

Talent Acquisition and Technology Leadership: A Study of Digital Platforms*

Laureen de Barsy[†] and Axel Gautier[‡]

March 20, 2026

Abstract

This paper traces inventors from firms acquired by Big Tech platforms and identifies those who continue to innovate for the acquiring firm after the transaction. Using matched firm-level data and patent records, we show that inventors whose pre-acquisition work lies closer to the acquirers core technological domains are more likely to remain active innovators within the acquirer. We then explore potential mechanisms underlying this pattern. First, we find that inventors specialized in core technologies are easier for acquirers to evaluate ex ante, which may partly explain their higher post-acquisition retention. Yet, once integrated, these highly skilled core inventors are frequently redirected away from the acquirers core technological fields. Taken together, our results suggest that Big Tech primarily acquires core-technology inventors because their value is easier to assess, not necessarily to keep them focused on those core areas.

1 Introduction

In the digital economy, knowledge is what creates value. As an alternative to internal R&D efforts, companies can generate this knowledge by leveraging the expertise of other firms. When it is patented, knowledge can be accessed through licensing agreements or acquired via patent assignments. It can also be copied (e.g. reverse engineering, industrial espionage). But these are temporary measures, as patents expire and technologies evolve.¹ The talent of

*The authors thank Patrice Bougette, Malka Guillot, Valerio Sterzi, Maren Ulm and Barnabe Walheer for their help and comments. This paper is part of the ARC project on *digital platforms* funded by the University of Liege.

[†]HEC Liège, University of Liège, LCII, Belgium. E-mail: ldebarsy@uliege.be

[‡]HEC Liège, University of Liège, LCII, Belgium and CESifo. E-mail: agautier@uliege.be.

¹[Higgins and Rodriguez, 2006] find that companies facing expiring patents are more likely to engage in mergers and acquisitions.

the people who generated the knowledge, on the other hand, is an asset that can produce a continuous flow of future knowledge. In this paper, we are interested in how firms integrate such talent into their own research teams to access external knowledge.

Directly hiring talent from a competitor is not always easy. Within Silicon Valley, entrepreneurs might fear for their reputation and investor relationships ([Polsky and Coyle, 2013]). Knowledge is also sometimes embedded in a team of people and could dissipate if the team is torn apart ([Jaravel et al., 2018]). Acquiring the entire firm instead could be more efficient in accessing its talent. The practice of acquiring a firm with the main aim to access its know-how and human capital is often referred to as ‘acqui-hiring’ ([Polsky and Coyle, 2013]).²

An acquirer who successfully retains the acqui-hired staff and integrates them effectively can benefit from knowledge transfer and access to expertise.³ The practice allows to quickly onboard an entire team through one transaction ([Kim, 2020]), and to avert knowledge leaks that could accelerate the depreciation of the acquired human capital ([Selby and Mayer, 2013]). Entrepreneurs themselves may also prefer acqui-hiring over defection because selling a startup to a leading company often elevates their status within Silicon Valley ([Polsky and Coyle, 2013]), and because it may be financially advantageous compared to direct talent recruitment due to the favorable tax treatment on capital gains versus compensation income ([Polsky and Coyle, 2013]).⁴

For Alphabet, Apple, Meta, Amazon and Microsoft (aka “Big Tech”), gaining access to the target’s talent is an important driver of start-ups acquisitions. Acquiring the talent from innovative start-ups is a way for incumbents to source knowledge that is critical to maintain an existing technological leadership⁵ ([Puranam et al., 2006]) or, instead, to venture into new product areas where the acquirer’s own experience is limited ([Varian, 2021]). With this pa-

²In an ‘acqui-hiring’ context, the acquiring firm is primarily seeking experience, expertise and engineering talent, not necessarily an existing product ([Varian, 2021]).

³In R&D-intensive industries, the retention of employees tacit knowledge is key ([Grant, 1996]). But there are many reasons why the acquirer might not be able to retain or properly integrate the acqui-hired staff, see for instance [Block et al., 2017]; [Campbell et al., 2012]; [Michaels et al., 2001]; [Ranft and Lord, 2000]; [Ranft and Lord, 2003]; [Seitz and Kopp, 2023] and [Xiao and Dahlstrand, 2023].

⁴Despite these advantages for the parties to the merger, scholars warn of the inefficiencies associated with the concentration of inventors in large incumbents, where their innovative output is expected to be lower than in young firms ([Akcigit and Goldschlag, 2023]), and with “talent hoarding”, when acquisition aims to deprive a competitor in which the startup employees would have been more productive ([Benkert et al., 2023]; [Bryan and Hovenkamp, 2020]) and obtain monopsony power over specialised talent ([Bar-Isaac et al., 2025]).

⁵Such practice could be viewed as a substitute to the - much less desirable - exclusionary practices (e.g. reducing interoperability with the startup’s product or by imitating its main features) in which digital platforms engage to drive startups away from their core market ([Motta and Peitz, 2021], [Motta and Shelegia, 2024]).

per, we aim to provide an empirical analysis of the strategies behind the practice of talent acquisition along these goals of technology leadership and diversification. To do so, we want to go further than testing whether or not the target inventor keeps working at the acquirer’s (like in studies focusing on the retention rate⁶). Instead, we want to study the profiles of inventors who keep *innovating* for their acquirer after acquisition. We ask: Are inventors of technologies in which Big Tech is already strong more likely to further innovate for their acquirer?

To answer this question, we first construct a database of all the firms acquired by Big Tech, which we match to firm-level data from Orbis Global and to patent data from the USPTO PatentsView database. We then develop our analysis at the level of inventors from Big Tech-acquired firms. We identify these inventors from the patents they filed at Big Tech-acquired firms, so we focus on inventors who have filed at least one patent application before being acquired. Among these target inventors, we want to identify those who will develop intellectual property for their acquirer. To do so, we check when the name of an inventor previously filing patents for the target is found after acquisition in a patent filed by the acquirer. And we can test whether this varies with the nature of the innovation developed by the target inventor pre-acquisition. We find that 74% of Big Tech targets are associated with at least one inventor further patenting for their acquirer, and that inventors working pre-acquisition on technologies that are closer to their acquirers “core technologies” (i.e. patented technologies of which a tech giant owns a significant share) are more likely to keep innovating for their acquirer after acquisition.

Next, we test two hypotheses that could explain this result. We first suggest that Big Tech might more easily assess the value of inventors when they work on its core technologies, and hence better exploit their talent, while talented inventors active in technologies outside of their acquirers core business might not be recognised for their true worth. This hypothesis is supported by the finding that, for the latter “non-core” inventors, talent does not translate into a higher probability to keep innovating for their acquirer. However, once acquired, more talented core inventors seem to move away from their acquirers existing core businesses. These results suggest that Big Tech acquires inventors in its core technology fields mainly because it can better assess their value, rather than to maintain their focus on those core technologies.

⁶See for instance [Seitz and Kopp, 2023], who hand-collected data on founders retention, [Xiao and Dahlstrand, 2023], who used employer-employee data of the Swedish high-tech sectors, and [Ranft and Lord, 2003], who ran a survey of managers to identify the retention of key employees.

Related literature

Our paper is related to the literature on the interactions between the technologies of merging firms.

At the product level, theory predicts that the merger between substitute technologies should lead lower ex-post R&D efforts due to the termination of concurrent R&D programs ([Cassiman et al., 2005]), while merging complementary technologies brings about synergies and economies of scope, which should in turn stimulate the R&D process ([Caves, 1989]; [Cohen and Levin, 1989]; [Röller et al., 2006]). At the firm level, empirical studies of high-tech industries usually find that the greatest innovative output occurs when there is a high degree of overlap in the technological profiles between the acquirer and the target ([Cloudt et al., 2006]; [Kapoor and Lim, 2007]). However, in the case of Big Tech acquisitions, the acquirer is disproportionately bigger than its target so the effect on the aggregated R&D output is unlikely to be observable. What can be observed, instead, is what happens to the acquired knowledge, and how this relates to the ex-ante technological similarities between the acquirer and the target.

Mergers and acquisitions are a crucial means for both enhancing and diversifying a firm’s internal knowledge base ([Rosenkopf and Almeida, 2003], [Zheng et al., 2021]). The acquisition of related firms complements the acquirer’s internal knowledge base, whereas acquiring unrelated firms broadens the scope of knowledge ([Lodh and Battaglion, 2015]). Case studies of Big Tech acquisitions usually find that acquirers are strengthening their own segments. For instance, [Argentesi et al., 2021] find that acquisitions by Meta and Amazon focus on areas of economic activity in which they are already strong. Similarly, [Gautier and Lamesch, 2021] find that Microsoft, Amazon and Apple mostly acquire products targeted to their main user segment. This might be explained by the fact that companies with a technologically similar patent portfolio can better integrate the target’s knowledge ([Ahuja and Katila, 2001]; [Arts et al., 2021a]; [Cassiman and Veugelers, 2006]). Similarly, technological similarities between the acquirer and the target are expected to play a role in the future of acquired inventors.

On the one hand, the acquisition of smaller firms brings in specialized expertise and talent

that can help the acquirer expand to areas where it has limited experience ([Varian, 2021]). On the other hand, the acquirer might better assess and integrate new ideas when the acquired inventors’ expertise aligns with its existing R&D portfolio. In an empirical study in the field of biotechnology, [Verginer et al., 2022] find that inventors who operate within the same patent classes as their acquirer tend to maintain higher productivity levels following the acquisition. In addition, from the inventor’s perspective, an expertise distinct from that of the acquiring firm could be more valued outside of the merged entity and hence increase the likelihood of departure post-acquisition ([Verginer et al., 2022]). With this paper, we want to test how the findings of this literature extend to the digital world, and whether Big Techs target inventors whose expertise aligns with their acquirer’s existing R&D portfolio are more or less likely to keep innovating for their acquirer.

We describe the construction of our dataset and the variables of interest at the firm, inventor and technology levels in Section 2. Section 3.1 sets up our research questions and empirical strategies, of which Sections 4.1 and 4.2 discuss some extensions. Section 5 concludes.

2 Data

2.1 Firms’ characteristics

We identify firms acquired by Big Tech and the dates at which their acquisitions were announced from four different databases: Standard & Poors CapIQ (2022), Geoff, Marshall and Parker (2021), [Gautier and Lamesch, 2021], and the US Patent and Trademarks Office (USPTO) Patent Assignment Dataset (2022). On this basis, we identify 859 firms acquired by Big Tech between January 1996 and January 2021.

Firm level data is collected from the Orbis Global database. Out of the 859 Big Tech-acquired firms that we identified, 395 can be found in Orbis Global.⁷ We collect information on the firm’s country of origin, number of employees, incorporation date, and funding amount. Orbis contains some missing values for the number of employees and the funding amount; we add an online search step to try and fill them in. Table 1 presents some summary statistics on the obtained dataset.

⁷Targets that are located in Asia, Canada or South America are less likely to be found in Orbis, as well as targets acquired before 2006.

The distribution of the number of employees and of the funding data is highly skewed (see Appendix A). To better capture the information contained in the number of employees data, we define a variable $FirmSize^T$ based on the OECD thresholds: small firms with < 50 employees, medium firms with $[50; 250[$ employees, and large firms with ≥ 250 employees. Similarly, we split the sample into three categories based on the quantiles of the funding data: $Funding^T \in \{\leq \$230M;]\$230M, \$1,730M]; > \$1,730M\}$.

Table 1: Big Tech acquired firms

	Origin		EmplNbr			Funding (\$1M)			Incorp	
	obs.	US = 1	obs.	Mean	SD	obs.	Mean	SD	obs.	[min,max]
AMZN	45	76%	24	3877	17716	24	1570	7306	47	1978, 2020
APPL	59	58%	38	708	86	49	56	130	61	1992, 2019
FCBK	50	62%	28	194	797	28	24	45	53	1989, 2020
GOOG	107	76%	59	422	2472	56	143	596	112	1967, 2020
MSFT	121	73%	60	293	1237	65	259	1516	122	1978, 2019
TOTAL	382	71%	209	687	6186	222	297	2553	395	1967, 2020

This table presents some summary statistics on Big Tech targets matched with Orbis data. $US = 1$ when the Orbis variable *CountryISOcode* is associated with the value "US", *EmplNbr* is the value taken by the Orbis variable *Numberofemployees* in the year before acquisition, and *Funding* is the sum of the Orbis variable *Shareholdersfunds* up to the year before acquisition.

2.2 Inventors' characteristics

To collect information on inventors acquired by Big Tech, we will be using the content of patent documents, with a focus on US patents filed by Big Tech platforms (i.e. the acquirers) and by Big Tech-acquired firms (i.e. the targets). Patents are attributed to the acquirer if they are filed under the acquirer's name, or if they are filed under the target's name after acquisition.⁸

Patent data is collected from the USPTO PatentsView database (e.g. patent number, patent date, application identifier, publication author, CPC technology field and inventor's names⁹). Out of the 859 identified Big Tech's targets, 252 have filed at least one patent

⁸Around 5% of the patents associated with a target's name are filed after acquisition. In a robustness check, we will further only attribute to the acquirer those patents filed under the acquirers name.

⁹Harmonized inventors' names can be found at <https://patentsview.org/download/data-download-dictionary>.

application before being acquired.

2.2.1 Patent information

The USPTO PatentsView database contains patent-level data (see Appendix B for descriptive statistics) that can be used to describe the profiles of target inventors. We construct the following variables at the inventor-level:

- the total number of patents in which the inventor is listed,
- the number of patents in which the inventor is listed as first author,
- the number of patents originating from the US in which the inventor is listed,
- the number of patents in which the inventor is listed together with some co-author,
- the number of months since the inventors first filing before acquisition,
- the number of months since the inventors last filing before acquisition.

These variables are constructed over all the patents filed by a given inventor for the target firm.

2.2.2 Technology leadership

We aim to determine whether the acquired inventor was working on a technology in which her acquirer is focusing its own innovative efforts. To do so, we identify technologies belonging to her acquirer’s “core” fields in the year of acquisition.

Core technologies are patented technologies of which a tech giant owns a significant share. This is translated in our patents context as: a significant share of the total number of patents classified in that technology field. So core technologies are defined based on the relative frequency at which they appear in a tech giant’s patent portfolio.

The technology fields to which a patent belongs is recorded in the CPC classification, which contains 131 subsections at the two-digits level.¹⁰ To identify Big Tech “core” fields, we first compute, at the yearly level, the number of patents classified in each of the 131 cpc subsections across the whole USPTO patent database. Next, we compute the share represented by each tech giant’s portfolio in these respective subsections.¹¹ We consider that a

¹⁰See detailed list: <https://www.uspto.gov/web/patents/classification/cpc/html/cpc.html>

¹¹Most Big Tech’s patents are classified in the Physics Section, e.g. ‘Computing; Calculating or Counting’ (CPC G06).

given cpc subsection represents a Big Tech core technology field, in a given year, if the Big Tech’s portfolio contains at least 1%¹² of all occurrences of that technology in that year. Because big tech platforms might change the fields in which they specialize over time, this definition allows a dynamic setting in which we can identify whether the acquired technology belongs to a core field at the time of acquisition.

Based on this information at the patent-level, we can construct a variable $\overline{Core}_i$ at the inventor-level, defined as the share of core fields averaged across all the patents filed by inventor i :

$$\overline{Core}_i = \frac{1}{P} \sum_p \frac{1}{F} \sum_f I_{f,p,i}$$

where $I_{f,p,i} = 1$ if a given field f listed in the patent p filed by the inventor i is associated with at least one of the acquirer’s core fields in the year of acquisition.

