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Organizational capital and firm risk – Testing the outside option[☆]

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ABSTRACT

We examine organizational capital risk on a micro level by identifying 120,017 quasi-voluntary inventor moves between firms over three decades. Consistent with survey results from Eisfeldt and Papanikolaou (2013), we find that a 10% increase in organizational capital results in a 1.8% greater annual exit of firm inventors. Exit risk is higher 1) where employees are more transferable between firms and 2) among financially constrained firms that cannot compensate valuable employees competitively. Valuations are lower for firms with greater levels of inventor turnover / outflows.

1. Introduction

While physical capital represents a secure asset of the firm, intangible capital that is held by the firm's skilled employees (who can leave at any time) is less secure and is known as organizational capital (Prescott and Vischer, 1980). The threat of the loss of "key talent" employees is called the *outside option hypothesis*, and it represents an increased risk for firms with high levels of organizational capital (Eisfeldt and Papanikolaou, 2013 (E&P); Israelsen and Yonker, 2017). This risk emanates from "talent bargaining" between employees and the firm and proceeds as follows according to E&P. The introduction of a breakthrough technology in a new firm with related technologies (i.e., a "frontier technology shock") provides an attractive outside option for skilled employees to exit and work for the new firm (a "reallocation" in E&P). The old firms can respond by increasing compensation for the skilled employees to retain them and/or improving the firms' technological ability to the level of the tech frontier (a "restructuring" in E&P) to eliminate the outside option threat. However, if the value of reallocation for the employees exceeds the value that restructuring through retention of the employees (via additional compensation) provides to the old firms, the employees will exercise their outside option and reallocate to the new firms.

An opposing view is that organizational capital (O/K) exit is of minimal risk to firms. Limited transferability of skills in firm-specific industries may reduce the risk that skilled employees will be particularly beneficial to related firms. Many studies have also argued that SG&A spending (the usual proxy for O/K) represents risk for other reasons, as SG&A is a broad measure covering almost all expenses not related to the direct costs of producing goods. Some of these studies argue that high SG&A could represent agency costs (Anderson, Banker, and Janakiraman, 2003). Cook et al. (2021) find that it is current operating lease expenses that are driving 1) the Anderson, Banker, and Janakiraman (2003) sticky cost measure, 2) the "fixedness" of Novy-Marx's (2011) operating leverage measure, and 3) the

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inflexibility of Gu, Hackbarth and Johnson's (2018) inflexibility measure. Perhaps the greatest concern is that the studies arguing that O/K and labor mobility create risk factors (Eisfeldt and Papanikolaou, 2013; Donangelo, 2014) focus mainly on survey data or industry-level effects. Eisfeldt and Papanikolaou (2013) do provide some direct empirical evidence of the outside option hypothesis at the executive level in terms of restructuring decisions (top three officer compensation) and reallocation decisions (CEO turnover). However, there are numerous additional factors that affect executive-level employment choices. In addition, executives tend to be more focused on general management skills than developing their own technological abilities. Thus, they may be less affected by frontier technology shocks.

Our study contributes to this debate by examining reallocation decisions by a much broader set of skilled employees of a firm. Specifically, we create multiple filters to isolate quasi-voluntary inventor moves and ultimately evaluate the movement of 120,017 inventors between publicly traded firms. We create two proxies for O/K risk from these inventor moves: 1) the number of inventors moving in and out of the firm or industry (*Velocity*) in the spirit of Hyde (1998), and 2) the net number of inventors exiting the firm or industry (*Outflow*) similar to Qiu and Wang (2021). Higher velocity suggests a greater ease of labor movement and implies a higher risk for loss of O/K. Even though general skills can be picked up by inflows, high velocity still represents a loss of firm-specific skills that will have to be replaced with training. Similarly, a higher outflow suggests the firm/industry is susceptible to the loss of both general and firm-specific skills.

We find strong support for the outside option hypothesis. Specifically, we find that a 10% increase in O/K results in a 1.8% greater loss in firm inventors per year, thus supporting the traditional interpretation of this measure as a proxy for O/K loss risk. These results only hold where employee transferability is high. We also find that higher velocities or outflows lead to lower future firm valuations. These results hold in both our patent-inventor dataset and our firm-year level dataset.

