (van de Vrande et al. 2009; Zahra et al. 2005). While research finds that large firms that produce products (as opposed to services) are more likely to register or use intellectual property (Gallié and Legros 2012; Chen and Wu 2020), few works examine the impact of this factor on the decision to license-in within start-ups. However, at the firm-level, there is a general finding that strategic choices (e.g. on the level of risk, breadth of product lines, and speed-to market) all affirm the utility of licensing-in (Authane-Gima 2003), as do the scarcity of resources, both human and financial. Such resources have been shown to enhance open innovation (Dreschler and Natter 2012), particularly for inward licensing (Dohse et al. 2019; Jang et al. 2019), including in international settings.

While these findings are laudable, large gaps remain in empirical studies concerning specifically the licensing-in adoption decision. For example, van de Vrande et al. (2009) looked at open innovation in a sample of Dutch firms, but explicitly excluded micro-enterprises (less than ten employees) which are at the heart of our own work on start-ups. Further, we evade the lack of formalism of works like van de Vrande et al. (2009) which did not use econometric methods, or formal model building. Our article builds on such early works in a more targeted way and aims to add value in a research sense by examining the impact of multiple determinants of licensing-in using an advanced econometric analysis of a large longitudinal sample of US start-ups.

The advantages of licensing-in to a start-up (*viz* its accelerated development stage, and its competitive advantage over incumbent rivals) extends from academic research to practice and policy. Schafer (2002) was one of the first business practitioners to identify licensing-in specifically as a US business model and referred to it as being possibly a fad because 'business models go in and out of fashion'. That has proven pessimistic. While slow to start, licensing-in has become highly favoured by investors, mainly because experience has shown that it accelerates company development, USITC (2020). This is because with licensing-in there is an enhanced route to an economic payoff.

To explain, with standard venture capital intervention in promising start-ups the payoff is often considerably delayed to when the firm goes public, in the hope then of providing a high return on the original investment, Reid (1998). By contrast, licensing-in appeals to ambitious owner managers, who aim for a more favourable economic existence than trying to breathe life into failed products of giant companies. Rather, this type of owner manager wants to see their start-up being a quick-actioning tool *for* innovation, rather than an alternative tool *to* innovation.

By their nature, start-up owner managers are attracted to processes that enable risk attenuation and cost reduction that can be achieved by licensing-in, Blank and Dorf (2020). To acquire these benefits, the licensee needs to look at the track record of the licensor and gauge its reliability and capacity e.g. in terms of financial and technical support. In turn, the licensor might wish to agree a flexible royalty arrangement that allows for trigger events like an increase in licensee costs (on the downside), or an achievable rise in product price (on the upside). If the licensee is able to get technological leverage from its imported innovations, enabling it to develop independently new IP, it might want to substantiate a proprietorial right over such derivative work, and in this case, the licensor might want to receive a 'grant-back' in recognition of earlier support for the licensee, Laursen et al. (2017).

In looking at broader implications of the adoption pattern of licensing-in, one must bear in mind that the international dimension can be important. To illustrate, while PR China already has a strong technological base, there is clear evidence, see Wang and Li-Ying (2014), that indigenous firms which engage in *international* licensing-in enjoy positive spill-over performance benefits from this in terms of their best use of *indigenous* licensing-in. This insight is potentially relevant to other international settings, including of course the USA.

For US start-ups, Belingheri and Leone (2017) find that their IP strategies to be more flexible than incumbent firms. This is especially true of licensing-in from external companies, which enables immediate access to viable external technologies at the start of their business life cycle, a phenomenon they call 'walking into the room with IP'.

2. Methods

Our modelling approach assumes a managerial model of the start-up, in which the owner manager maximises a utility (U) function whose arguments include intellectual property (IP) types, and further economic, financial, and organizational control variables. This utility function is denoted U_{ij} (.) where the index *i* denotes an IP type like licensing-in and the index *j* denotes a specific start-up. To create an estimable econometric model of the start-up, we adopt the random utility approach of Hensher and Johnson (2018), specified as:

$$U_{ij} = A_{ij} + \mu_{ij} \tag{1}$$

where the A_{ij} in equation (1) are deterministic and the μ_{ij} are random variables which are independently and identically distributed over IP types (indexed *i*) and start-ups (indexed *j*). We represent the choice set as $\{C_j\}$, which here reduces to the simple choice between 'adopting licensing-in' and 'not adopting licensing-in'. We represent the probability that the j'th start-up adopts licensing-in, the i'th IP type, as follows:

$$P_j(i) = \text{Prob}\,(U_{ij} > U_{kj}) = \text{Prob}\,(A_{ij} + \mu_{ij} > A_{kj} + \mu_{kj}) = \text{Prob}\,(\mu_{kj} - \mu_{ij} < A_{ij} - A_{kj}) \tag{2}$$

where inequalities in equation (2) hold for all (i,k) in the choice set for the j'th start-up.

Assuming the A_{ij} and A_{kj} have linear parameterisations, our estimable model is a binary probit with $P_j(i = 1) = \Phi(\boldsymbol{\beta}'\mathbf{x})$ for the unit standard normal cumulative density function Φ, parameter vector $\boldsymbol{\beta}$ and data vector $\mathbf{x}$, Greene (2020, Part IV). On the above basis, our probit took the implemented form of equation (3) below:

$$\text{Prob (Adoption of Licensing-in)} \equiv y = F(\text{Start-up Characteristics, Other IP types, Controls, Random Variables}) \tag{3}$$

In implementing the model given in equation (3) we used panel binary probit estimation, with y = 1 if the start-up had adopted licensing-in during a particular year, and = 0 if not. In equation (3) the 'Start-up Characteristics' included employee size, incorporation, ownership, financial structure (e.g. debt, equity). 'Other IP types' included patents, licensing-out, copyrights, trademarks etc. 'Controls' included years, sectors, and the knowledge intensity of services or the high technology nature of manufacturing firms. The 'Random Variables' involved the composition of the error term μ_{ij} with various other error terms arising from our test procedures. Brief definitions and associated descriptive statistics of variables are provided in Section 3 along with a brief justification for their inclusion.

Parameter estimates of $\boldsymbol{\beta}$ were computed using Stata® software for panel probits controlling, by year, region and sector, for fixed-effects and clustering the errors by firm j (see Section 3, Table 2, column 2). From these estimates, we derived marginal effects ($\partial y/\partial x$) and elasticities (Ey/Ex), see Section 3, Table 2 (columns three and four). Gauss-Hermite quadrature was used to maximize the likelihood function, typically converging in four iterations. Our panel estimation was concluded by testing for endogeneity, see Hausman (1978), and sample selection bias, see Vella (1998).

3. Data and descriptive statistics

Our study uses the Kauffman Firm Survey, Robb and Reedy (2011), to explore the licensing-in activities of US firms for their first 8 years of operation from 2004 to 2011. In the base year of 2004, 4,928 surveys were completed, representing a 43% response rate when sampling weights are applied (Ballou et al. 2008). These firms were then tracked annually, with respondent numbers falling year-by-year due to attrition, refusals, change of contact and business exits. Data were collected by a self-administered web survey, backed up by Computer-Assisted Telephone Interviewing (CATI).

We used a total sample of 22,264 observations. This sample started with 4,866 firms founded in 2004, which were tracked until the seventh follow-up, at which point there were 2,046 firms remaining. These observations covered all NAICS sectors from 11 to 92. The average size of start-up's by employees in our sample was 2.9 (st. dev. = 6.1). Our Kauffman Firm Survey data are known to be a good reflection, over many dimensions, of the population of start-ups in the USA, see Farhat et al. (2018).