On average, 34% of the fields listed in patents filed by a target inventor belong to one of her acquirer’s core technologies at the time of acquisition. However, we observe very high peaks on the upper and lower bounds of the distribution of the $\overline{Core}_i$ variable: out of 4,966 target inventors,¹³ 1,077 (22%) are associated exclusively with core technologies, and 2,573 (52%) are not associated with any core technology.

For this reason, we also construct a binary variable $Core_i$, capturing whether an inventor i is active in her acquirer’s core technology fields:

$$Core_i = \max I_{p,i}$$

where $I_{p,i} = 1$ if a given patent p filed by the inventor i is associated with at least one of the acquirer’s core fields in the year this patent was acquired.¹⁴

¹²Based on this threshold, half of the acquired patents are associated with a Big Tech core technology.

¹³Out of the 5,056 inventors from firms acquired by Big Tech between 1996 and 2021, 90 are only listed in Reissue or Design patents, which are not associated with information on the patent’s CPC classification. So the variable $\overline{Core}_i$ can be constructed for 4,966 inventors.

¹⁴See Appendix C for statistics on $Core$ aggregated at the target level.

2.2.3 Market value

We construct a proxy for market value based on three indicators of a patent’s economic value: family size, grant lag and number of claims. The definitions of these variables and the reasoning behind their inclusion in the market value index are presented in Appendix D.

To construct the market value index, we propose two approaches. First, we define a simple linear combination of the three indicators of a patent’s value. By taking the average value¹⁵ of this linear combination for all the patents p filed by a given inventor i , we can define a first measure of the market value of the inventor’s innovation history:

$$MarketVal_i = \frac{1}{P} \sum_p \{FamilySize_p - GrantLag_p + AdjClaims_p\} \quad (a)$$

This index is further normalized such as to be comprised between 0 and 1 by min/max scaling.¹⁶

To improve on this first definition, we propose a second approach. We define a vector that captures as much as possible of the variation in the data along the three indicators of a patent’s value. We thus intend to approximate our 3-D value space by a linear combination of all 3 (normalized) indicators along which the spread of patents is maximised. This vector is computed using a *Principal Components Analysis*, as described in Appendix E. By taking the total value of this vector for all the patents p filed by a given inventor i , we can define a second measure of the market value of the inventor’s innovation history:

$$MarketVal_i = \sum_p \{ev^1 \widetilde{FamilySize}_p + ev^2 \widetilde{GrantLag}_p + ev^3 \widetilde{AdjClaims}_p\} \quad (b.1)$$

where ev^x are the coordinates of the vector.

In other words, the value of the inventor’s innovation history is computed as the weighted

¹⁵In this simple definition of the index, the three indicators of a patent’s value have not been normalised, so indicators with higher expected values have more weight. The indicator with the highest weight is the family size: $E[FamilySize] > E[GrantLag] > E[AdjClaims]$. Aggregating by taking the mean value across all the patents filed by a given inventor ensures that we are not artificially boosting the index for inventors associated with proportionally higher levels of the family size variable.

¹⁶Min/max scaling: $\tilde{X} = (X - \min(X)) / (\max(X) - \min(X))$.

sum of all the patents filed by this inventor pre-acquisition, where the weights capture these patents' market values. Because this definition allows to maximise the variation in our data, i.e. to best differentiate inventors based on their innovation history, we will use it as the baseline definition of the market value index.

Two important methodological choices have been made to construct this index. First, the summation over all the patents filed by a given inventor means that prolific inventors (i.e. filing many patents) will be on average associated with a higher market value. The reasoning behind this choice is that the more patents over which an inventor can be observed, the more information the acquirer can obtain about her innovation history. However, this choice implies a size effect that inflates the market value index for more productive inventors. For this reason, we also propose an alternative index by taking the *average* value of the vector for all the patents filed by a given inventor:

$$MarketVal_i^{bis} = \frac{1}{P} \sum_p \{ev^1 \widetilde{FamilySize}_p + ev^2 \widetilde{GrantLag}_p + ev^3 \widetilde{AdjClaims}_p\} \quad (b.2)$$

A second methodological choice in the definition of our market value index is the exclusion of a variable capturing the technological importance of a patent for the development of subsequent technologies; the number of citations it receives (forward citations). This is because forward citations are a stock that builds over time, so patents published at different times cannot be compared. To overcome this problem, we propose to consider the number of forward citations received by a patent *over a period of five years* after its publication date. This means that this variable can only be used for patents published at least five years before the end of our study period (in July 2022), so in July 2017. Because publication typically occurs around 18 months after the filing date ([Squicciarini et al., 2013]), we restrict this third specification of our market value index to patents filed - and hence inventors acquired - before January 2016. Forward citations are added to the market value index linearly:

$$MarketVal_i^{ter} = \sum_p \{ev^{t1} \widetilde{FamilySize}_p + ev^{t2} \widetilde{GrantLag}_p + ev^{t3} \widetilde{AdjClaims}_p + ev^{t4} \widetilde{FwdCit}_p\} \quad (b.3)$$

2.2.4 Talent acquisition

Our main variable of interest captures whether an inventor keeps patenting for her acquirer after acquisition. We collect information on the unique inventor id(s) in the target’s patent portfolio, and check whether these same id(s) can be found in the acquirer’s portfolio after acquisition: $Talent_i = 1$ if an inventor’s id i in the target’s patent portfolio can be found in the acquirer’s portfolio.¹⁷ This allows us to identify inventors who keep patenting for their acquirer. Those inventors who don’t ($Talent_i = 0$) could have either stopped patenting altogether after the acquisition, or they could be patenting for some other firm; in both cases, they are not developing intellectual property for their acquirer.¹⁸

This measure can be further refined to better capture potential synergies deriving from acquisition by focusing on cases where newly hired inventors collaborate with the acquirer’s staff: $Talent_i^* = 1$ if the acquirer’s portfolio contains a patent associated with an inventor’s id i from the target’s portfolio together with an inventor’s id from a patent published by the acquirer pre-acquisition.

From Appendix F, we can see that, in 74% of cases, at least one start-up inventor will be further patenting for their acquirer and, in 49% of cases, they do so in collaboration with some of their acquirer’s existing employees. After normalizing by the total number of inventors, we can also see that inventors hired at Facebook’s are proportionally more likely to keep developing patented technologies than inventors hired at Google’s or Microsoft’s.

2.3 Working sample

We describe in Table 2 below the profiles of target inventors at the time of their acquisition by a tech giant, separately for inventors who will keep innovating for their acquirer (i.e. who will file some patent for their acquirer after acquisition) and those who won’t.

¹⁷Some inventors (< 1% sample) filed patents for different targets pre-acquisition. For these inventors, we consider only their last employer (i.e. the target for which they last filed a patent) before acquisition.

¹⁸Let us note that using patent data to identify target inventors suffers from a limitation; it only captures inventors who publish patents. Some technologies might not be patented, because they are simply not patentable, or due to a low probability of imitation and/or high costs of patenting.

Table 2: Statistics over all the patents filed by Big Tech-acquired inventors

	Stop innovating 3293 (65.13%)	Keep innovating 1763 (34.87%)	Test
Patents (Total)	8559	6950	.
Patents over last 9m (Total)	714	1388	.
Patents (Mean)	2.60 (5.59)	3.94 (6.12)	<0.00
Patents over last 9m (Mean)	1.33 (0.74)	1.98 (2.86)	<0.00
First author patents (%)	0.55 (0.46)	0.58 (0.43)	0.05
First author patents over last 9m (%)	0.47 (0.48)	0.54 (0.46)	0.01
Core patents (%)	0.44 (0.48)	0.49 (0.49)	<0.00
Core patents over last 9m (%)	0.57 (0.49)	0.53 (0.49)	0.14
Market value (Mean)	-0.04 (0.08)	-0.05 (0.18)	0.18
Market value over last 9m (Mean)	-0.04 (0.08)	-0.05 (0.19)	0.02
US patents (%)	0.83 (0.38)	0.79 (0.41)	<0.00
US patents over last 9m (%)	0.82 (0.39)	0.74 (0.44)	0.00
Co-authored patents (%)	0.94 (0.22)	0.94 (0.20)	0.78
Co-authored patents over last 9m (%)	0.95 (0.21)	0.95 (0.21)	0.79
Months between first filing and acquisition	52.02 (38.06)	40.33 (32.10)	<0.00
Months between last filing and acquisition	40.00 (34.31)	22.21 (22.74)	<0.00

Mean (Standard deviation): p-value from a pooled t-test.

Frequency (Percent%): p-value from Pearson test.

This table presents patent statistics at the inventor-level. Negative average Market values come from the fact that patents filed by Big Tech-acquired inventors are less valuable than the average patent in the USPTO database. However, acquired patents are different in many respects from the average patent. The market value index should not be used to compare inventors across the whole patent database. Instead, we will be using it to compare acquired inventors among themselves.

Out of the 5,056 inventors from firms acquired by Big Tech between 1996 and 2021, 1,763 (35%) will file some patent for their acquirer after acquisition. Interestingly, we observe that inventors who keep innovating for their acquirer had filed on average more patents pre-acquisition, so they were on average more prolific than inventors who stop patenting after acquisition. They were also more often identified as “first author” of the patent, indicating a lead over the research project, and had filed, on average, more patents originating from outside the United States. In addition, these inventors who keep patenting for their acquirer appear to have started filing patents for the target later in time, so they could be considered more “junior” inventors. Finally, they tend to file their last patent for the target closer to the acquisition date, which is a sign that they were still active short before acquisition.

3 Innovating for the acquirer

In this section, we will examine the question of whether and why inventors of Big Tech core technologies (i.e. who have filed some “core” patents) are more likely to further innovate for their acquirer. To do so, we want to isolate the effect of working on a core technology from other potential determinants of whether a target inventor keeps innovating for her acquirer.

We consider the following inventor’s characteristics (at the time of acquisition): the number of patents filed by the inventor for the target, whether the inventor has filed some patent as first author - since “lead” engineers are more likely to have been the targets of the acquirer - and whether the inventor has filed some patent originating from the US. We also include the inventor’s first patent filing - as a proxy for how experienced she is - and her last filing before acquisition - which captures whether the inventor was still active at the time of acquisition. Finally, the outcomes of interest (*Talent* and *Talent**) are constructed based on whether an inventor was *ever* found in her acquirer patent portfolio after acquisition. The period over which these outcomes are measured thus varies depending on the time at which the inventor joins the acquirer’s team (i.e. the acquisition date). For this reason, we must control for the length of the period over which the outcome is measured; the number of months between acquisition and the end of the study period (in July 2022). In a robustness check, we will propose a more conservative approach with regard to the comparability of the outcome across inventors by defining a fixed study period.

First, we test whether the technological environment in which Big Tech acquisitions take place influences talent engagement (Section 3.1). We find that inventors working pre-acquisition on technologies in which their acquirer has been focusing its own innovative efforts are more likely to keep innovating for their acquirer after acquisition. Second, we will evaluate two hypotheses that could explain this finding: i. Big Tech could more easily assess the value of inventors when they work on its core technologies (Section 4.1), ii. Big Tech could be acquiring talent with the aim to have more people working on these core technologies in its research team (Section 4.2).

3.1 Baseline - Inventors of Big Tech core technologies

In this section, we want to explore the role of Big Tech technology leadership on the likelihood for acqui-hired inventors to further innovate for their acquirer. Studies such as [Argentesi et al., 2021]

and [Gautier and Lamesch, 2021] suggest that acquirers focus on reinforcing their existing segments. Conversely, Big Tech may acquire smaller firms to leverage specialized expertise and talent for expansion into peripheral activities ([Varian, 2021]). With this baseline analysis, we aim to test empirically whether inventors of technology fields in which Big Tech is already strong are more likely to further innovate for their acquirer.

We consider all inventors of Big Tech-acquired technologies. Among these target inventors, we identify those who keep innovating for their acquirer from the patents they file post-acquisition. The outcome variable $Talent_i = 1$ when the inventor i 's id can be found in her acquires patent portfolio after acquisition, 0 otherwise. The probability for a start-up inventor to file some patent for her acquirer is modelled as follows:

$$P(Talent_i = 1) = F \left(\alpha + \beta Core_i + \tau MSinceAcqui_i + \sum_k \gamma_k X_{i,k} + \sum_l \zeta_l Y_{i,l} + \mu BT_i \right) \quad (1)$$

where $F(z) = \frac{e^z}{(1+e^z)}$ is the cumulative logistic distribution.

The regressor of interest ($Core_i \in \{0, 1\}$) captures whether inventor i has filed some patent belonging to one of her acquirer's core technology fields (i.e. fields of which the acquirer owns at least 1% of all published patents) by the time of acquisition. $MSinceAcqui_i$ captures the number of months between acquisition and the end of the study period. Inventor-level controls X_i include the number of patents filed by the inventor for the target ($PatentsCount_i$), the year in which the inventor filed a patent for the first time ($FirstFiling_i$), whether the inventor filed a patent originating from the United States ($US_i \in \{0, 1\}$), whether the inventor filed some patent as first author ($FirstAuthor_i \in \{0, 1\}$), and the number of months since the inventor's last patent filing for the target ($MSinceLastFil_i$). We also include the acquirer's identity fixed effects ($BT_i \in \{GOOG, APPL, FCBK, AMZN, MSFT\}$). Target-level controls Y_i include the firm's incorporation year ($Incorp_i^T$), country of origin ($US_i^T \in \{0, 1\}$), number of employees ($FirmSize_i^T \in \{< 50, [50; 250[, \geq 250\}$), and funding amount category ($Funding_i^T \in \{\leq \$230M;]\$230M, \$1,730M\}; > \$1,730M\}$).

Estimates

The parameters of Model (1) estimated by Maximum Likelihood can be found in Table ?? when the outcome variable is defined based on all target inventors found in the acquirers portfolio after acquisition ($Talent_i$), and in Appendix G when the outcome variable only considers those target inventors collaborating with some of their acquirers employees after acquisition ($Talent_i^*$). We see that having filed a core patent is positively associated with the probability of further patenting for the acquirer.

The β parameters can be more easily interpreted in odds ratios (e^β). If we look at the most complete model in Table ?? (last column), we have $e^{\hat{\beta}} = 1.76^{***}$; the odds of further patenting for the acquirer are about 76% greater for inventors active in their acquirer's core technology fields at acquisition. From Appendix G, we see that these inventors are also on average more likely ($e^{\hat{\beta}} = 1.59^*$) to further patent for their acquirer in collaboration with some of the acquirers existing employees.