2. Data and methodology

We use three main sources for patent and inventor data: 1) Hall, Jaffe and Trajtenberg (2001) NBER patent database, 2) Kogan, Papanikolaou, Seru, and Stoffman (2017) patent database (KPSS), and 3) Harvard Business School (HBS) patent dataverse of Li et al. (2014) for inventor names and home addresses. The intersection of these datasets constrains our patent and inventor dataset from 1976 to 2006.[1] We obtain financial data from CRSP and Compustat for the period 1976 – 2010. We utilize stock return and financial data for four years past the end of our patent filing sample to measure future performance effects of inventor switches. We describe the variables constructed from these datasets in Appendix A.

2.1. Inventor mobility

Donangelo (2014) notes that proxies for labor mobility are often subject to significant endogeneity problems due to events causing the separation. For example, firms could be acquired specifically for their O/K (Li, Li, Wang, and Zhang, 2018). Therefore, we remove firms with involuntary inventor moves (bankruptcy, merger, etc.) from our dataset.

We begin the construction of our dataset of inventor firm switchers by identifying quasi-voluntary inventor switches from firm-to-firm based on their patent filings. We use the Li et al. (2014) inventor database and filter the data based upon prior matching algorithms from Marx, Strumsky, and Fleming (2009). We then screen the data in two stages to identify inventors who are likely to have voluntarily switched firms. The first stage proceeds as follows:

1) We require all inventors to work for publicly traded firms in our patent databases.
2) We identify "switchers" as inventors who filed a patent with a different publicly traded firm than their most recent prior patent filing.
3) We exclude inventors that appear to switch back to the source firm, as it may signify two inventors with the same name simultaneously filing patents over time.

The second stage screens for quasi-voluntary inventor moves as follows:

1) We exclude inventor moves from all prior merger activity identified from SDC Platinum.
2) We exclude all switches "out" of a firm when the source firm is not in existence at the time of the destination firm filing. This eliminates forced moves due to bankruptcy or delisting.
3) We exclude all switches "in" to a firm when the source firm is not in existence at the time of the destination firm filing. This reduces a skills bias where, for example, inventors relocate only within a certain industry.

Our final sample includes 120,017 inventor moves by 585,113 inventors.

[1] For some analyses, this date range does not start until after 1976 due to lack of data availability. Although Noah Stoffman has recently extended the KPSS patent dataset through 2020, our analyses stop in 2006 primarily because 1) the patent data derived from Hall, Jaffe, and Trajtenberg (2001) ends in 2006 and contains some patent information that is not available on KPSS (although we extend the data to 2010 based on KPSS citation data), and 2) the inventor dataset of Li et al. (2014) stops in 2010. We use forward data through 2010 based on future citations.

2.2. Patent-inventor and firm level summary statistics

Table 1 Panel A provides patent-inventor level descriptive statistics. The average inventor in our sample files around 4 patents during our 30-year sample period with an average time between patent filings of slightly over two and one-half years. The average firm spends 6.6% annually on R&D as a percent of assets and files 1,570 patents. Panel B presents descriptive statistics on the firm-level dataset for the years 1976-2010 and contains 31,406 firm-year observations. Inventor labor velocity and outflow only record nonzero values if a firm has produced patents. Firm size is smaller and O/K larger in Panel B than Panel A, as the patent filings dataset skews toward large firms which typically produce more patents.

3. Results

3.1. Inventor flows and organizational capital (O/K)

We first attempt to validate E&P by determining whether there is a direct relationship between O/K and the tendency of inventors to switch firms voluntarily. Before evaluating cumulative switchers by firm, we use an ordered logit model to control for individual inventor characteristics and analyze the impact of O/K on individual firm switches. We include the inventor-specific controls of Marx, Strumsky, and Fleming (2009), specified in Appendix A, and add controls for firm performance (*Size, Market/book, Momentum, R&D intensity*) which could impact the propensity of an inventor to switch firms (Eisfeldt and Papanikolaou, 2013; Donangelo, 2014). Finally, we include *Employees* as a control on labor flow. We examine the relationship between O/K and individual inventor switches to another firm in our patent-inventor sample as follows:

$$Switch_{i,t} = \propto_0 + \Delta Z_{i,t} + \theta M_{i,t} + \Omega A_{i,t} + \Phi E_{i,t} + \eta_i + \nu_{i,t} + \varepsilon_{i,t} \tag{1}$$

where i and t represent firm and year, respectively. $Switch_{i,t}$ indicates each inventor switch in or out of the firm (for the ordered logit: -1 = out, 0 = no move since the last patent filing, 1 = in; for the standard logit: 0 = out, 1 = in). $\propto_0$ is the intercept term, $\Delta Z_{i,t}$ represents O/K, $\theta M_{i,t}$ represents the inventor-specific controls, $\Omega A_{i,t}$ represents the firm performance characteristics controls, $\Phi E_{i,t}$ represents labor controls, η_i is a fixed unobservable firm (industry) specific factor, $\nu_{i,t}$ is a time-varying unobserved factor, and $\varepsilon_{i,t}$ represents the error term.