Brief definitions of all variables are contained in Table 1, and a fuller explanation of these definitions is provided in the supplementary material (Appendix A). Our dependent variable, *Licensing-in*, is explained by typical determinants some which are referred to in Section 2 above. Firm characteristics include *Size*, as open innovation tends to more driven by larger than smaller firms (van de Vrande et al. 2009; Licthenthaler 2008; Dohse et al. 2019). Measures capturing ownership status include *Incorporated* and *Team*, similar to Zahra et al. (2005) and Dohse et al. (2019), and measures of the resources of the firms include assets (*Purchased*), financial assets (*Equity*, *Debt*) and human capital (*PhD*), following Cassiman and Veugelers (2006) who argue that a lack of resources positively influence the licensing-in of IP. Other works supporting a positive effect for human capital include Dohse et al. (2019). As indicated above, Gallié and Legros (2012), in investigating firm IP protection, find that industrial firms are more likely to use formal IP than service firms, and therefore include the product profile of the firms as one of their regressors. Most papers find a strong positive effect of internal R&D on licensing-in or open innovation (Cassiman and Veugelers 2006; Hung and Tang 2008; Tsai and Chang 2008; Tsai and Wang 2007; Dohse et al. 2019; Wang and Li-Ying 2014; Lichtenthaler 2008). The technological regime of the start-up is captured in our paper by our *High-tech* variable and the knowledge intensity of services (*Low/High Knowledge IS*). They are included as controls in our estimation in a similar fashion to Spithoven et al. (2013). We are influenced by Hung and Tang (2008) who find that firms with higher technological capability are parsimonious with their resources and see licensing-in as a 'lean' alternative. While the complex interrelationships among different types of IP is discussed by Amara et al. (2008) and captured in recent studies such as Lee et al. (2017), this largely explores only the internal effect of licensing-in on licensing-out (Sikimic et al. 2016; Hu et al. 2015). By contrast, we go beyond this, and look at the impact of a more comprehensive range of IP types on the adoption of a specific IP type. In doing so, we also include four regional dummies to capture the influence of four broad census bureau regions in the USA (e.g. northeast, mid-west, south and west). We use sectoral, regional and year dummies to capture these diverse fixed effects in our panel estimation.

Table 1 gives a clear characterisation of our average start-up. The typical start-up is incorporated, sole owner-managed, and functions in rented premises or from home. It has about three employees and has a small amount of equity invested in the firm. It tends to be service based and is typically not high-tech. Start-ups more often rated themselves as using high (rather than low) knowledge intensive services businesses. Some owner managers had a PhD but the average count (0.10) was less than one. About 20% of the start-ups spent money on R&D. In terms of the range of IP types, copyrights were the type most commonly held, followed by trademarks and then patents. Licensing-in occurred for 6% of start-ups and licensing-out for 2% of start-ups.

Table 1. Definitions of Variables, Means and Standard Deviations.

Variable	**Definition**	**Mean**	**SD**
Size	A count of all FT and PT employees	2.9	6.1
Debt	Total owner and total business debt (categorial)	2.9	3.2
Team	=1 if more than one owner; = 0 otherwise	0.38	0.49
Purchased	=1 if purchased premises; = 0 otherwise	0.064	0.25
Incorporated	=1 if incorporated; = 0 otherwise	0.65	0.48
Equity	Total owner manager equity (categorial)	2.15	2.80
Service	=1 if a business sells a service; = 0 otherwise	0.86	0.35
Product	=1 if a business sells a product; = 0 otherwise	0.49	0.50
PhD	Count of owners with PhD degree	0.10	0.36
R&D spend	=1 if spends money on R&D; = 0 otherwise	0.19	0.39
High-tech	=1 if 28 Chemicals, 35 Industrial, 36 Electrical, 38 Instruments; = 0 otherwise	0.13	0.33
Patents	Count of patents	0.17	2.00
Copyrights	Count of copyrights	1.49	12.00
Trademarks	Count of trademarks	0.28	1.46
Licensing-out	=1 Licensing out any form of legal property rights; = 0 otherwise	0.02	0.14
Licensing-in	=1 Licensing in any form of legal property rights; =0 otherwise	0.06	0.23
Manufacturing	= 1 if Manufacturing; = 0 otherwise	0.14	0.34
Construction	= 1 Construction; 0 = otherwise	0.080	0.2187
Wholesale/Retail	= 1 Wholesale and Retail; 0 = otherwise	0.14	0.35
Low Knowledge IS	= 1 Low Knowledge Intensive Services; = 0 otherwise	0.24	0.43
High Knowledge IS	= 1 High Knowledge Intensive Services; = 0 otherwise	0.38	0.49