Table 3: Inventors innovating for their acquirer, Model (1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent											
Core	0.543*** (8.22)	0.495*** (7.37)	0.417*** (6.07)	0.360*** (5.09)	0.313*** (3.50)	0.291*** (3.19)	0.292*** (3.19)	0.452*** (3.82)	0.445*** (3.73)	0.510*** (3.54)	0.563*** (3.66)
MonthsSinceAcqui	0.010*** (14.46)	0.010*** (15.40)	0.027*** (19.06)	0.027*** (18.61)	0.029*** (19.02)	0.012*** (6.72)	0.013*** (7.11)	0.017*** (7.83)	0.017*** (7.83)	0.019*** (7.97)	0.020*** (8.04)
PatentsCount		0.069*** (9.11)	0.105*** (11.79)	0.105*** (11.63)	0.105*** (11.57)	0.040*** (4.66)	0.034*** (4.09)	0.035*** (3.73)	0.036*** (3.75)	0.032*** (3.41)	0.032*** (3.37)
FirstFiling			0.180*** (13.92)	0.182*** (13.40)	0.187*** (13.55)	-0.022 (-1.14)	-0.011 (-0.56)	-0.018 (-0.83)	-0.018 (-0.83)	-0.034 (-1.40)	-0.038 (-1.56)
US				-0.432*** (-5.22)	-0.260*** (-3.02)	-0.227** (-2.57)	-0.227** (-2.56)	-0.264** (-2.08)	-0.014 (-0.03)	-0.106 (-0.24)	-0.610 (-1.09)
MonthsSinceLastFiling						-0.030*** (-14.17)	-0.029*** (-13.74)	-0.030*** (-12.79)	-0.030*** (-12.78)	-0.034*** (-12.93)	-0.036*** (-13.08)
FirstAuthor							0.294*** (4.21)	0.334*** (4.31)	0.334*** (4.32)	0.272*** (3.23)	0.266*** (3.10)
Incorp ^T								0.009 (1.04)	0.009 (1.02)	-0.014 (-1.34)	-0.018* (-1.65)
US ^T									-0.255 (-0.67)	-0.064 (-0.15)	0.358 (0.68)
FirmSize ^T										-0.568*** (-7.31)	-0.611*** (-5.28)
Funding ^T											0.082 (0.67)
Constant	-1.841*** (-20.31)	-2.114*** (-21.88)	-365.246*** (-14.00)	-369.611*** (-13.46)	-378.974*** (-13.61)	43.302 (1.11)	20.953 (0.53)	15.684 (0.35)	15.850 (0.35)	94.411* (1.89)	112.447** (2.19)
Observations	4966	4966	4966	4806	4806	4806	4806	4051	4051	3593	3519
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

^t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.2 Robustness checks

To test for the robustness of our results, we replicate our baseline analysis with alternative definitions of the dependent (*Talent*) and independent (*Core*) variables. The parameter of Model (1) estimated based on this alternative specification are presented in Appendix I.

3.2.1 Alternative definitions of the dependent variable

Fixed observation period To better ensure the comparability of the outcome of interest (*Talent* or *Talent**) across all inventors, we propose to construct the analysis based on a fixed time period. The idea is that the period over which we test whether a target inventor is found in her acquirer patent portfolio would be the same for all inventors.

We choose to define $Talent_i = 1$ when the inventor i 's id can be found in her acquires patent portfolio within 4 years after acquisition ($Talent_i = 0$ if she never patents for her acquirer *or* if she does so more than 4 years after acquisition). We thus ignore all inventors who were acquired less than 4 years before the end of the data collection in July 2022. So we consider inventors acquired up until July 2018.¹⁹

Just like for the baseline estimates, we find that inventors active in their acquirer's core technology fields are on average more likely to further patent for their acquirer, and the effect is even larger: the odds of further patenting for the acquirer are about 2.61 times greater for inventors active in their acquirer's core technology fields (see Table 12).

Two months buffer after acquisition As a second robustness check, we want to accommodate a period during which uncertainty persists regarding the patented technology investigator (whether still target or already acquirer).

We choose to define $Talent_i = 1$ when the inventor i 's id can be found in her acquires patent portfolio from two months onwards after acquisition ($Talent_i = 0$ if she never patents for her acquirer *or* if she does so less than two months after acquisition).

¹⁹This 4 years threshold also allows to account for an observed drop in the probability to further patent for the acquirer when acquired after 2018 (see Appendix H). This can partially be explained by the fact that the USPTO PatentsView data covers granted patents, so the most recent patents are less likely to be observed simply because they might not be granted yet.

On this basis, we observe that inventors active in their acquirer’s core technology fields are 2.16 time more likely to further patent for their acquirer (see Table 14). So our previous results are also robust to this alternative specification.

Inventors filing under the acquirer’s name So far, we have included in the acquirer’s portfolio all the patents filed under the acquirer’s name *or* under the target’s name after acquisition. This means that an inventor who keeps filing patents under her target’s name after acquisition is considered as patenting for her acquirer. Of all the inventors associated with $Talent_i = 1$ in our baseline analysis, 19% have not filed any patent under their acquire’s name.

One could argue that inventors who don’t use their acquirer’s name when filing a patent after acquisition are not fully integrated whithin their acquirer’s research lab. Instead, they stay somehow more independent and this might go along with a research history that is more distant from their acquirer’s core fields, which might drive our β estimates downwards. For this reason, we propose to check for the robustness of our results to restricting $Talent_i = 1$ to those target inventors filing some patents under their acquirer’s name.

The outcome of this alternative specification confirms our intuition, as the β estimates appear even larger than in the baseline analysis: inventors active in their acquirer’s core technology fields are on average 2.93 times more likely to further patent under their acquirer’s name after acquisition (see Table 16).

3.2.2 Alternative definitions of the independent variable

Inventors of core technologies within a year As an additional robustness check, we want to test whether our results hold when using an alternative definition of the regressor of interest; instead of capturing whether an inventor has *ever* filed some patent belonging to one of her acquirer’s core technologies, $Core_i \in \{0, 1\}$ will now capture whether she does so *within a year* before acquisition.

Our results show that the coefficient associated with $Core_i$ is still positive, but it is no longer statistically significant for the more complete model specifications (see last columns of the regression output in Table 18). This absence of statistical significance could be explained by the reduced sample size; only 852 inventors (17% of inventors from Big Tech targets) have been active in their acquirer’s core technology fields within a year of their acquisition. So

statistical power might not be sufficient to estimate the most complete versions of our model (i.e. including all control variables).

Core technologies defined at the 3-digit level We define Big Techs core technologies based on the relative frequency at which those technologies appear in Big Techs patent portfolios. For our baseline analysis, we computed the number of patents classified in each cpc subsection at the two-digits level (CPC section symbol followed by a two-digit number, e.g. G06 for ‘Computing; Calculating or Counting’). With this robustness check, we propose a more precise mapping by narrowing the definition to the three-digit level (e.g. G06F for ‘Electric Digital Data Processing’). Using this alternative definition of core technologies, the variable *Core* can be constructed in the same way as before (see Section 2.2.2).

In Table 20, we see that our main results are robust to this alternative definition; inventors active in their acquirers core (3-digit) technology fields are 1.62 time more likely to further patent for their acquirer.

4 Extension: Assessing potential explanations for our baseline results

In the previous section, we found that inventors working pre-acquisition on technologies in which their acquirer is focusing its own innovative efforts are more likely to keep innovating for their acquirer after acquisition. In this section, we examine two potential explanations for this finding.

4.1 1st hyp.: Inventors of core technologies are more easily assessed

Could Big Tech more easily assess the value of inventors when they work on its core technologies, and hence better exploit their talent, which would explain that these inventors are more likely to stay active after acquisition?

To examine this first hypothesis, we use the $MarketVal_i$ index to proxy for the value of inventor i s innovation history (i.e. the market value of the patents this inventor filed pre-acquisition, as defined in Section 2.2.3). Next, we rewrite Model (1) to allow the effect of this value index on the probability for the inventor to keep innovating for her acquirer to vary

depending on whether the inventor has filed some core patent ($Core_i$):

$$P(Talent_i = 1) = F(\alpha' + \beta_1 Core_i + \beta_2 MarketVal_i + \beta_3 Core_i MarketVal_i + \tau' MSinceAcqui_i + \sum_k \gamma'_k X_{i,k} + \sum_l \zeta'_l Y_{i,l} + \mu' BT_i) \quad (2)$$

We observe that patents filed by target inventors working on core technologies are on average more valuable than patents filed by target inventors working on peripheral technologies. For inventors associated with $Core_i = 1$, the odds ratio for a one-unit increase in the value of their innovation history is $e^{\beta_2 + \beta_3}$, for those with $Core_i = 0$ it is e^{β_2} .

Estimates

The parameter estimates of Model (2) are presented in Table 4. Based on the baseline definition of the $MarketVal_i$ index (see equation (b.1)), we estimate that, for inventors active in technologies outside of their acquirers core business ($Core_i = 0$), a history of more valuable patents does not translate into a higher probability to keep innovating for their acquirer; they actually have 97% fewer chances to do so ($e^{\hat{\beta}_2} = .03^{***}$) for each unit increase in their innovation value.

The coefficient associated with $MarketVal_i$ captures two mechanisms: inventors who stay at their acquirer's are expected to be more likely to further patent if they have a more valuable innovation history, but a more valuable innovation history might also help them find another job more easily at some other firm's. Based on our results, the latter mechanism seems to be stronger for non-core inventors. In Appendix N, we can see that these results are robust to using the alternative definitions of the market value index (see equations (a), (b.2) and (b.3)).

These findings suggest that talented inventors active in technologies outside of their acquirers core business might not be recognized for their true worth at their acquirer's. Instead, a history of more valuable patents might help them find another job in which their talent could be better exploited. This corroborates the hypothesis according to which being better assessed by their acquirer partly explains why inventors of core technologies are more likely to keep innovating for their acquirer.

A question that naturally arises from this result is whether these inventors of valuable core technologies are expected to keep working in similar technology fields after acquisition. Is Big Tech hiring experts because it wants to develop their areas of expertise, or is it hiring

Table 4: Inventors innovating for their acquirer, Model (2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent											
Core=1	0.646*** (8.94)	0.560*** (7.67)	0.510*** (6.81)	0.474*** (6.20)	0.433*** (4.63)	0.381*** (4.01)	0.376*** (3.95)	0.564*** (4.55)	0.559*** (4.49)	0.612*** (4.11)	0.687*** (4.30)
Market Value	-1.686*** (-3.66)	-0.968** (-2.08)	-2.296*** (-4.53)	-2.660*** (-5.13)	-3.632*** (-6.76)	-2.592*** (-4.84)	-2.424*** (-4.52)	-2.561*** (-4.33)	-2.560*** (-4.33)	-3.223*** (-5.11)	-3.358*** (-5.23)
Core=1 $\times$ Market Value	2.072*** (3.86)	1.318** (2.41)	1.940*** (3.32)	2.453*** (4.10)	3.436*** (5.57)	2.843*** (4.69)	2.717*** (4.48)	3.395*** (4.97)	3.392*** (4.97)	3.662*** (5.18)	3.860*** (5.37)
MonthsSinceAcqui	0.009*** (13.87)	0.010*** (14.87)	0.028*** (19.23)	0.029*** (18.87)	0.031*** (19.46)	0.014*** (7.30)	0.014*** (7.58)	0.018*** (8.09)	0.018*** (8.09)	0.021*** (8.46)	0.022*** (8.54)
PatentsCount		0.066*** (8.60)	0.101*** (11.29)	0.100*** (11.09)	0.099*** (10.90)	0.037*** (4.34)	0.032*** (3.83)	0.031*** (3.38)	0.032*** (3.39)	0.030*** (3.22)	0.030*** (3.21)
FirstFiling			0.196*** (14.46)	0.200*** (14.04)	0.212*** (14.49)	0.002 (0.09)	0.010 (0.48)	0.001 (0.04)	0.001 (0.04)	0.004 (0.15)	0.004 (0.14)
US				-0.455*** (-5.44)	-0.257*** (-2.94)	-0.218** (-2.43)	-0.217** (-2.42)	-0.262** (-2.06)	-0.091 (-0.23)	-0.245 (-0.56)	-0.731 (-1.30)
MonthsSinceLastFiling						-0.029*** (-13.54)	-0.028*** (-13.20)	-0.029*** (-12.45)	-0.029*** (-12.44)	-0.033*** (-12.24)	-0.034*** (-12.34)
FirstAuthor							0.260*** (3.67)	0.299*** (3.82)	0.300*** (3.82)	0.224*** (2.62)	0.214** (2.45)
Incorp ^T								0.012 (1.27)	0.012 (1.26)	-0.012 (-1.13)	-0.018 (-1.60)
US ^T									-0.174 (-0.46)	0.029 (0.07)	0.485 (0.91)
FirmSize ^T										-0.589*** (-7.48)	-0.597*** (-5.08)
Funding ^T											0.039 (0.32)
Constant	-1.896*** (-19.84)	-2.127*** (-21.21)	-397.615*** (-14.54)	-406.559*** (-14.10)	-429.059*** (-14.54)	-4.857 (-0.12)	-21.036 (-0.51)	-27.318 (-0.57)	-27.166 (-0.57)	15.161 (0.29)	27.368 (0.50)
Observations	4880	4880	4880	4720	4720	4720	4720	3967	3967	3509	3435
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the best talents, regardless of their specialization, to further expand into peripheral fields? This question will be examined in the next section.

4.2 2nd hyp.: Big Tech acquires talent to improve its core technologies

We have argued so far that inventors of core technologies can be better assessed by their potential acquirer, which could partially explain that they are more likely to keep innovating after acquisition. But uncertainty persists as to what Big Tech ends up using this talent for once it has joined the new research team. Are they simply more often further innovating for their acquirer because they were better assessed in the first place, or could it be a strategy for Big Tech to acquire inventors skilled in its core technologies with the aim to have more people working on these technologies in its research team? In other words, are these inventors of core technologies hired for their general talent, or for their expertise in specific fields?

To examine this question, we want to assess whether the best inventors of Big Tech core

technologies keep working on these technologies after they joined their acquirer’s team. We thus focus on inventors who are further innovating for their acquirer (i.e. who have filed some patent for the target before being acquired *and* for their acquirer after acquisition, $Talent_i = 1$). This means that our analysis is prone to a selection bias: the technology choices of inventors who do not keep patenting for their acquirer are not observed, while patenting for the acquirer might not be random. For instance, those inventors with a more positive relation between their innovation value and the probability to file core patents could be less likely to keep patenting for their acquirer and hence to be observed.

[Inventor keeps innovating for the acquirer [Inventor focuses on core technologies [1] [0]] [0]]

So there might be two dimensions to the relationship between an inventor’s innovation value and her propensity to keep working on her acquirer’s core technologies. First, the direct effect of the inventor’s ability to develop certain technologies. Second, the fact that some inventors might be *selectively* less likely to be observed after acquisition (e.g. if they don’t comply with what is expected of them based on their value type). To study the determinants of how inventors direct their innovative effort while keeping constant the effect of selection into further innovating for the acquirer, we propose to use a [Heckman, 1979]-type selection model.

We collect information on how close the patents filed by target inventors are to their acquirer’s technology. In Section 2.2.2, we defined the $\overline{Core}_i$ variable as the share of fields listed in patents filed by inventor i that belong to her acquirer’s core business. This variable can be constructed with a time dimension based on the patents filing dates; up to two years before the acquisition of the target, and over a period of two years starting two months after acquisition. This two months buffer aims to accommodate a period during which uncertainty persists regarding the patented technology investigator. We obtain a dataset at the inventor-level with information on the share of core fields before acquisition ($\overline{Core}_i^{Before}$), for both inventors who keep patenting for their acquirer and those who don’t, and on the share of core fields over a period starting two months after acquisition ($\overline{Core}_i^{After}$), for inventors who keep patenting for their acquirer only.^{20 21}

²⁰Out of the 2,645 inventors observed (up to 2 years) before acquisition, 1,037 inventors keep patenting for their acquirer (of which 1,013 are associated with some information on *MarketVal* and all inventor-level control variables), coming from 134 targets, and 1,608 do not keep patenting for their acquirer (of which 1,501 are associated with some information on *MarketVal* and all inventor-level control variables), coming from 144 targets.