Consistent with E&P, Table 2 Panel A Model (1) shows a significant positive relationship between inventor switches out of firms and O/K. The result is economically significant with a 10% increase in O/K resulting in a 1.8% increase in annual inventor exits.[2] To avoid selection bias, we limit our sample to include only patenting firms, and in models (1,3-4) we control for *R&D Intensity* and *Employees*. In Model (4) we additionally limit the sample to innovative industries following Hirshleifer, Low, and Teoh (2012) and include patent switches only when TSLP is less than 5 years. In the introduction, we also note that firm switches are more likely to occur when a frontier technology shock is affecting an industry. In this scenario, firms that do not have the financial means to restructure and/or increase compensation to their valuable employees should be more likely to experience employee exits. To test this, in models (2-4) we limit the sample to the top tercile of firms by the annual level of the KZ financial constraints index of Lamont, Polk, and Saaá-Requejo (2001) to better capture dynamic firms more likely to be affected by a frontier technology shock. Our results are even stronger than the full sample in these latter models.

Panel A models (2-4) support the argument that financially constrained firms should be more likely to experience employee exits if E&P's model holds. Table 2 Panel B models (1-6) provide further support by separating the sample annually into terciles based on 1) the SA financial constraints index of Hadlock and Pierce (2010) and 2) external finance dependent industry rankings from Acharya and Xu (2017). We find that firms facing financial constraints or potential loss of external financing face a greater risk of employee exit from higher O/K (we provide more evidence in the internet appendix using firm size and age as alternative financial constraint proxies). Panel B models (7-9) provide additional robustness and find that firms experiencing a prior inventor exit spend more on future O/K. We limit our sample to younger firms in models (8) and (9) based on arguments in E&P suggesting stronger effects in young firms. This event suggests departure benefits (reallocation) for their skilled employees exceed the firm's restructuring benefits (i.e., compensation), and firms must increase O/K to hire and train replacements and to retain employees in order to reduce the outside option risk.[3]

3.2. Organizational capital impact on talent retention and transferability

In order to provide robustness to our patent-inventor sample results, we next examine the effect of *O/K* on the retention of talented employees and their movement between firms in our firm-year sample in Table 3. We include as controls those in E&P (*Size, Market/*

[2] We divide the absolute value of the coefficient in Model (1) by the median number of inventors per firm. Median inventors per firm = (median patents per firm) / (median patents per inventor).

[3] Departure benefits may also be higher for skilled employees with more general skills. While some studies suggest high O/K firms may be naturally associated with lower general skills, Custodio, Ferreira, and Matos (2013) find that general skill employees are more valuable than those with firm-specific skills, and thus may provide greater benefits to competitors. We provide evidence in the internet appendix that high O/K and industry velocity are associated with lower future general skills training by firms using the generality measure of Hall, Jaffe, and Trajtenberg (2001), providing modest evidence that firms recognize the outside option threat.

Table 1
Patent-Inventor and Firm Level Descriptive Statistics. This table presents descriptive statistics for the patent-inventor and firm level samples. Panel A describes our patent-inventor filings sample ranging from 1976-2006, which contains individual patent filings for each inventor and lists the organizational capital proxy, patent filing control variables from Marx, Strumsky, and Fleming (2009), and firm performance variables for the final sample where each of these items contains nonmissing values. Panel B lists firm-year level descriptive statistics ranging from 1976-2010 for inventor switches by firm-year, the organizational capital proxy, firm level performance measures, and other key measures and controls. Size is in billions, employees in thousands. Variable definitions and scaling are given in Appendix A.