Table 2. Panel Probit ML Estimates

Variables	Parameters β (Standard error)	Marginal effects dy/dx (Standard error)	Ey/Ex Elasticities
1. Size	0.0118***	0.0002***	0.0974
	(0.0041)	(0.0001)	(0.0342)
2. Debt	0.0104	0.0001	0.0872
	(0.0082)	(0.0001)	(0.0688)
3. Team of Owners	0.1167*	0.0017*	0.1284
	(0.0657)	(0.0010)	(0.0726)
4. Purchased	-0.1834	-0.0021*	-0.0345
	(0.1279)	(0.0010)	(0.0240)
5. Incorporated	0.1011	0.0014	0.1894
	0.0711	(0.0010)	(0.1334)
6. Owners' Equity	0.0310***	0.0004***	0.1915
	(0.0084)	(0.0001)	(0.0525)
7. Service	0.0013	0.0000	0.0031
	(0.0811)	(0.0011)	(0.2033)
8. Product	0.3664***	0.0055***	0.5072
	(0.0588)	(0.0012)	(0.0830)
9. PhD	0.0972	0.0014	0.0270
	(0.0688)	(0.0010)	(0.0192)
10. Spend on R&D	0.3072***	0.0057***	0.1614
	(0.0583)	(0.0016)	(0.0309)
11. High tech	0.1147	0.0018	0.0425
	(0.0810)	(0.0015)	(0.0300)
12. Patents	0.0190**	0.0003**	0.0088
	(0.0080)	(0.0001)	(0.0037)
13. Copyrights	0.0043***	0.0001***	0.0179
	(0.0013)	(0.0000)	(0.0053)
14. Trademarks	0.0209	0.0003	0.0158
	(0.0163)	(0.0002	(0.0124)
15. Licensing out	1.708***	0.1781***	0.0817
	(0.1220)	(0.0324)	(0.0063)
16. Low-Knowledge IS	0.0806	0.0012	0.0565
	(0.1025)	(0.0016)	(0.0718)
17. High-Knowledge IS	0.2375***	0.0036**	0.2641
	(0.0883)	(0.0016)	(0.0986)
18. Other	0.0032	0.0000	0.0001
	(0.2933)	(0.0042)	(0.0083)
19. Mills Ratio	-3.223***	-0.0455	-1.2356
	(0.6644)	(0.0113)	(0.2577)
20. Constant	-2.731***		
	(0.184)		
No. of Observations	22,264		
Number of groups	4,866		
Wald χ^2	596.41		
p-value	0.0000		

Note: Robust standard errors in parentheses; ***** p < 1%, ** p < 5%, * p < 10%**; Estimates include regional and sector controls and fixed year effects.

4. Results

From Table 2, we see that the model as a whole has good characteristics. For brevity, the main controls, years and regions, which are treated as fixed effects in our estimates, are omitted from Table 2. Full detail is given in supplementary material (Appendix B). Potential problems of sample selection bias and endogeneity have been resolved for the model, and the fit of the model (Wald χ^2) is good (p-value = 0.000), see last two rows in Table 2. We see that *Size* (first row Table 2), which is measured as headcount, is highly significant, and positive, but its marginal effect is small, as is its elasticity. However, *influential* as well as *highly significant* in Table 2 are the variables: *Owners' Equity* (line 6), *Product* (line 8) and *Spend on R&D* (line 10), all with positive elasticities of 0.19, 0.51, and 0.16, respectively. All of these elasticities imply considerable leverage on the probability of adoption of licensing-in. The significance of equity committed to the start-up, the product (rather than a service) significance, and the significance of R&D expenditure, as variables, are all indicative of the resolve of the owner manager to make a success of the start-up.

Also noteworthy is the elasticity of just over a half (0.5072) for the *Product* variable (line 8 in Table 2). It indicates that producing a product, rather than a service, is especially important to the adoption of licensing-in, though a shift in the *Product* variable would not necessarily be an easy strategy for some start-ups to achieve. All the aforementioned elasticities are positive but less than unity. Nevertheless, they do indicate material effects on the probability of licensing-in, which owner managers, and enterprise advisors alike, should take seriously. For example, a 10% increase in the spend on R&D will result in a roughly 2% increase in the adoption of licensing-in, and a 10% increase in owner manager's equity would result in an additional roughly 2% increase in licensing-in adoption. Each, both, or all of these are manageable strategies for most start-ups, which collectively can have a large effect on licensing-in adoption.