²¹For inventors who keep patenting for their acquirer, we find no significant difference between the share of core fields before and after acquisition: based on a t-test, we cannot reject that the mean value of $\overline{Core}_i$ across all inventors filing before and after acquisition (.409 and .407, respectively) is the same. So, on average, we do

shouldn't go beyond 2m+24m=26m because would lose Motorola, which patents belonged to Google for only 29 months after acquisition

Now, we want to assess whether target inventors who have patented more valuable inventions pre-acquisition are more likely to keep working on their acquirers core technologies. The regression equation thus aims to capture the effect of the market value of the inventors innovation history ($MarketVal_i$) on the share of core fields averaged across all the patents filed by this inventor after acquisition ($\overline{Core}_i^{After}$):

$$\begin{aligned} \overline{Core}_i^{After} = \\ \alpha + \eta_1 MarketVal_i + \eta_2 Core_i^{Before} + \eta_3 MarketVal_i Core_i^{Before} + \sum_k \gamma_k x_{i,k} + \mu BT_i + u_i \end{aligned} \quad (3)$$

where x_i contains the year in which the inventor filed a patent for the first time ($FirstFiling_i$), whether the inventor filed a patent originating from the United States (US_i), the share of patents the inventor filed as first author ($FirstAuthorSh_i$), the number of months between acquisition and the end of the study period ($MSinceAcqui_i$), and $u_i \sim N(0, \sigma)$. $Core_i^{Before}$ accounts for the fact that high levels of $\overline{Core}_i^{After}$ could be associated with two different scenarios: an inventor starts patenting in her acquirer's core fields after acquisition ($Core_i^{Before} = 0$), or she keeps patenting in these same fields she was already working on before acquisition ($Core_i^{Before} = 1$). Since we want to explain why core inventors are more likely to further innovate for their acquirer after acquisition, we are interested in the case where $Core_i^{Before} = 1$. We do not include target-level controls because the sample size shrinks greatly with regards to the number parameters to be estimated: of all inventors who keep patenting for their acquirer, we would end up with 631 inventors coming from 44 targets (without these controls, we have 1010 inventors coming from 125 targets)

Selection model

In order to correct for selection, we need to define an exclusion restriction. We choose the variable associated with the number of months since the inventor's last patent filing for the target ($MSinceLastFil_i$), which is a proxy for whether the inventor is still active at the time of acquisition.

not observe a shift in the probability for a target inventor to patent technologies belonging to her acquirer's core field.

Exogeneity The instrument we propose is expected to be uncorrelated with u_i : being active at the time of acquisition should not be directly linked with the share of core fields in the patents an inventor files after acquisition. It is difficult to test for the validity of this exclusion restriction based on $\overline{Core}_i^{After}$, because the effect of $MSinceLastFil_i$ could be direct, but also indirect through the probability of being observed after acquisition ($Talent_i = 1$). Hence, we propose to test it based on $\overline{Core}_i^{Before}$.

We estimate the Pearson (1896) product-moment correlation coefficient between $\overline{Core}_i^{Before}$ and $MSinceLastFil_i$ on the full sample of inventors who keep patenting for their acquirer and those who don't. We obtain a correlation coefficient of -0.008 that is not different from zero at all standard confidence levels. We conclude that the correlation between our instrument and the share of core fields in the patents an inventor files *before* acquisition is not significant. This suggest that the direct effect of this instrument on the share of core fields *after* acquisition should also be insignificant, and that only an indirect effect through the probability of being observed after acquisition would remain.

Relevance The instrument we propose could also be correlated with the inventor-level controls (in x_i and BT_i), so these controls may influence $Talent_i$ via $MSinceLastFil_i$. To isolate the direct effect of $MSinceLastFil_i$ on $Talent_i$ from the effect these controls may have on $Talent_i$ through $MSinceLastFil_i$, we include x_i and BT_i in the selection equation, of which we define a Probit estimate:

$$P(Talent_i = 1) = \Phi(\alpha^1 + \eta_1^1 MarketVal_i + \eta_2^1 Core_i^{Before} + \eta_3^1 MarketVal_i Core_i^{Before} + \sum_k \gamma_k^1 x_{i,k} + \mu^1 BT_i + \kappa MSinceLastFil_i) \quad (4)$$

where Φ is the standard cumulative normal distribution.

To be relevant, the instrument must be correlated with the probability to be observed after acquisition; the κ parameter from this selection equation must be significantly different from zero. We can check this from Appendix O, presenting the first-step parameter estimates from equation (4). We confirm the relevance of our instrument based on the significance of the $\hat{\kappa}$ parameter (-0.01^{***}).

Estimates

Using Heckmans (1979) procedure, we estimate the two-step parameters from the regression equation (3) augmented with the nonselection hazard computed from the fitted values of the selection equation (4):

$$\begin{aligned} \overline{Core}_i^{After} = & \alpha^2 + \eta_1^2 MarketVal_i + \eta_2^2 Core_i^{Before} + \eta_3^2 MarketVal_i Core_i^{Before} \\ & + \sum_k \gamma_k^2 x_{i,k} + \mu^2 BT_i + \lambda \frac{\phi(\widehat{P(Talent_i = 1)})}{\Phi(\widehat{P(Talent_i = 1)})} + v_i \quad (5) \end{aligned}$$

where ϕ and Φ are the standard normal probability density and cumulative distribution functions, respectively.

Provided that *MSinceLastFil* is a valid exclusion restriction, which we argued in the previous section, these parameters capture the responses in the observed values of $\overline{Core}^{After}$ to independent variations in the regressors, i.e. keeping constant the effect of selection into $Talent = 1$.

Table 5 presents the two-step parameter estimates from model (5), where the parameter associated with *MarketVal* thus captures the share of the variation in $\overline{Core}^{After}$ explained by the exogenous part of the market value of the inventor’s innovation history. The two-step parameter estimates of $\eta_1^2 + \eta_3^2$ is negative ($-.18^{***}$), so core inventors who have patented more valuable inventions pre-acquisition are *less* likely to keep innovating in their acquirer’s core technologies (and this is independent from whether they keep innovating for their acquirer at all).²²

Next to our baseline definition of the independent variable, *MarketVal*, this model is also estimated based on the three alternative market value indices defined in equations (a), (b.2) and (b.3). As can be seen from Appendix P, our results are robust to these alternative definitions: $\hat{\eta}_1^2 + \hat{\eta}_3^2 = -.29^{**}$ (for *MarketVal*), -1.76^{***} (for *MarketVal^{bis}*) and $-.16^{***}$ (for *MarketVal^{ter}*).

Our results thus show the opposite of what would be expected if Big Tech were acquiring

²²We also observe that the λ parameter associated with the nonselection hazard in the second step of the selection model is not significant. This means that there does not seem to be a bias due to, for instance, inventors associated with both a high innovation history market value and many core patents not being observed.

Table 5: Heckman two-step parameters

MeanCore_After	
MarketVal	0.034 (0.093)
Core_Before = 1	0.654*** (0.022)
Core_Before=1 $\times$ MarketVal	-0.216* (0.120)
MSinceAcqui	-0.000 (0.000)
FirstFiling	0.004 (0.003)
US	-0.080*** (0.018)
FirstAuthorSh	0.042** (0.018)
Constant	-8.926 (5.757)
lambda	-0.022 (0.068)
Observations	2,515
BT dummies	Yes
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1	

inventors skilled in its core technologies to increase the number of in-house researchers focused on these areas. Instead, core inventors with a history of more valuable patents appear to direct their innovation efforts towards novel research projects.

5 Conclusion

In this paper, we analyse the innovative activity of inventors from firms acquired by Big Tech. Drawing on firm-level and patents databases, we find that inventors working pre-acquisition on technologies in which their acquirer is focusing its own innovative efforts are more likely to keep filing patents for their acquirer after acquisition.

As we show, this outcome can be partially attributed to Big Tech’s enhanced talent assess-

ment capabilities in its core technology fields, which explains that inventors of core technologies are more likely to stay active after acquisition. However, we also find that, once acquired, these talented core inventors are redirected towards fields in which their acquirer has less expertise. These results suggest that Big Tech acquires inventors in its core technology fields mainly because it can better assess their value, rather than to maintain their focus on those core technologies.

This paper highlights the interplay between talent acquisition and technological specialisation in the digital economy. Our analysis focuses on inventors joining their acquirer's team. An interesting extension for future research would be to investigate what happens to inventors who leave their company after its acquisition by a tech giant and join some other firms.

References

- [Ahuja and Katila, 2001] Ahuja, G. and Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic management journal*, 22(3):197–220.
- [Akcigit and Goldschlag, 2023] Akcigit, U. and Goldschlag, N. (2023). Where have all the” creative talents” gone? employment dynamics of us inventors. Technical report, National Bureau of Economic Research.
- [Anderson, 2017] Anderson, B. (2017). Selection models and weak instruments. Accessed on February 28, 2024.
- [Argentesi et al., 2021] Argentesi, E., Buccirosi, P., Calvano, E., Duso, T., Marrazzo, A., and Nava, S. (2021). Merger policy in digital markets: an ex post assessment. *Journal of Competition Law & Economics*, 17(1):95–140.
- [Arts et al., 2021a] Arts, S., Cassiman, B., and Hou, J. (2021a). Technology differentiation, product market rivalry, and m&a transactions. Technical report, Working paper.
- [Arts et al., 2021b] Arts, S., Hou, J., and Gomez, J. C. (2021b). Natural language processing to identify the creation and impact of new technologies in patent text: Code, data, and new measures. *Research Policy*, 50(2):104144.
- [Bar-Isaac et al., 2025] Bar-Isaac, H., Johnson, J. P., and Nocke, V. (2025). Acquihring for monopsony power. *Management Science*.
- [Benkert et al., 2023] Benkert, J.-M., Letina, I., and Liu, S. (2023). Startup acquisitions: Acquihires and talent hoarding. *arXiv preprint arXiv:2308.10046*.
- [Block et al., 2017] Block, J. H., Fisch, C. O., and Van Praag, M. (2017). The schumpeterian entrepreneur: a review of the empirical evidence on the antecedents, behaviour and consequences of innovative entrepreneurship. *Industry and innovation*, 24(1):61–95.
- [Bryan and Hovenkamp, 2020] Bryan, K. A. and Hovenkamp, E. (2020). Antitrust limits on startup acquisitions. *Review of Industrial Organization*, 56:615–636.
- [Cabral, 2018] Cabral, L. (2018). Standing on the shoulders of dwarfs: Dominant firms and innovation incentives. *Available at SSRN 3235598*.
- [Caffarra et al., 2020] Caffarra, C., Crawford, G., and Valletti, T. (2020). *Antitrust Chronicle*, 2(2):1–9.

- [Campbell et al., 2012] Campbell, B. A., Ganco, M., Franco, A. M., and Agarwal, R. (2012). Who leaves, where to, and why worry? employee mobility, entrepreneurship and effects on source firm performance. *Strategic Management Journal*, 33(1):65–87.
- [Cassiman et al., 2005] Cassiman, B., Colombo, M. G., Garrone, P., and Veugelers, R. (2005). The impact of m&a on the r&d process: An empirical analysis of the role of technological- and market-relatedness. *Research policy*, 34(2):195–220.
- [Cassiman and Veugelers, 2006] Cassiman, B. and Veugelers, R. (2006). In search of complementarity in innovation strategy: Internal r&d and external knowledge acquisition. *Management science*, 52(1):68–82.
- [Caves, 1989] Caves, R. E. (1989). Mergers, takeovers, and economic efficiency: foresight vs. hindsight. *International Journal of Industrial Organization*, 7(1):151–174.
- [Certo et al., 2016] Certo, S. T., Busenbark, J. R., Woo, H.-s., and Semadeni, M. (2016). Sample selection bias and heckman models in strategic management research. *Strategic Management Journal*, 37(13):2639–2657.
- [Christensen, 2013] Christensen, C. M. (2013). *The innovator’s dilemma: when new technologies cause great firms to fail*. Harvard Business Review Press.
- [Cloudt et al., 2006] Cloudt, M., Hagedoorn, J., and Van Kranenburg, H. (2006). Mergers and acquisitions: Their effect on the innovative performance of companies in high-tech industries. *Research policy*, 35(5):642–654.
- [Clougherty et al., 2016] Clougherty, J. A., Duso, T., and Muck, J. (2016). Correcting for self-selection based endogeneity in management research: Review, recommendations and simulations. *Organizational Research Methods*, 19(2):286–347.
- [Cohen and Levin, 1989] Cohen, W. M. and Levin, R. C. (1989). Empirical studies of innovation and market structure. *Handbook of industrial organization*, 2:1059–1107.
- [Dijk et al., 2021] Dijk, E., Moraga-González, J. L., and Motchenkova, E. (2021). How do start-up acquisitions affect the direction of innovation? *The Journal of Industrial Economics*.
- [Ezrachi and Stucke, 2022] Ezrachi, A. and Stucke, M. E. (2022). HarperCollins.
- [Gans, 2016] Gans, J. (2016). *The disruption dilemma*. MIT press.

- [Gautier and Lamesch, 2021] Gautier, A. and Lamesch, J. (2021). Mergers in the digital economy. *Information Economics and Policy*, 54:100890.
- [Gdula, 2021] Gdula, O. E. (2021). *Essays on empirical econometrics*. PhD thesis, University of Oxford.
- [Grant, 1996] Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic management journal*, 17(S2):109–122.
- [Hahn and Hausman, 2003] Hahn, J. and Hausman, J. (2003). Weak instruments: Diagnosis and cures in empirical econometrics. *American Economic Review*, 93(2):118–125.
- [Harhoff and Wagner, 2009] Harhoff, D. and Wagner, S. (2009). The duration of patent examination at the european patent office. *Management Science*, 55(12):1969–1984.
- [Heckman, 1979] Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, pages 153–161.
- [Henderson and Clark, 1990] Henderson, R. M. and Clark, K. B. (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative science quarterly*, pages 9–30.
- [Higgins and Rodriguez, 2006] Higgins, M. J. and Rodriguez, D. (2006). The outsourcing of r&d through acquisitions in the pharmaceutical industry. *Journal of financial economics*, 80(2):351–383.
- [Holmes et al., 2012] Holmes, T. J., Levine, D. K., and Schmitz Jr, J. A. (2012). Monopoly and the incentive to innovate when adoption involves switchover disruptions. *American Economic Journal: Microeconomics*, 4(3):1–33.
- [Jaravel et al., 2018] Jaravel, X., Petkova, N., and Bell, A. (2018). Team-specific capital and innovation. *American Economic Review*, 108(4-5):1034–1073.
- [Kapoor and Lim, 2007] Kapoor, R. and Lim, K. (2007). The impact of acquisitions on the productivity of inventors at semiconductor firms: A synthesis of knowledge-based and incentive-based perspectives. *Academy of Management Journal*, 50(5):1133–1155.
- [Katz, 2021] Katz, M. L. (2021). Big tech mergers: Innovation, competition for the market, and the acquisition of emerging competitors. *Information Economics and Policy*, 54:100883.
- [Kim, 2020] Kim, J. D. (2020). Startup acquisitions as a hiring strategy: Worker choice and turnover. *Available at SSRN 3252784*.