Panel A: Patent-Inventor Sample Stats				Percentile			
	N	Mean	S.D.	5%	25%	75%	95%
Organizational Capital	94,518	0.841	0.403	0.27	0.53	1.07	1.58
Switch (Into Firm)	89,252	0.086	0.280	0.00	0.00	0.00	1.00
Switch (Out of Firm)	86,880	0.061	0.239	0.00	0.00	0.00	1.00
Firm Specificity	94,518	0.248	0.197	0.03	0.09	0.33	0.67
Patents Per Firm	94,518	1,570.143	2,368.053	22	180	1754	7855
Tech Specialization	94,518	5,671.827	2,477.133	2,397	3,750	7,222	10,000
Patents Per Inventor	94,518	4.271	2.923	1	2	6	10
TSLP	94,518	2.503	2.581	1	1	3	8
Size	94,518	40.900	63.900	0.38	3.18	48.90	198.00
Market / Book	94,518	1.039	0.947	0.23	0.43	1.32	2.83
Momentum	94,518	0.063	0.080	-0.07	0.03	0.10	0.19
R&D Intensity	94,518	0.066	0.045	0.01	0.04	0.09	0.14
Employees	94,518	98.686	128.274	1.88	15.70	119.20	344.55
SA Index	94,497	-4.182	0.437	-4.64	-4.51	-4.04	-3.28
KZ Index	85,072	-0.199	10.476	-6.31	-1.85	0.94	4.66

Panel B: Firm-Year Sample Stats	N	Mean	S.D.	5%	Median	95%
Labor Velocity	31,406	2.436	14.963	0.000	0.000	10.000
Labor Outflow	31,406	0.733	8.940	-1.000	0.000	3.000
Organizational Capital	31,406	1.157	0.897	0.203	0.936	2.909
Patents	11,614	80.571	191.435	1.000	14.000	406.000
Size	31,406	2.805	14.765	0.007	0.202	9.742
Market / Book	31,406	0.652	10.687	0.095	0.452	2.132
Momentum	31,406	0.128	0.579	-0.608	0.043	1.188
R&D Intensity	31,406	0.054	0.089	0.000	0.021	0.206
Garmaise Index	31,406	3.821	2.260	0.000	4.000	7.000
HP Herfindahl Index	17,343	2416.058	1932.268	451.203	1865.137	6421.511
HP Competitor Freq	17,345	62.726	73.407	4.000	39.000	260.000
Employees	31,184	8.631	18.778	0.076	1.606	45.758
Tobin's Q	31,406	1.677	1.995	0.507	1.149	4.460

Book, and *Momentum*) along with *R&D Intensity*. We first confirm a positive relationship between O/K and skilled employee presence in models (1-2). We proxy for skilled employee presence by patent production since the number of inventors on a patent can vary. Models (3-6) show that O/K relates positively to labor outflow and velocity only in external finance dependent industries (Acharya and Xu, 2017), providing robustness to our results in Table 2. In the internet appendix, we repeat models (3-6) for the full sample 1) in years (0-2) and (3-5), and 2) at the industry level while controlling for noncompete law bans. These alternative specifications yield similar results.

While our Table 2 discussion footnotes that firms may attempt to limit transferability of their key employees by reducing general skills training, even firm-specific skills can provide value to related firms and increase outside option risk (e.g., Li, Li, Wang, and Zhang, 2018). If O/K is indeed related to the outside option, then the impact of O/K on labor velocity should be higher when transferability is greater. Table 3 Panel B compares low vs. high levels of transferability splitting the sample annually by the following: 1) Employee Contract Mobility (Garmaise (2011) Index), 2) Hoberg and Phillips (2016) competition, and 3) Hoberg and Phillips (2016) competitor frequency. In all three cases we find our results are positive and significant only in the high transferability group, providing further support for the outside option hypothesis.

3.3. *Identification: sample matching and 2SLS regression modeling*

Our direct measure of inventor flows between firms addresses many concerns about endogeneity and provides evidence supporting E&P. While it is difficult to adequately address the many endogenous relationships between O/K and firm risk, we connect our findings to E&P and provide further robustness in Table 4 by relating our findings to firm risk as measured by valuation. We use both labor outflow and velocity as treatment variables and use Tobin's Q as the dependent variable. Model (1) uses the full sample, while we add