We note further that, in Table 2, generally other IP types like *Patents* (line 12), *Copyrights* (line 13) and *Licensing-out* (line 15) also have positive effects on adoption of licensing-in. This view encourages the interpretation of start-ups seeking the best IP *portfolio* composition, Uzuegbunam et al. (2019), rather than just using a single method of protecting its capacity for innovation. Finally, we note the use of high knowledge information methods (see variable *High Knowledge IS*, last line of estimates, Table 2) is positive, highly significant and has one of the largest elasticities (0.26). We note further that the use of *High Knowledge IS* (38%) (ultimate line, Table 1) is much greater than that for *Low Knowledge IS* (24%) (penultimate line, Table 1). *Low Knowledge IS* has a very small elasticity, and is not significant in the probit anyway (see line 16, Table 2) but *High Knowledge IS* is highly significant (see line 17, Table 2), with a relatively large elasticity, suggesting that start-ups take advantage of its higher leverage (in terms of elasticity of response) on adoption of licensing-in. We tested the robustness of our modelling by running the estimates of our model for the economic pre-crisis (2004-2007) and post-crisis (2008-2011) subperiods. Our findings from this were largely very similar for our model e.g. in terms of the magnitudes, signs, and significance of the key variables. Slight differences were that patents were less significant during the crisis period, and PhD students were more significant (and positive).[1]

5. Conclusions

This article provides an econometric analysis of the determinants of licensing-in, using a large sample of US start-ups from the Kauffman Firm Survey. It models a managerial utility-maximizing start-up, using random utility methods. This leads to a panel binary probit specification, estimated by maximum likelihood, which explains the probability of adopting

[1] These estimates are available from the authors on request.

licensing-in by economic and financial variables, IP types and control variables. The article finds that the principal determinants of licensing-in were owner managers' equity, the selling of products (rather than services) and the expenditure on R&D. Further, the start-up's use of high knowledge information was a significant positive determinant of licensing-in adoption. These findings are both economically insightful, as a practical demonstrations of intellectual property reasoning, as well as being useful to advisory bodies like business incubators (of which there are nearly two thousand in the USA), enterprise trusts, development companies etc. whose roles are the support of new businesses and the encouragement of more diverse means of stimulating and protecting innovations within them. This is particularly the case as Ahn et al. (2015) find that SMEs can benefit from open innovation and collaborating with external partners. To facilitate this, as suggested by Lichtenthaler (2011), they need to develop organisational capabilities to manage open innovation, particularly in evading the inefficiencies that currently exist in the markets for new technologies (Gambardella et al. 2007; Gans and Stern 2003). The rapid pace of technological change and high levels of market competition (Pereira et al. 2015; Lee et al. 2017) raise similar contemporary challenges to organizational capabilities of start-ups. To meet the policy challenge of strengthening the technological capabilities of start-up firms it is important that support agencies play a positive role in enabling new start-ups to exploit new technologies in emerging markets, see Vega-Jurado et al. (2009). Further research, building on our modelling, could examine how and why the determinants of licensing-in by start-ups vary by the type of IP acquired.

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Appendix A. Definitions of Variables, Means and Standard Deviations.

Table 1A. Definitions of Variables, Means and Standard Deviations.

Variable	Definition	N	Mean	SD	Min	Max
Size (*c5_num_employees*)	A count of all full-time and part-time employees excluding contract workers and the business owner(s)	24,429	2.9367	6.1482	0	61
Debt *(tot_debt_r*)	Includes total debt of the owner operators and total debt of the business (bank and non-bank debt sources). It is captured on an ordered scale where 0=$0; 1= less than $500; 2=$501-$1,000; 3=$1,001- $2,000; 4=$2,000-$5,000; 5=$5,001 to $10,000; 6=$10,001 to $25,000; 7=$25,001 to $100,000; 8 =$100,001 to $1,000,000; and 9=greater than $1,000,000.	24,483	2.8857	3.1711	0	9
Team of owners (*Recode of c2_owners*)	=1 if a business with more than one owner; = 0 otherwise	24,660	0.3811	0.4856	0	1
Purchased *(Recode of c8_primary_loc)*	=1 if the business operates out of premises which the business purchased; = 0 otherwise	24,650	0.0643	0.2453	0	1
Incorporated (Recode of *c1z_confirm_legal_status)*	=1 if the business is incorporated; = 0 otherwise	24,650	0.6475	0.4777	0	1
Total equity of owners *(tot_equity_owner_operators_r)*	Includes total equity of the owner operators. It is captured on an ordered scale where 0=$0; 1= less than $500; 2=$501-$1,000; 3=$1,001- $2,000; 4=$2,000-$5,000; 5=$5,001 to $10,000; 6=$10,001 to $25,000; 7=$25,001 to $100,000; 8 =$100,001 to $1,000,000; and 9=greater than $1,000,000.	24,387	2.1494	2.8010	0	9
Service (*d1a_provide_service*)	=1 if a business sells a service; = 0 otherwise	24,570	0.8610	0.3459	0	1
Product (*d1b_provide_product*)	=1 if a business sells a product; = 0 otherwise	24,567	0.4861	0.4998	0	1
PhD (Recode of *g9_education_owner*)	Count of owners with PhD degree	25,542	0.0945	0.3608	0	6
Expenditure on R&D (*f19_res_dev*)	=1 if the business spent money on research and development of new products and services during calendar; = 0 otherwise.	24,343	0.1890	0.3915	0	1