- [Lanjouw and Schankerman, 2001] Lanjouw, J. O. and Schankerman, M. (2001). Characteristics of patent litigation: a window on competition. *RAND journal of economics*, pages 129–151.
- [Lanjouw and Schankerman, 2004] Lanjouw, J. O. and Schankerman, M. (2004). Patent quality and research productivity: Measuring innovation with multiple indicators. *The Economic Journal*, 114(495):441–465.
- [Leone et al., 2007] Leone, A. J., Rock, S., and Willenborg, M. (2007). Disclosure of intended use of proceeds and underpricing in initial public offerings. *Journal of Accounting Research*, 45(1):111–153.
- [Lodh and Battaggion, 2015] Lodh, S. and Battaggion, M. R. (2015). Technological breadth and depth of knowledge in innovation: the role of mergers and acquisitions in biotech. *Industrial and Corporate Change*, 24(2):383–415.
- [Metz et al., 2023] Metz, C., Weise, K., Grant, N., and Isaac, M. (2023). Ego, fear and money: How the a.i. fuse was lit. Accessed on August 14, 2024.
- [Michaels et al., 2001] Michaels, E., Handfield-Jones, H., and Axelrod, B. (2001). *The war for talent*. Harvard Business Press.
- [Motta and Peitz, 2021] Motta, M. and Peitz, M. (2021). Big tech mergers. *Information Economics and Policy*, 54:100868.
- [Motta and Shelegia, 2024] Motta, M. and Shelegia, S. (2024). The “kill zone”: When a platform copies to eliminate a potential threat. *Journal of Economics Management Strategy*, 34(3):657–673.
- [Pforr, 2014] Pforr, K. (2014). *The Stata Journal*, 14(4):847–862.
- [Polsky and Coyle, 2013] Polsky, G. D. and Coyle, J. F. (2013). Acqui-hiring. *Duke Law Journal*, 63(2):281.
- [Puranam et al., 2006] Puranam, P., Singh, H., and Zollo, M. (2006). Organizing for innovation: Managing the coordination-autonomy dilemma in technology acquisitions. *Academy of Management journal*, 49(2):263–280.
- [Ranft and Lord, 2000] Ranft, A. L. and Lord, M. D. (2000). Acquiring new knowledge: the role of retaining human capital.

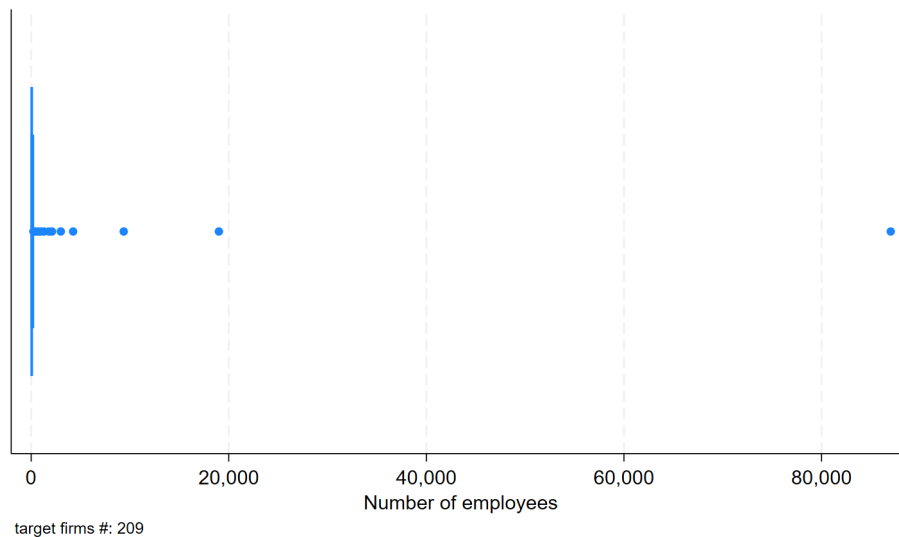
- [Ranft and Lord, 2003] Ranft, A. L. and Lord, M. D. (2003). Acquiring new technologies and capabilities: A grounded model of acquisition implementation. *Quality control and applied statistics*, 48(5):581–584.
- [Régibeau and Rockett, 2010] Régibeau, P. and Rockett, K. (2010). Innovation cycles and learning at the patent office: does the early patent get the delay? *The Journal of Industrial Economics*, 58(2):222–246.
- [Röller et al., 2006] Röller, L.-H., Stennek, J., and Verboven, F. (2006). Efficiency gains from mergers. *European merger control: do we need an efficiency defence*, pages 84–201.
- [Rosenkopf and Almeida, 2003] Rosenkopf, L. and Almeida, P. (2003). Overcoming local search through alliances and mobility. *Management science*, 49(6):751–766.
- [Schmidt, 2023] Schmidt, H. (2023). Merger regulation in the digital economy and the forgotten goal of innovation. *Journal of Antitrust Enforcement*, 11(Supplement_1):i102–i126.
- [Seitz and Kopp, 2023] Seitz, N. and Kopp, J. (2023). Does acqui-hiring really pay offs? an empirical investigation of founders’ retention. In *Academy of Management Proceedings*, volume 2023, page 15156. Academy of Management Briarcliff Manor, NY 10510.
- [Selby and Mayer, 2013] Selby, J. and Mayer, K. J. (2013). Startup firm acquisitions as a human resource strategy for innovation: The acquire phenomenon. *Academy of Management Proceedings*, 2013(1):17109.
- [Shane, 2001] Shane, S. (2001). Technological opportunities and new firm creation. *Management science*, 47(2):205–220.
- [Squicciarini et al., 2013] Squicciarini, M., Dernis, H., and Criscuolo, C. (2013). Measuring patent quality: Indicators of technological and economic value. *OECD Science, Technology and Industry Working Papers*, 3.
- [Stock et al., 2002] Stock, J. H., Wright, J. H., and Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, 20(4):518–529.
- [Tong and Frame, 1994] Tong, X. and Frame, J. D. (1994). Measuring national technological performance with patent claims data. *Research Policy*, 23(2):133–141.
- [Varian, 2021] Varian, H. R. (2021). Seven deadly sins of tech? *Information Economics and Policy*, 54:100893.

- [Verginer et al., 2022] Verginer, L., Parisi, F., de Jeude, J. v. L., and Riccaboni, M. (2022). The impact of acquisitions on inventors’ turnover in the biotechnology industry. *arXiv preprint arXiv:2203.12968*.
- [Xiao and Dahlstrand, 2023] Xiao, J. and Dahlstrand, Å. L. (2023). Skill-biased acquisitions? human capital and employee mobility in small technology firms. *Small Business Economics*, 60(3):1219–1247.
- [Zheng et al., 2021] Zheng, L., Ulrich, K., and Sendra-García, J. (2021). Qualitative comparative analysis: Configurational paths to innovation performance. *Journal of business research*, 128:83–93.

A Distribution of Orbis firm-level data

justification=centering

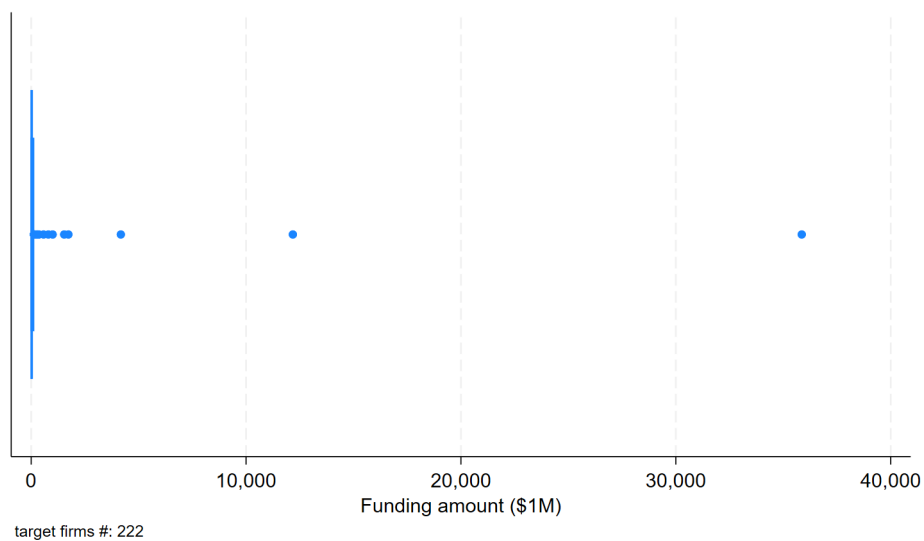
Figure 1: Number of employees at acquisition (boxplot)



Note: The three outlier observations are LINKEDIN (9,372 employees), MOTOROLA MOBILITY (19,000 employees) and WHOLE FOODS MARKET (87,000 employees).

justification=centering

Figure 2: Funding amount at acquisition (boxplot)



Note: The three outlier observations are FITBIT (\$4.17 billion), LINKEDIN (\$12.18 billion) and WHOLE FOODS MARKET (\$35.86 billion).

B Descriptive statistics on USPTO patent-level data

Table 6: Statistics over all the patents filed by Big Tech-acquired inventors (at the patent-level)

	US patents		Core patents		Patents market value		Co-authored patents		Filing dates	
	obs.	count (%)	obs.	count (%)	obs.	mean (SD)	obs.	count (%)	obs.	[min,max]
AMZN	588	498 (85%)	527	341 (65%)	460	-.01 (.03)	596	499 (84%)	596	1995m6, 2020m6
APPL	700	510 (73%)	724	280 (39%)	714	-.01 (.03)	730	613 (84%)	739	1988m6, 2019m11
FCBK	55	44 (80%)	133	108 (81%)	132	-.02 (.03)	136	114 (84%)	136	1998m11, 2019m1
GOOG	2057	1859 (90%)	1950	465 (24%)	1932	-.02 (.04)	2076	1783 (86%)	2082	1995m6, 2020m9
MSFT	1439	1027 (71%)	1430	1151 (80%)	1407	-.01 (.04)	1452	1022 (70%)	1454	1987m5, 2020m4
TOTAL	4839	3938 (81%)	4764	2345 (49%)	4645	-.02 (.04)	4990	4031 (81%)	5007	1987m5, 2020m9

C Core variable aggregated at the target level

We can assess whether a target T is active in its acquirer’s core technology fields:

$$Core_T = \max I_{t,T}$$

where $I_{t,T} = 1$ if a given patent t of the target’s portfolio is associated with at least one of its acquirer’s core fields in the year this patent was acquired.

Table 7: Big Tech acquired patents portfolios

	Count	Core _T = 1
AMZN	27	19 (70%)
APPL	52	27 (52%)
FCBK	17	10 (59%)
GOOG	67	40 (60%)
MSFT	88	81 (92%)
TOTAL	251	177 (71%)

From Table 7, we can see that 71% of Big Tech targets own at least one patent belonging to their acquirers core business.

D Components of the market value index

We construct a market value index using indicators of a patent’s economic value: family size, grant lag and number of claims. For each of these variables, we explain here, based on the OECD note accompanying the related data ([Squicciarini et al., 2013]), why they are good measures of a patents economic value.

Family size

A patent family is a set of patents filed in several countries but with a common priority filing. The size of patent families is proxied by the number of patent offices at which a given invention has been protected. Because extending a patent protection to other countries implies additional costs and delays, applicants are more likely to go through that procedure for more valuable patents.

Grant lag

The grant lag variable is constructed based on the number of days elapsing between the patent application and granting date. In line with the argument that applicants try to accelerate the grant procedure for their most valuable patents, the length of the grant lag period has been shown to be negatively correlated with the value of a patent ([Harhoff and Wagner, 2009]; [Régibeau and Rockett, 2010]).

Adjusted number of claims

A patent is composed of claims, which relate to the technologies that are legally protected by the patent. Therefore, the more claims a patent contains, the broader the rights conferred by this patent. It has been shown that patents containing more claims have, on average, a higher market value ([Tong and Frame, 1994]; [Lanjouw and Schankerman, 2001], [lanjouw2004patent]). Because technology fields seem to vary in the average number of claims per patent, this variable is further adjusted. The number of citations to prior art by a patent is used to account for the development level of the technology area to which this patent belongs, and the adjusted variable is defined as the number of claims over the number of citations.

E Market Value Index

As a measure of innovation market value, we propose to define one vector that approximates the information contained in three (or, in an alternative specification, four) distinct indicators:

family size, grant lag, adjusted number of claims (and forward citations). To do so, we follow a Principal Component Analysis. First, all these variables are normalized such as to be centered in 0:

$$\tilde{X} = [(X - \min(X)) / (\max(X) - \min(X))] - \text{mean}(X)$$

Next, we center our observations around a point that has as coordinates the average values of all three (normalized) indicators. The vector that maximises the variation in the data along the three market value indicators is calculated as the line that best fits the data while going through this center.

The obtained vector is defined by three values, each of which capturing the importance of the associated market value indicator in positioning the vector in space (see Table 8). We obtain the values of the principal components in our sample by projecting our data onto this vector. Because changing the signs of the components does not change the variance that they contain (we are just projecting on a vector that is pointing in one direction or 180 away in the other direction), we can define the signs of the indicators based on the relation the associated metric is expected to have with market value: positive for family size, number of claims and forward citations, negative for grant lag.

Table 8: Market value components

	Weights (ev^x)	
Family size	0.49	0.52
Grant lag	-0.64	-0.49
Adjusted claims #	0.59	0.43
Forward citations #		0.55
Eigenvalue Proportion	37%	29%
Patents #	7,031,531	5,962,352

Note: This table presents the eigenvectors from the Principal Component Analysis eigen decomposition.

Patents associated with higher values of this projection can thus be considered as more valuable. The proportion of the variation in the data that the market value index accounts for can be computed as the distance between these data projections and the center of the data. This distance is called the eigenvalue (ev) of a component. As we can see from Table 8,

the projection of the three market value indicators account for 37% of the variation in the data.

Appendix I

F Descriptive statistics on the Talent variable

The talent acquisition indices can be better compared across acquirers after normalizing by the total number of inventors working at the target T and at the acquirer A :

$$Talent_{A,T} = \frac{\log(\sum_i \{Talent_i\} + e^1)}{InventorsNbr_T + InventorsNbr_A}$$

where the numerator is log-transformed such as to reduce the influence of outliers.

justification=centering

Figure 3: Talent indices by acquirer - Distribution

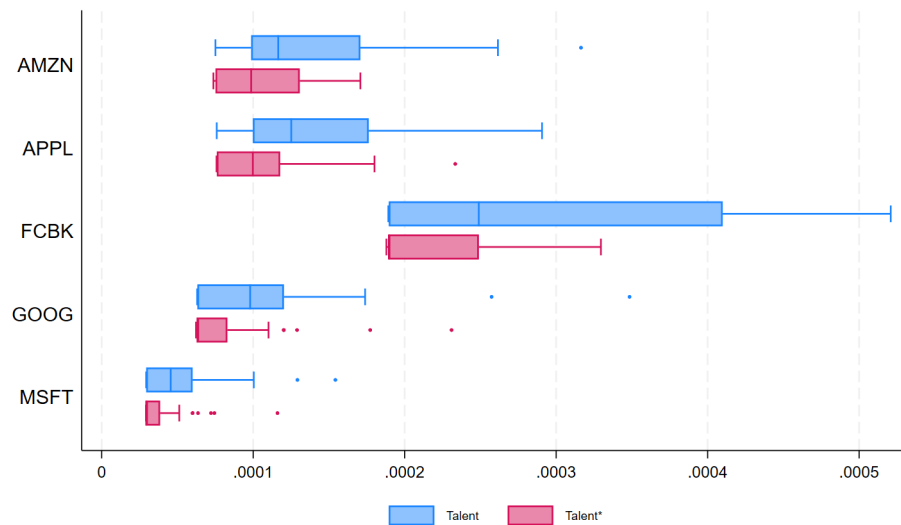


Table 9: Big Tech targets' economic activities (NACE Rev. 2, core code)

Description	NACE code
Printing and reproduction of recorded media	18
Manufacture of computer, electronic and optical products	26
Manufacture of electrical equipment	27
Manufacture of machinery and equipment n.e.c.	28
Manufacture of motor vehicles, trailers and semi-trailers	29
Manufacture of other transport equipment	30
Repair and installation of machinery and equipment	33
Wholesale trade, except of motor vehicles and motorcycles	46
Retail trade, except of motor vehicles and motorcycles	47
Warehousing and support activities for transportation	52
Accommodation	55
Food and beverage service activities	56
Publishing activities	58
Movie, video and television production, sound recording and music publishing	59
Programming and broadcasting activities	60
Telecommunications	61
Computer programming, consultancy and related activities	62
Information service activities	63
Financial service activities, except insurance and pension funding	64
Legal and accounting activities	69
Activities of head offices; management consultancy activities	70
Architectural and engineering activities; technical testing and analysis	71
Scientific research and development	72
Advertising and market research	73
Other professional, scientific and technical activities	74
Travel agency, tour operator reservation service and related activities	79
Security and investigation activities	80
Office administrative, office support and other business support activities	82
Education	85
Human health activities	86
Creative, arts and entertainment activities	90
Sports activities and amusement and recreation activities	93

This table was constructed by identifying, out of the 88 NACE 2 digits-classes, those classes associated with companies acquired by Big Tech. We identify the "main" economic activities (in blue) by selecting NACE codes associated with minimum four targets.

Table 10: Big Tech acquired patents portfolios			
	Count	$\sum_i Talent_i > 1$	$\sum_i Talent^*_i > 1$
AMZN	27	21 (78%)	15 (56%)
APPL	52	40 (77%)	30 (58%)
FCBK	18	11 (61%)	8 (44%)
GOOG	67	50 (75%)	28 (42%)
MSFT	88	64 (73%)	43 (49%)
TOTAL	252	186 (74%)	124 (49%)

G Model 1 - Estimation results for *Talent**

Table 11: Inventors innovating for their acquirer together with some acquirer's employees

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent*											
Core	0.577*** (5.22)	0.548*** (4.93)	0.508*** (4.53)	0.541*** (4.68)	0.379*** (2.59)	0.344** (2.34)	0.340** (2.31)	0.433** (2.12)	0.392* (1.91)	0.536** (2.13)	0.461* (1.74)
MonthsSinceAcqui	0.009*** (10.32)	0.010*** (10.74)	0.016*** (8.09)	0.016*** (7.58)	0.016*** (7.68)	0.008*** (3.07)	0.009*** (3.54)	0.016*** (5.03)	0.016*** (4.98)	0.022*** (5.79)	0.024*** (5.65)
PatentsCount		0.031*** (4.25)	0.037*** (4.76)	0.035*** (4.56)	0.034*** (4.66)	0.020*** (2.93)	0.018** (2.50)	0.016* (1.85)	0.016* (1.91)	0.016* (1.67)	0.017* (1.83)
FirstFiling			0.075*** (3.68)	0.073*** (3.40)	0.078*** (3.66)	-0.026 (-0.94)	-0.008 (-0.27)	0.014 (0.42)	0.013 (0.39)	0.044 (1.15)	0.046 (1.17)
US				0.058 (0.39)	0.255* (1.70)	0.281* (1.86)	0.285* (1.88)	0.250 (1.28)	1.387*** (2.67)	1.277** (2.27)	-0.396 (-0.37)
MonthsSinceLastFiling						-0.015*** (-5.09)	-0.013*** (-4.48)	-0.013*** (-3.75)	-0.013*** (-3.76)	-0.015*** (-3.80)	-0.016*** (-3.78)
FirstAuthor							0.411*** (3.56)	0.393*** (2.97)	0.396*** (2.99)	0.373** (2.52)	0.360** (2.36)
Incorp ^T								0.017 (0.98)	0.015 (0.86)	-0.011 (-0.57)	0.003 (0.15)
US ^T									-1.157** (-2.35)	-1.112** (-2.13)	0.126 (0.12)
FirmSize ^T										-0.509*** (-4.26)	-0.761*** (-4.42)
Funding ^T											0.427** (1.98)
Constant	-3.759*** (-26.46)	-3.895*** (-26.55)	-154.576*** (-3.78)	-150.476*** (-3.49)	-160.365*** (-3.75)	48.670 (0.88)	11.906 (0.21)	-65.652 (-0.94)	-59.635 (-0.85)	-71.341 (-0.90)	-102.684 (-1.22)
Observations	4966	4966	4966	4806	4806	4806	4806	4051	4051	3593	3519
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

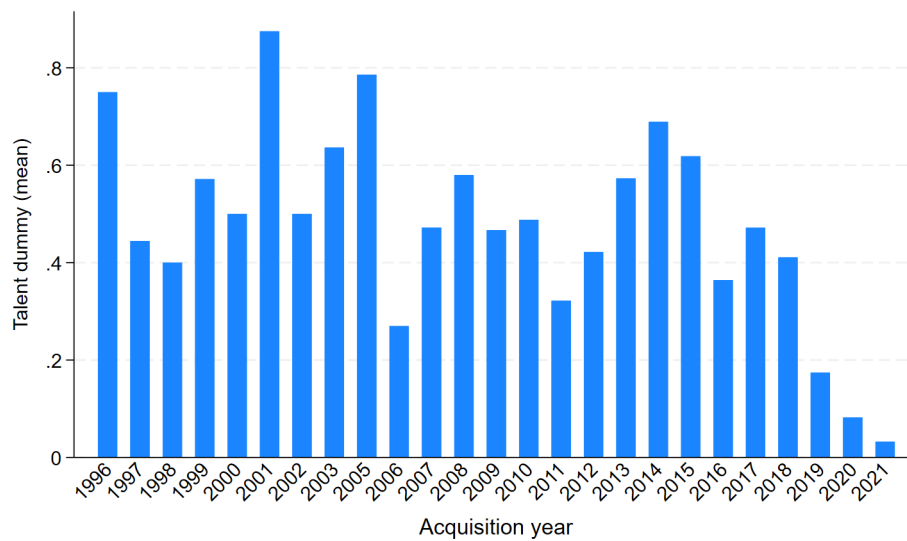
t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

H Observational cut in the patents database

justification=centering

Figure 4: Talent dummy over acquisition year



I Model 1 - robustness check: Fixed observation period

Table 12: Inventors innovating for their acquirer

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent											
Core	0.409*** (5.86)	0.292*** (4.00)	0.159** (2.11)	0.060 (0.76)	0.331*** (3.00)	0.343*** (3.09)	0.345*** (3.10)	0.642*** (4.36)	0.664*** (4.46)	0.779*** (3.91)	0.958*** (4.46)
MonthsSinceAcqui	-0.000 (-0.30)	-0.000 (-0.15)	0.019*** (11.80)	0.020*** (11.94)	0.022*** (12.73)	0.008*** (3.40)	0.008*** (3.44)	0.009*** (3.36)	0.009*** (3.33)	0.007** (2.11)	0.007* (1.84)
PatentsCount		0.247*** (13.82)	0.336*** (16.29)	0.341*** (16.17)	0.340*** (16.04)	0.214*** (9.15)	0.198*** (8.49)	0.156*** (6.82)	0.154*** (6.79)	0.139*** (6.04)	0.141*** (6.00)
FirstFiling			0.209*** (13.79)	0.211*** (13.57)	0.222*** (13.97)	0.053** (2.14)	0.057** (2.29)	0.030 (1.15)	0.029 (1.13)	-0.002 (-0.07)	-0.002 (-0.08)
US				-0.608*** (-6.45)	-0.325*** (-3.12)	-0.317*** (-3.00)	-0.312*** (-2.94)	-0.317** (-2.23)	-0.783* (-1.73)	-0.091 (-0.17)	-0.221 (-0.34)
MonthsSinceLastFiling						-0.021*** (-8.37)	-0.021*** (-8.32)	-0.024*** (-8.72)	-0.024*** (-8.76)	-0.030*** (-9.66)	-0.031*** (-9.93)
FirstAuthor							0.293*** (3.81)	0.331*** (3.91)	0.332*** (3.92)	0.268*** (2.91)	0.252*** (2.68)
Incorp ^T								0.035** (2.39)	0.037** (2.52)	0.009 (0.44)	-0.003 (-0.12)
US ^T									0.476 (1.09)	-0.310 (-0.58)	-0.183 (-0.28)
FirmSize ^T										-0.428*** (-4.33)	-0.353** (-2.41)
Funding ^T											-0.029 (-0.17)
Constant	-0.573*** (-5.05)	-1.118*** (-9.12)	-422.337*** (-13.83)	-427.680*** (-13.59)	-449.468*** (-13.98)	-107.060** (-2.14)	-114.695** (-2.29)	-129.441** (-2.23)	-133.155** (-2.29)	-13.223 (-0.19)	10.247 (0.14)
Observations	3946	3946	3946	3852	3852	3852	3852	3240	3240	2861	2787
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Inventors innovating for their acquirer together with some acquirer's employees

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent*											
Core	0.506*** (4.25)	0.472*** (3.92)	0.428*** (3.51)	0.462*** (3.66)	0.362** (2.19)	0.345** (2.09)	0.338** (2.04)	0.426* (1.88)	0.420* (1.83)	0.590** (2.05)	0.512* (1.66)
MonthsSinceAcqui	0.003*** (2.79)	0.004*** (3.04)	0.010*** (4.14)	0.010*** (4.26)	0.011*** (4.56)	0.003 (1.05)	0.004 (1.31)	0.008** (2.04)	0.008** (2.04)	0.015*** (3.35)	0.023*** (4.32)
PatentsCount		0.074*** (7.29)	0.082*** (7.64)	0.080*** (7.42)	0.075*** (6.86)	0.051*** (4.41)	0.045*** (3.87)	0.041*** (2.88)	0.041*** (2.88)	0.036** (2.37)	0.040*** (2.60)
FirstFiling			0.066*** (2.97)	0.071*** (3.06)	0.074*** (3.29)	-0.021 (-0.72)	-0.009 (-0.30)	0.015 (0.41)	0.015 (0.41)	0.064 (1.50)	0.072 (1.62)
US				0.092 (0.58)	0.503*** (2.94)	0.545*** (3.16)	0.556*** (3.22)	0.435* (1.94)	0.555 (0.91)	0.400 (0.59)	0.004 (0.00)
MonthsSinceLastFiling						-0.014*** (-4.27)	-0.013*** (-3.91)	-0.012*** (-3.24)	-0.012*** (-3.24)	-0.013*** (-2.86)	-0.013*** (-2.78)
FirstAuthor							0.357*** (2.85)	0.383*** (2.64)	0.383*** (2.64)	0.389** (2.47)	0.383** (2.36)
Incorp ^T								0.036 (1.62)	0.035 (1.55)	0.021 (0.71)	0.050 (1.47)
US ^T									-0.124 (-0.21)	-0.159 (-0.24)	-0.567 (-0.51)
FirmSize ^T										-0.337** (-2.23)	-0.960*** (-4.13)
Funding ^T											1.052*** (3.72)
Constant	-3.026*** (-16.63)	-3.284*** (-17.36)	-136.072*** (-3.04)	-145.943*** (-3.13)	-153.097*** (-3.35)	40.563 (0.67)	15.686 (0.26)	-104.822 (-1.30)	-102.801 (-1.27)	-172.135* (-1.77)	-248.347** (-2.36)
Observations	3946	3946	3946	3852	3852	3852	3852	3240	3240	2861	2787
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

J Model 1 - robustness check: Two months buffer after acquisition

Table 14: Inventors innovating for their acquirer

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent											
Core	0.525*** (7.80)	0.485*** (7.12)	0.406*** (5.81)	0.352*** (4.89)	0.324*** (3.54)	0.297*** (3.18)	0.297*** (3.16)	0.525*** (4.25)	0.512*** (4.12)	0.718*** (4.53)	0.770*** (4.52)
MonthsSinceAcqui	0.011*** (15.74)	0.011*** (16.47)	0.029*** (19.67)	0.029*** (19.00)	0.030*** (19.45)	0.014*** (7.38)	0.014*** (7.81)	0.018*** (8.44)	0.018*** (8.43)	0.023*** (8.85)	0.024*** (9.05)
PatentsCount		0.055*** (7.82)	0.088*** (10.63)	0.089*** (10.65)	0.089*** (10.49)	0.028*** (3.65)	0.024*** (3.18)	0.024*** (2.89)	0.024*** (2.91)	0.022*** (2.72)	0.021*** (2.64)
FirstFiling			0.188*** (14.13)	0.185*** (13.35)	0.191*** (13.61)	-0.021 (-1.12)	-0.010 (-0.51)	-0.025 (-1.16)	-0.025 (-1.16)	-0.050** (-2.11)	-0.057** (-2.31)
US				-0.454*** (-5.42)	-0.280*** (-3.21)	-0.245*** (-2.73)	-0.246*** (-2.73)	-0.246* (-1.89)	0.151 (0.38)	0.268 (0.59)	-0.263 (-0.46)
MonthsSinceLastFiling						-0.031*** (-14.62)	-0.030*** (-14.17)	-0.031*** (-13.28)	-0.031*** (-13.26)	-0.035*** (-13.32)	-0.037*** (-13.47)
FirstAuthor							0.292*** (4.13)	0.331*** (4.21)	0.332*** (4.22)	0.274*** (3.20)	0.279*** (3.19)
Incorp ^T								0.021** (2.15)	0.021** (2.12)	-0.001 (-0.07)	-0.001 (-0.08)
US ^T									-0.404 (-1.06)	-0.272 (-0.64)	0.016 (0.03)
FirmSize ^T										-0.541*** (-6.76)	-0.689*** (-5.74)
Funding ^T											0.237* (1.78)
Constant	-2.032*** (-21.70)	-2.253*** (-22.78)	-382.220*** (-14.21)	-374.657*** (-13.41)	-387.719*** (-13.67)	42.031 (1.09)	18.405 (0.47)	5.990 (0.13)	6.610 (0.14)	101.278** (1.99)	114.766** (2.17)
Observations	4966	4966	4966	4806	4806	4806	4806	4051	4051	3593	3519
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Inventors innovating for their acquirer together with some acquirer's employees