High tech *(hightech)*	=1 if 28 Chemicals and allied products, 35 Industrial machinery and equipment, 36 Electrical and electronic equipment or 38 Instruments and related products; = 0 otherwise	25,542	0.1281	0.3342	0	1
Patents (*total_patents*)	Count of patents of the business	24,335	0.1717	1.9919	0	100
Copyrights (*total_copyrights*)	Count of copyrights of the business	24,058	1.4881	12.2427	0	250
Trademarks (*total_trademarks*)	Count of registered trademarks of the business	23,987	0.2809	1.4617	0	100
Out-licensing *(Recode of d4_a_lic_out_patent d4_b_lic_out_copyright and d4_c_lic_out_trademark)*	=1 out-licensing; = 0 otherwise	25,542	0.0039	0.0642	0	1
Licensing -in *(Recode of d5_a_lic_in_patent d5_b_lic_in_copyright and d5_c_lic_in_trademark)*	=1 licensing-in; = 0 otherwise	24,310	0.0573	0.2323	0	1
Manufacturing (reference) (*Recode of naics_code)*	= 1 Manufacturing; = 0 otherwise	25,513	0.1444	0.3415	0	1
Construction (*Recode of naics_code)*	= 1 Construction; = 0 otherwise	25,513	0.0796	0.2707	0	1
Wholesale Retail (*Recode of naics_code)*	= 1 Wholesale and Retail; = 0 otherwise	25,513	0.1436	0.3507	0	1
Low Knowledge IS (*Recode of naics_code)*	= 1 Low KIS; = 0 otherwise	25,513	0.2383	0.4261	0	1
Knowledge IS (*Recode of naics_code)*	= 1 Knowledge Intensive Services= 0 otherwise	25,513	0.3828	0.4861	0	1
Other (*Recode of naics_code)*	= 1 Other; = 0 otherwise	25,513	0.0113	0.1058	0	1
Year 2004 (reference) *(year)*	=1 2004; = 0 otherwise	25,542	0.1928	0.3945	0	1
Year 2005 *(year)*	=1 2005; = 0 otherwise	25,542	0.1593	0.3659	0	1
Year 2006 *(year)*	=1 2006; = 0 otherwise	25,542	0.1407	0.3479	0	1
Year 2007 *(year)*	=1 2007; = 0 otherwise	25,542	0.1254	0.3312	0	1
Year 2008 *(year)*	=1 2008; = 0 otherwise	25,542	0.1100	0.3130	0	1
Year 2009 *(year)*	=1 2009; = 0 otherwise	25,542	0.1014	0.3019	0	1
Year 2010 *(year)*	=1 2010; = 0 otherwise	25,542	0.0900	0.2863	0	1
Year 2011 *(year)*	=1 2011; = 0 otherwise	25,542	0.0801	0.2175	0	1
North East (reference) *(Recode of census_region*)	= 1 North East; = 0 otherwise	24,369	0.1618	0.4377	0	1
Mid-West *(Recode of census_region*)	= 1 Mid-West; = 0 otherwise	24,369	0.2566	0.4367	0	1
South *(Recode of census_region*)	= 1 South; = 0 otherwise	24,369	0.3228	0.4680	0	1
West *(Recode of census_region*)	= 1 West; = 0 otherwise	24,369	0.2588	0.4380	0	1

Note: Data source is the Kauffmann data https://www.kauffman.org/entrepreneurship/research/kauffman-firm-surv.

Appendix B. Panel Probit ML Estimates.

Table 2A. Panel Probit ML Estimates.

Variables	Parameters *β* (Standard error)	Marginal effects dy/dx (Standard error)	Ey/Ex Elasticities
1. Size	0.0118***	0.0002***	0.0974
	(0.0041)	(0.0001)	(0.0342)
2. Debt	0.0104	0.0001	0.0872
	(0.0082)	(0.0001)	(0.0688)
3. Team of Owners	0.1167*	0.0017*	0.1284
	(0.0657)	(0.0010)	(0.0726)
4. Purchased	-0.1834	-0.0021*	-0.0345
	(0.1279)	(0.0010)	(0.0240)
5. Incorporated	0.1011	0.0014	0.1894
	0.0711	(0.0010)	(0.1334)
6. Owners' Equity	0.0310***	0.0004***	0.1915
	(0.0084)	(0.0001)	(0.0525)
7. Service	0.0013	0.0000	0.0031
	(0.0811)	(0.0011)	(0.2033)
8. Product	0.3664***	0.0055***	0.5072
	(0.0588)	(0.0012)	(0.0830)
9. PhD	0.0972	0.0014	0.0270
	(0.0688)	(0.0010)	(0.0192)
10. Spend on R&D	0.3072***	0.0057***	0.1614
	(0.0583)	(0.0016)	(0.0309)
11. High tech	0.1147	0.0018	0.0425
	(0.0810)	(0.0015)	(0.0300)
12. Patents	0.0190**	0.0003**	0.0088
	(0.0080)	(0.0001)	(0.0037)
13. Copyrights	0.0043***	0.0001***	0.0179
	(0.0013)	(0.0000)	(0.0053)
14. Trademarks	0.0209	0.0003	0.0158
	(0.0163)	(0.0002	(0.0124)
15. Licensing out	1.708***	0.1781***	0.0817
	(0.1220)	(0.0324)	(0.0063)
16. Low-Knowledge IS	0.0806	0.0012	0.0565
	(0.1025)	(0.0016)	(0.0718)
17. High-Knowledge IS	0.2375***	0.0036**	0.2641
	(0.0883)	(0.0016)	(0.0986)
18.Construction	-0.3085**	-0.0032***	-0.0712
	(0.1472)	(0.0011)	(0.0341)
19.Wholesale Retail	-0. 0264	-0.0004	-0.0110
	(0.1028)	(0.0014)	(0.0429)
20. Other	0.0032	0.0000	0.0001
	(0.2933)	(0.0042)	(0.0083)
21. West	0.0737	0.0011	0.0558
	(0.0969)	(0.0015)	(0.0734)
22. South	0.1158	0.0017	0.1093
	(0.0932)	(0.0015)	(0.0880)
23. Mid-West	0.1384	0.0021	0.1021
	(0.0948)	(0.0016)	(0.0700)
24. Year 2005	-0.1166*	-0.0015*	-0.0552
	(0.0638)	(0.0008)	(0.0302)

25. Year 2006	-0.1128	-0.0014*	-0.0449
	(0.0704)	(0.0008)	(0.0280)
26. Year 2007	-0.0793	-0.0010	-0.0264
	(0.0756)	(0.0009)	(0.0251)
27. Year 2008	-0.1584**	-0.0019**	-0.0499
	(0.0796)	(0.0009)	(0.0251)
28. Year 2009	-0.1769**	-0.0021**	-0.0512
	(0.0837)	(0.0009)	(0.0243)
29. Year 2010	-0.2706***	-0.0029***	-0.0700
	(0.0920)	(0.0009)	(0.0239)
30. Year 2011	-0.3030***	-0.0031***	-0.0740
	(0.0969)	(0.0008)	(0.0230)
31. Mills Ratio	-3.223***	-0.0455***	-1.2356
	(0.6644)	(0.0113)	(0.2577)
32. Constant	-2.731***		
	(0.184)		
No. of Observations	22,264		
Number of groups	4,866		
Wald χ^2	596.41		
p-value	0.0000		

Note: Robust standard errors in parentheses; *** p < 1%, ** p < 5%, * p < 10%.