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent*											
Core	0.570*** (5.12)	0.541*** (4.82)	0.501*** (4.44)	0.528*** (4.53)	0.368** (2.49)	0.331** (2.23)	0.328** (2.20)	0.450** (2.17)	0.406* (1.94)	0.614** (2.40)	0.553** (2.04)
MonthsSinceAcqui	0.009*** (10.60)	0.010*** (11.02)	0.016*** (8.13)	0.016*** (7.65)	0.016*** (7.76)	0.008*** (3.07)	0.009*** (3.54)	0.017*** (5.09)	0.017*** (5.04)	0.022*** (5.89)	0.024*** (5.75)
PatentsCount		0.031*** (4.29)	0.038*** (4.79)	0.036*** (4.61)	0.035*** (4.70)	0.021*** (2.94)	0.018** (2.52)	0.016* (1.88)	0.017* (1.95)	0.016 (1.63)	0.017* (1.80)
FirstFiling			0.073*** (3.60)	0.072*** (3.34)	0.078*** (3.67)	-0.028 (-1.02)	-0.010 (-0.35)	0.013 (0.40)	0.012 (0.37)	0.043 (1.13)	0.045 (1.16)
US				0.022 (0.15)	0.214 (1.42)	0.241 (1.59)	0.246 (1.62)	0.235 (1.19)	1.508*** (2.88)	1.347** (2.37)	-0.274 (-0.25)
MonthsSinceLastFiling						-0.016*** (-5.23)	-0.014*** (-4.63)	-0.013*** (-3.92)	-0.013*** (-3.92)	-0.016*** (-3.90)	-0.016*** (-3.90)
FirstAuthor							0.411*** (3.53)	0.405*** (3.02)	0.408*** (3.04)	0.389*** (2.60)	0.379** (2.46)
Incorp ^T								0.013 (0.78)	0.011 (0.64)	-0.013 (-0.68)	0.003 (0.12)
US ^T									-1.296*** (-2.61)	-1.185** (-2.24)	-0.020 (-0.02)
FirmSize ^T										-0.493*** (-4.06)	-0.757*** (-4.34)
Funding ^T											0.454** (2.06)
Constant	-3.810*** (-26.61)	-3.949*** (-26.69)	-152.145*** (-3.69)	-148.679*** (-3.43)	-162.083*** (-3.76)	53.131 (0.96)	16.497 (0.29)	-57.509 (-0.82)	-50.621 (-0.72)	-65.914 (-0.83)	-101.421 (-1.19)
Observations	4966	4966	4966	4806	4806	4806	4806	4051	4051	3593	3519
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

K Model 1 - robustness check: Filing under the acquirer's name

Table 16: Inventors innovating for their acquirer

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent											
Core	0.539*** (7.78)	0.503*** (7.19)	0.440*** (6.18)	0.438*** (5.96)	0.473*** (5.03)	0.441*** (4.60)	0.441*** (4.59)	0.855*** (6.64)	0.828*** (6.40)	1.003*** (5.91)	1.076*** (5.77)
MonthsSinceAcqui	0.010*** (14.61)	0.010*** (15.27)	0.023*** (16.55)	0.024*** (16.14)	0.025*** (16.66)	0.010*** (5.52)	0.010*** (5.87)	0.014*** (6.55)	0.014*** (6.53)	0.017*** (6.65)	0.019*** (7.14)
PatentsCount		0.047*** (7.04)	0.069*** (9.14)	0.068*** (8.91)	0.067*** (8.71)	0.018*** (2.66)	0.015** (2.30)	0.011 (1.61)	0.011* (1.67)	0.010 (1.43)	0.009 (1.28)
FirstFiling			0.142*** (10.84)	0.145*** (10.48)	0.157*** (11.14)	-0.038** (-2.01)	-0.028 (-1.48)	-0.037* (-1.73)	-0.037* (-1.74)	-0.056** (-2.38)	-0.064*** (-2.60)
US				-0.196** (-2.27)	-0.089 (-0.99)	-0.051 (-0.56)	-0.050 (-0.54)	0.161 (1.21)	1.068*** (2.63)	1.905*** (3.88)	0.891 (1.45)
MonthsSinceLastFiling						-0.029*** (-13.78)	-0.028*** (-13.34)	-0.028*** (-12.29)	-0.028*** (-12.27)	-0.033*** (-12.56)	-0.035*** (-12.77)
FirstAuthor							0.230*** (3.18)	0.302*** (3.74)	0.304*** (3.75)	0.245*** (2.74)	0.266*** (2.91)
Incorp ^T								0.018* (1.75)	0.017 (1.64)	-0.005 (-0.38)	0.009 (0.59)
US ^T									-0.920** (-2.36)	-1.478*** (-3.17)	-0.999* (-1.70)
FirmSize ^T										-0.556*** (-6.71)	-0.880*** (-6.93)
Funding ^T											0.524*** (3.62)
Constant	-2.193*** (-23.07)	-2.385*** (-23.88)	-288.803*** (-10.92)	-294.374*** (-10.56)	-318.900*** (-11.22)	74.151* (1.96)	54.792 (1.43)	33.702 (0.74)	36.144 (0.79)	118.828** (2.33)	106.533* (1.95)
Observations	4966	4966	4966	4806	4806	4806	4806	4051	4051	3593	3519
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Inventors innovating for their acquirer together with some acquirer's employees

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent*											
Core	0.604*** (5.38)	0.575*** (5.09)	0.532*** (4.68)	0.566*** (4.82)	0.411*** (2.77)	0.377** (2.54)	0.374** (2.50)	0.463** (2.24)	0.421** (2.02)	0.553** (2.18)	0.476* (1.78)
MonthsSinceAcqui	0.009*** (10.14)	0.010*** (10.56)	0.016*** (8.08)	0.016*** (7.60)	0.016*** (7.72)	0.008*** (3.25)	0.010*** (3.75)	0.017*** (5.07)	0.017*** (5.02)	0.022*** (5.74)	0.024*** (5.55)
PatentsCount		0.031*** (4.26)	0.038*** (4.80)	0.036*** (4.61)	0.035*** (4.70)	0.022*** (3.06)	0.019*** (2.63)	0.017** (2.02)	0.018** (2.08)	0.017* (1.83)	0.018** (1.97)
FirstFiling			0.079*** (3.81)	0.077*** (3.54)	0.084*** (3.87)	-0.017 (-0.60)	0.003 (0.10)	0.023 (0.67)	0.022 (0.64)	0.052 (1.33)	0.054 (1.36)
US				0.063 (0.42)	0.262* (1.72)	0.287* (1.87)	0.292* (1.90)	0.265 (1.33)	1.458*** (2.80)	1.365** (2.41)	-0.331 (-0.31)
MonthsSinceLastFiling						-0.015*** (-4.85)	-0.013*** (-4.21)	-0.012*** (-3.52)	-0.012*** (-3.53)	-0.015*** (-3.70)	-0.016*** (-3.71)
FirstAuthor							0.444*** (3.79)	0.445*** (3.30)	0.448*** (3.32)	0.443*** (2.93)	0.429*** (2.75)
Incorp ^T								0.022 (1.24)	0.019 (1.12)	-0.008 (-0.43)	0.004 (0.18)
US ^T									-1.214** (-2.46)	-1.201** (-2.29)	0.096 (0.09)
FirmSize ^T										-0.532*** (-4.39)	-0.761*** (-4.35)
Funding ^T											0.389* (1.79)
Constant	-3.800*** (-26.38)	-3.939*** (-26.47)	-163.047*** (-3.90)	-160.213*** (-3.63)	-173.335*** (-3.96)	30.316 (0.54)	-9.735 (-0.17)	-93.429 (-1.30)	-86.997 (-1.21)	-92.224 (-1.13)	-122.266 (-1.42)
Observations	4966	4966	4966	4806	4806	4806	4806	4051	4051	3593	3519
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

L Model 1 - robustness check: Inventors of core technologies w/i a year

Table 18: Inventors innovating for their acquirer

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent											
Core	1.053*** (13.10)	0.971*** (11.89)	0.625*** (7.20)	0.575*** (6.50)	0.485*** (5.20)	0.123 (1.26)	0.129 (1.31)	0.093 (0.82)	0.093 (0.82)	0.219* (1.72)	0.212 (1.62)
MonthsSinceAcqui	0.009*** (14.71)	0.010*** (15.65)	0.024*** (17.29)	0.025*** (17.12)	0.027*** (17.76)	0.012*** (6.44)	0.012*** (6.84)	0.016*** (7.46)	0.016*** (7.47)	0.018*** (7.58)	0.019*** (7.64)
PatentsCount		0.063*** (8.36)	0.097*** (10.89)	0.097*** (10.84)	0.099*** (10.94)	0.042*** (4.89)	0.037*** (4.30)	0.039*** (4.05)	0.039*** (4.07)	0.035*** (3.66)	0.035*** (3.62)
FirstFiling			0.157*** (11.76)	0.161*** (11.55)	0.168*** (11.90)	-0.021 (-1.10)	-0.010 (-0.52)	-0.020 (-0.91)	-0.020 (-0.91)	-0.031 (-1.30)	-0.037 (-1.52)
US				-0.480*** (-5.84)	-0.296*** (-3.43)	-0.256*** (-2.91)	-0.256*** (-2.89)	-0.346*** (-2.76)	0.051 (0.13)	-0.106 (-0.24)	-0.806 (-1.44)
MonthsSinceLastFiling						-0.029*** (-13.32)	-0.028*** (-12.88)	-0.029*** (-12.12)	-0.029*** (-12.10)	-0.033*** (-12.28)	-0.035*** (-12.38)
FirstAuthor							0.295*** (4.23)	0.328*** (4.25)	0.329*** (4.26)	0.270*** (3.21)	0.267*** (3.11)
Incorp ^T								0.018** (2.08)	0.018** (2.03)	-0.007 (-0.75)	-0.009 (-0.87)
US ^T									-0.401 (-1.06)	-0.175 (-0.42)	0.321 (0.60)
FirmSize ^T										-0.629*** (-8.29)	-0.731*** (-6.63)
Funding ^T											0.170 (1.42)
Constant	-1.751*** (-22.63)	-2.010*** (-23.89)	-318.017*** (-11.83)	-327.476*** (-11.61)	-341.571*** (-11.95)	41.696 (1.07)	19.245 (0.49)	2.407 (0.05)	2.990 (0.07)	76.934 (1.55)	92.799* (1.82)
Observations	4966	4966	4966	4806	4806	4806	4806	4051	4051	3593	3519
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Inventors innovating for their acquirer together with some acquirer's employees

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent*											
Core	0.901*** (7.15)	0.855*** (6.74)	0.745*** (5.53)	0.712*** (5.18)	0.539*** (3.69)	0.333** (2.19)	0.331** (2.17)	0.417** (2.28)	0.422** (2.31)	0.633*** (3.03)	0.668*** (3.11)
MonthsSinceAcqui	0.009*** (10.11)	0.010*** (10.51)	0.014*** (6.86)	0.014*** (6.58)	0.014*** (6.90)	0.007*** (3.00)	0.009*** (3.47)	0.016*** (4.93)	0.016*** (4.92)	0.021*** (5.66)	0.023*** (5.56)
PatentsCount		0.029*** (4.30)	0.033*** (4.57)	0.032*** (4.48)	0.032*** (4.59)	0.022*** (3.11)	0.019*** (2.65)	0.017* (1.94)	0.018** (2.00)	0.017 (1.63)	0.018* (1.79)
FirstFiling			0.049** (2.35)	0.051** (2.33)	0.059*** (2.73)	-0.025 (-0.90)	-0.006 (-0.23)	0.014 (0.43)	0.014 (0.41)	0.045 (1.18)	0.046 (1.17)
US				0.001 (0.01)	0.238 (1.59)	0.263* (1.74)	0.269* (1.78)	0.212 (1.10)	1.483*** (2.86)	1.357** (2.40)	-0.455 (-0.42)
MonthsSinceLastFiling						-0.013*** (-4.28)	-0.012*** (-3.72)	-0.010*** (-2.88)	-0.010*** (-2.87)	-0.012*** (-2.98)	-0.012*** (-2.87)
FirstAuthor							0.412*** (3.57)	0.393*** (2.97)	0.397*** (2.99)	0.375** (2.53)	0.362** (2.37)
Incorp ^T								0.023 (1.36)	0.019 (1.16)	-0.009 (-0.51)	0.005 (0.22)
US ^T									-1.283*** (-2.63)	-1.270** (-2.43)	0.120 (0.11)
FirmSize ^T										-0.589*** (-5.31)	-0.822*** (-5.02)
Funding ^T											0.430** (1.98)
Constant	-3.672*** (-27.94)	-3.803*** (-27.98)	-102.226** (-2.44)	-106.210** (-2.42)	-122.038*** (-2.81)	46.306 (0.84)	9.548 (0.17)	-77.997 (-1.11)	-70.419 (-1.00)	-76.396 (-0.96)	-106.287 (-1.26)
Observations	4966	4966	4966	4806	4806	4806	4806	4051	4051	3593	3519
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

M Model 1 - robustness check: Core defined at the 3-digit level

Table 20: Inventors innovating for their acquirer

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent											
Core	0.514*** (7.53)	0.467*** (6.75)	0.404*** (5.72)	0.350*** (4.81)	0.320*** (3.43)	0.276*** (2.90)	0.272*** (2.85)	0.480*** (4.17)	0.474*** (4.10)	0.507*** (3.66)	0.484*** (3.37)
MonthsSinceAcqui	0.010*** (14.41)	0.011*** (15.32)	0.027*** (19.20)	0.028*** (18.78)	0.029*** (19.12)	0.012*** (6.80)	0.013*** (7.18)	0.017*** (8.03)	0.017*** (8.03)	0.020*** (8.12)	0.021*** (8.14)
PatentsCount		0.070*** (9.19)	0.106*** (11.87)	0.105*** (11.74)	0.105*** (11.62)	0.040*** (4.72)	0.035*** (4.16)	0.036*** (3.79)	0.036*** (3.81)	0.033*** (3.50)	0.033*** (3.47)
FirstFiling			0.181*** (14.06)	0.184*** (13.56)	0.188*** (13.69)	-0.020 (-1.06)	-0.009 (-0.49)	-0.018 (-0.84)	-0.018 (-0.83)	-0.035 (-1.44)	-0.040 (-1.61)
US				-0.439*** (-5.33)	-0.266*** (-3.11)	-0.234*** (-2.65)	-0.234*** (-2.65)	-0.283** (-2.25)	-0.019 (-0.05)	-0.111 (-0.25)	-0.683 (-1.22)
MonthsSinceLastFiling						-0.030*** (-14.14)	-0.029*** (-13.70)	-0.029*** (-12.71)	-0.029*** (-12.70)	-0.034*** (-12.89)	-0.036*** (-13.06)
FirstAuthor							0.292*** (4.18)	0.332*** (4.28)	0.332*** (4.29)	0.269*** (3.20)	0.265*** (3.08)
Incorp ^T								0.014* (1.65)	0.014 (1.62)	-0.008 (-0.76)	-0.010 (-0.94)
US ^T									-0.268 (-0.71)	-0.070 (-0.17)	0.336 (0.63)
FirmSize ^T										-0.560*** (-7.21)	-0.646*** (-5.70)
Funding ^T											0.137 (1.14)
Constant	-1.882*** (-19.38)	-2.152*** (-20.97)	-368.165*** (-14.13)	-373.055*** (-13.63)	-381.985*** (-13.74)	40.299 (1.04)	17.974 (0.46)	5.870 (0.13)	6.196 (0.14)	83.754* (1.68)	98.801* (1.93)
Observations	4966	4966	4966	4806	4806	4806	4806	4051	4051	3593	3519
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Inventors innovating for their acquirer together with some acquirer's employees

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent*											
Core	0.629*** (5.50)	0.603*** (5.25)	0.568*** (4.91)	0.596*** (5.03)	0.472*** (3.17)	0.420*** (2.82)	0.411*** (2.74)	0.519*** (2.74)	0.490** (2.56)	0.350 (1.55)	0.294 (1.24)
MonthsSinceAcqui	0.010*** (10.64)	0.010*** (11.04)	0.017*** (8.31)	0.016*** (7.82)	0.016*** (7.88)	0.008*** (3.26)	0.009*** (3.72)	0.017*** (5.25)	0.017*** (5.20)	0.022*** (5.75)	0.023*** (5.62)
PatentsCount		0.031*** (4.28)	0.037*** (4.79)	0.036*** (4.61)	0.034*** (4.67)	0.021*** (2.94)	0.018** (2.53)	0.016* (1.90)	0.017* (1.95)	0.017* (1.80)	0.018* (1.94)
FirstFiling			0.075*** (3.71)	0.073*** (3.44)	0.079*** (3.72)	-0.023 (-0.84)	-0.005 (-0.17)	0.017 (0.52)	0.016 (0.49)	0.046 (1.21)	0.047 (1.21)
US				0.050 (0.34)	0.244 (1.63)	0.269* (1.79)	0.273* (1.81)	0.224 (1.16)	1.362*** (2.62)	1.228** (2.19)	-0.474 (-0.44)
MonthsSinceLastFiling						-0.015*** (-5.00)	-0.013*** (-4.39)	-0.012*** (-3.62)	-0.012*** (-3.63)	-0.015*** (-3.80)	-0.016*** (-3.79)
FirstAuthor							0.407*** (3.52)	0.389*** (2.94)	0.393*** (2.96)	0.369** (2.49)	0.357** (2.34)
Incorp ^T								0.019 (1.17)	0.017 (1.03)	-0.006 (-0.32)	0.007 (0.31)
US ^T									-1.153** (-2.35)	-1.132** (-2.17)	0.122 (0.11)
FirmSize ^T										-0.543*** (-4.64)	-0.801*** (-4.73)
Funding ^T											0.441** (2.09)
Constant	-3.873*** (-25.57)	-4.007*** (-25.72)	-155.213*** (-3.81)	-151.526*** (-3.54)	-162.413*** (-3.81)	42.629 (0.77)	5.852 (0.10)	-77.458 (-1.11)	-70.980 (-1.02)	-85.315 (-1.08)	-112.618 (-1.35)
Observations	4966	4966	4966	4806	4806	4806	4806	4051	4051	3593	3519
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

N Model II - Alternative Market Value Indices

Table 22: Inventors innovating for their acquirer, MarketValue definition (a)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent											
Core=1	0.458** (2.22)	0.412** (1.98)	0.314 (1.47)	0.170 (0.78)	-0.126 (-0.52)	-0.421* (-1.66)	-0.406 (-1.60)	-0.340 (-1.17)	-0.343 (-1.18)	-0.174 (-0.52)	-0.180 (-0.53)
MarketValue_bar	1.164** (2.41)	0.903* (1.85)	0.166 (0.33)	-0.189 (-0.38)	-1.032* (-1.92)	-1.905*** (-3.28)	-1.848*** (-3.17)	-1.107 (-1.64)	-1.109* (-1.65)	-2.023*** (-2.77)	-2.208*** (-2.94)
Core=1 × MarketValue_bar	0.200 (0.29)	0.217 (0.31)	0.327 (0.46)	0.649 (0.89)	1.478* (1.95)	2.414*** (3.02)	2.359*** (2.94)	2.669*** (2.91)	2.661*** (2.90)	2.319** (2.26)	2.577** (2.46)
MonthsSinceAcqui	0.009*** (13.90)	0.010*** (14.88)	0.027*** (18.81)	0.027*** (18.38)	0.029*** (18.94)	0.012*** (6.74)	0.013*** (7.11)	0.016*** (7.69)	0.016*** (7.68)	0.019*** (7.82)	0.020*** (7.89)
PatentsCount		0.066*** (8.76)	0.102*** (11.49)	0.103*** (11.39)	0.104*** (11.41)	0.038*** (4.53)	0.033*** (3.99)	0.033*** (3.56)	0.033*** (3.57)	0.032*** (3.37)	0.032*** (3.35)
FirstFiling			0.181*** (13.86)	0.185*** (13.38)	0.193*** (13.72)	-0.019 (-0.98)	-0.008 (-0.44)	-0.019 (-0.87)	-0.019 (-0.87)	-0.030 (-1.25)	-0.034 (-1.35)
US				-0.422*** (-5.04)	-0.239*** (-2.74)	-0.212** (-2.36)	-0.212** (-2.36)	-0.258** (-2.01)	-0.098 (-0.25)	-0.179 (-0.40)	-0.661 (-1.17)
MonthsSinceLastFiling						-0.030*** (-14.47)	-0.030*** (-14.04)	-0.031*** (-13.04)	-0.031*** (-13.03)	-0.036*** (-13.25)	-0.037*** (-13.41)
FirstAuthor							0.278*** (3.96)	0.320*** (4.10)	0.320*** (4.11)	0.256*** (3.02)	0.248*** (2.87)
Incorp ^T								0.012 (1.25)	0.012 (1.24)	-0.011 (-1.08)	-0.017 (-1.52)
US ^T									-0.163 (-0.43)	-0.006 (-0.01)	0.442 (0.83)
FirmSize ^T										-0.583*** (-7.36)	-0.598*** (-5.07)
Funding ^T											0.044 (0.35)
Constant	-2.125*** (-13.18)	-2.325*** (-14.17)	-368.144*** (-13.95)	-374.367*** (-13.45)	-390.551*** (-13.77)	37.879 (0.97)	16.627 (0.42)	13.516 (0.29)	13.611 (0.30)	83.648* (1.65)	102.000** (1.96)
Observations	4880	4880	4880	4720	4720	4720	4720	3967	3967	3509	3435
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Inventors innovating for their acquirer, MarketValue definition (b.2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent											
Core=1	0.534*** (6.46)	0.474*** (5.67)	0.431*** (5.09)	0.425*** (4.94)	0.403*** (4.08)	0.448*** (4.42)	0.442*** (4.36)	0.653*** (4.97)	0.648*** (4.91)	0.655*** (4.18)	0.748*** (4.46)
MarketValue_bis	6.915*** (5.15)	6.057*** (4.48)	2.167 (1.51)	0.786 (0.54)	-1.878 (-1.23)	-6.184*** (-3.74)	-5.854*** (-3.53)	-5.638*** (-3.12)	-5.647*** (-3.12)	-9.002*** (-4.47)	-9.602*** (-4.64)
Core=1 $\times$ MarketValue_bis	1.834 (0.88)	0.681 (0.33)	1.340 (0.63)	3.600 (1.63)	5.927*** (2.60)	9.919*** (4.14)	9.657*** (4.03)	12.571*** (4.60)	12.543*** (4.59)	9.299*** (3.09)	10.707*** (3.51)
MonthsSinceAcqui	0.010*** (14.60)	0.011*** (15.35)	0.027*** (18.54)	0.027*** (18.08)	0.029*** (18.71)	0.013*** (6.79)	0.013*** (7.15)	0.017*** (7.89)	0.017*** (7.89)	0.019*** (7.85)	0.020*** (7.90)
PatentsCount		0.061*** (8.07)	0.098*** (10.91)	0.098*** (10.80)	0.101*** (10.95)	0.037*** (4.37)	0.032*** (3.85)	0.032*** (3.45)	0.032*** (3.46)	0.033*** (3.45)	0.033*** (3.42)
FirstFiling			0.175*** (13.14)	0.179*** (12.68)	0.191*** (13.21)	-0.018 (-0.93)	-0.008 (-0.41)	-0.018 (-0.83)	-0.018 (-0.83)	-0.023 (-0.93)	-0.026 (-1.02)
US				-0.436*** (-5.14)	-0.262*** (-2.98)	-0.251*** (-2.76)	-0.250*** (-2.74)	-0.299** (-2.30)	-0.149 (-0.37)	-0.223 (-0.50)	-0.730 (-1.28)
MonthsSinceLastFiling						-0.031*** (-14.56)	-0.030*** (-14.10)	-0.031*** (-13.13)	-0.031*** (-13.12)	-0.038*** (-13.54)	-0.039*** (-13.71)
FirstAuthor							0.272*** (3.87)	0.314*** (4.02)	0.314*** (4.02)	0.244*** (2.87)	0.235*** (2.70)
Incorp ^T								0.013 (1.36)	0.013 (1.35)	-0.012 (-1.15)	-0.018 (-1.60)
US ^T									-0.152 (-0.40)	-0.004 (-0.01)	0.476 (0.89)
FirmSize ^T										-0.604*** (-7.45)	-0.601*** (-5.02)
Funding ^T											0.029 (0.23)
Constant	-1.709*** (-17.24)	-1.964*** (-18.74)	-355.003*** (-13.21)	-362.955*** (-12.74)	-386.660*** (-13.25)	35.282 (0.90)	14.925 (0.38)	9.500 (0.21)	9.573 (0.21)	69.737 (1.37)	86.885* (1.66)
Observations	4880	4880	4880	4720	4720	4720	4720	3967	3967	3509	3435
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

^t statistics in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Inventors innovating for their acquirer, MarketValue definition (b.3)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Talent											
Core=1	0.469*** (6.48)	0.408*** (5.55)	0.338*** (4.46)	0.282*** (3.62)	0.380*** (3.74)	0.342*** (3.28)	0.338*** (3.24)	0.553*** (3.95)	0.553*** (3.94)	0.529*** (2.91)	0.715*** (3.68)
MarketValue_ter	0.066 (0.14)	0.088 (0.19)	-0.838* (-1.69)	-1.145** (-2.29)	-1.898*** (-3.68)	-1.124** (-2.19)	-0.937* (-1.81)	-1.900*** (-3.13)	-1.900*** (-3.13)	-2.609*** (-4.05)	-2.733*** (-4.19)
Core=1 $\times$ MarketValue_ter	0.293 (0.57)	-0.284 (-0.53)	-0.050 (-0.09)	0.464 (0.79)	1.137* (1.87)	0.953* (1.66)	0.852 (1.48)	1.967*** (2.97)	1.967*** (2.97)	2.446*** (3.48)	2.618*** (3.69)
MonthsSinceAcqui	0.007*** (9.66)	0.008*** (10.57)	0.024*** (17.12)	0.025*** (16.72)	0.026*** (17.18)	0.009*** (4.87)	0.010*** (5.18)	0.014*** (6.38)	0.014*** (6.38)	0.017*** (6.44)	0.018*** (6.45)
PatentsCount		0.063*** (7.47)	0.108*** (10.70)	0.106*** (10.32)	0.106*** (10.21)	0.029*** (3.05)	0.023** (2.48)	0.020** (2.02)	0.020** (2.02)	0.021** (2.18)	0.020** (2.07)
FirstFiling			0.197*** (14.39)	0.196*** (13.59)	0.205*** (14.01)	-0.008 (-0.40)	0.001 (0.04)	-0.007 (-0.32)	-0.007 (-0.32)	-0.008 (-0.31)	-0.008 (-0.30)
US				-0.491*** (-5.52)	-0.207** (-2.13)	-0.164 (-1.64)	-0.157 (-1.56)	-0.273** (-2.06)	-0.273 (-0.57)	-0.086 (-0.15)	0.092 (0.13)
MonthsSinceLastFiling						-0.029*** (-13.75)	-0.028*** (-13.40)	-0.030*** (-12.74)	-0.030*** (-12.73)	-0.033*** (-12.38)	-0.035*** (-12.51)
FirstAuthor							0.303*** (4.03)	0.318*** (3.82)	0.318*** (3.82)	0.245*** (2.69)	0.228** (2.45)
Incorp ^T								0.022** (2.02)	0.022** (2.01)	0.011 (0.85)	-0.001 (-0.04)
US ^T									0.000 (0.00)	-0.150 (-0.27)	-0.169 (-0.25)
FirmSize ^T										-0.565*** (-6.15)	-0.441*** (-3.31)
Funding ^T											-0.115 (-0.84)
Constant	-1.493*** (-14.10)	-1.746*** (-15.61)	-399.746*** (-14.45)	-396.372*** (-13.64)	-415.995*** (-14.04)	16.344 (0.40)	-2.058 (-0.05)	-30.108 (-0.61)	-30.108 (-0.61)	-6.191 (-0.11)	17.849 (0.31)
Observations	4158	4158	4158	4009	4009	4009	4009	3383	3383	2955	2881
BT dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

O Probit estimates of the selection equation

Table 25: Heckman selection equation (4)

Talent	
MarketVal	-1.413*** (0.349)
Core_Before = 1	0.305*** (0.071)
Core_Before=1 × MarketVal	2.241*** (0.416)
MSinceAcqui	0.004*** (0.001)
FirstFiling	-0.037*** (0.013)
US	0.036 (0.068)
FirstAuthorSh	0.026 (0.067)
MSinceLastFiling	-0.011*** (0.002)
Constant	73.462*** (25.565)
Observations	2,515
BT dummies	Yes
Prob χ^2	0,00
Pseudo R ²	0,10

Standard errors in parentheses

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

The z-test for the significance of the coefficient of *MonthsSinceLastFiling* is associated with a p-value < 0.01; we conclude that this is a relevant instrument.

P Heckman selection model - Alternative Market Value Indices

Table 26: Heckman two-step parameters, MarketValue definition (a)

	(1) second	(2) select	(3) /mills
MarketVal.bar	0.056 (0.173)	-1.514*** (0.498)	
Core_Before = 1	0.760*** (0.073)	-1.046*** (0.219)	
Core_Before=1 $\times$ MarketVal	-0.345 (0.246)	4.269*** (0.686)	
MSinceAcqui	-0.000 (0.000)	0.004*** (0.001)	
FirstFiling	0.004 (0.003)	-0.045*** (0.012)	
width=0.5 US	-0.085*** (0.019)	0.038 (0.068)	
FirstAuthorSh	0.041** (0.019)	0.022 (0.067)	
MSinceLastFiling		-0.011*** (0.002)	
lambda			-0.036 (0.064)
Constant	-8.025 (5.829)	90.070*** (24.611)	
Observations	2,515	2,515	2,515
BT dummies	Yes	Yes	Yes

Standard errors in parentheses

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

Table 27: Heckman two-step parameters, MarketValue definition (b.2)

		(1)	(2)	(3)
		second	select	/mills
width=0.5	MarketVal.bis	0.248 (0.453)	-3.262** (1.587)	
	Core_Before = 1	0.634*** (0.023)	0.412*** (0.075)	
	Core_Before=1 $\times$ MarketVal	-2.003*** (0.696)	16.110*** (2.283)	
	MSinceAcqui	-0.000 (0.000)	0.004*** (0.001)	
	FirstFiling	0.005* (0.003)	-0.046*** (0.012)	
	US	-0.077*** (0.019)	-0.010 (0.069)	
	FirstAuthorSh	0.039** (0.019)	0.025 (0.068)	
	MSinceLastFiling		-0.011*** (0.002)	
	lambda			-0.087 (0.061)
	Constant	-10.668* (5.981)	91.533*** (24.807)	
	Observations	2,515	2,515	2,515
	BT dummies	Yes	Yes	Yes

Standard errors in parentheses

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

Table 28: Heckman two-step parameters, MarketValue definition (b.3)

		(1)	(2)	(3)
		second	select	/mills
width=0.5	MarketVal_ter	0.032 (0.075)	-0.570* (0.334)	
	Core_Before = 1	0.647*** (0.022)	0.238*** (0.082)	
	Core_Before=1 $\times$ MarketVal	-0.188** (0.089)	0.908** (0.362)	
	MSinceAcqui	0.000 (0.000)	0.001 (0.001)	
	FirstFiling	0.003 (0.003)	-0.033*** (0.013)	
	US	-0.121*** (0.019)	0.092 (0.079)	
	FirstAuthorSh	0.041** (0.019)	0.063 (0.074)	
	MSinceLastFiling		-0.008*** (0.002)	
	lambda			0.017 (0.085)
	Constant	-6.623 (5.596)	66.042*** (25.558)	
	Observations	1,965	1,965	1,965
	BT dummies	Yes	Yes	Yes

Standard errors in parentheses

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