Table 2
Patent-Inventor Level Switches and Organizational Capital. This table presents the relationship between O/K and individual inventor job switches in and out of a firm using the patent-inventor dataset. Panel A uses an ordered logit regression, with the dependent variable an indicator equal to -1 for switches out of a firm, 0 for no firm switching since the last patent-inventor filing, and 1 for switches into a firm. The two cutpoints for the ordered logit model are excluded. Model (1) reports full sample results, models (2-4) restrict results to the top tercile of the KZ financial constraints index, and Model (4) additionally restricts results to innovative industries and where the time since last patent < 5 years. Panel B models (1-6) use an ordered logit model and perform subsample tests on terciles of opportunities for employee advancement within the firm; i.e., the SA financial constraints index and external finance dependent industry ranking (Acharya and Xu, 2017). Each model is restricted to observations where TSLP < 5. Models (7-9) use OLS regressions with the lag of the switch variable from Panel A as the main independent variable and O/K as the dependent variable. The switch variable is based on the most recent prior inventor move relative to the inventor's present location based on the patent filing. Models (8-9) restrict to the top tercile by KZ index and where firm age is less than 15 years, while Model (9) also restricts to TSLP<5. All models in Panel B use controls from Panel A Model (2). Variable definitions and scaling are given in Appendix A, and continuous variables are winsorized at the 1% level. Tech Specialization is multiplied by 100,000. All regressions include year and firm fixed effects, heteroskedasticity robust standard errors clustered by firm, and p-values in parentheses. Observations and pseudo r-squared are included in Panel A. *,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Ordered logit regressions of inventor firm switches on organizational capital

	Full sample	High FinCon	High FinCon	Innov, TSLP<5, High FinCon
Variable	(1)	(2)	(3)	(4)
O/K	-0.3349**	-0.4730**	-0.6112***	-0.5995***
	(0.044)	(0.028)	(0.002)	(0.005)
Firm Specificity	0.0293***	0.0104	0.0097	0.0258
	(0.005)	(0.609)	(0.634)	(0.260)
Patents Per Firm	0.2181***	0.2311***	0.2790***	0.3594***
	(0.000)	(0.006)	(0.002)	(0.000)
Tech Specialization	6.7300***	6.1300***	6.1300***	8.5000***
	(0.000)	(0.000)	(0.000)	(0.000)
Patents Per Inventor	0.2633***	0.3007***	0.3025***	0.3987***
	(0.000)	(0.000)	(0.000)	(0.000)
TSLP	0.2298***	0.2634***	0.2633***	0.4379***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.0731	-0.1043	0.0809	0.1114
	(0.408)	(0.283)	(0.471)	(0.392)
Market / Book	-0.3184	0.1276	-0.1578	-0.1330
	(0.123)	(0.506)	(0.444)	(0.566)
Momentum	-0.0243	0.4329	0.2135	0.2835
	(0.950)	(0.460)	(0.691)	(0.642)
R&D Intensity	2.0278		1.9225	1.8758
	(0.242)		(0.209)	(0.264)
Employees	-0.3788***		-0.4960**	-0.4755*
	(0.002)		(0.026)	(0.056)
Year & Firm FE	Yes	Yes	Yes	Yes
Pseudo Rsq	0.107	0.131	0.132	0.107
No. Obs	84,534	28,568	28,568	25,248

Panel B. Subsample Tests
Employee Advancement Opportunities - Financially Constrained Firms

	Terciles - SA Index			Terciles – Ext Fin Dependent Inds		
	T1	T2	T3	T1	T2	T3
Variable	(1)	(2)	(3)	(4)	(5)	(6)
O/K	0.2375	-0.2371	-0.3769**	-0.3525	0.0122	-0.3617*
	(0.320)	(0.397)	(0.038)	(0.183)	(0.967)	(0.053)

Likelihood of Inventor Exit on O/K

	Full Sample	High Fincon & Firm Age < 15	High Fincon, TSLP < 5, Firm Age < 15
Variable	(7)	(8)	(9)
Prior Switch	-0.0078**	-0.0173**	-0.0181**
	(0.045)	(0.028)	(0.012)

rigor in models (2-6) as we utilize propensity score matching (PSM) and bias-adjusted Abadie and Imbens' matching (AIM) to reduce concerns of selection bias and to estimate the average treatment effect for the treated. In all models we find higher velocity and outflow significantly reduce Tobin's Q.[4]

[4] In untabulated results we replace the dependent variable (Tobin's Q) and find similar reductions with market/book ratio and increases with one-year returns net of the risk-free rate. In the internet appendix we show that returns increase monotonically as O/K increases, and we show a positive relationship between O/K and returns using IVs.

Table 3

Impact of Firm-Level O/K on Talent Retention and Transferability. This table presents the relationship between organizational capital and the retention and transferability of talented employees for our firm-year sample. Panel A uses panel regressions with the following dependent variables: total annual firm patent filings in models (1-2), labor outflow in models (3-4), and labor velocity in models (5-6). Models (1, 3-6) sum the dependent variable in years 0 to 2, while model (2) sums the dependent variable in years 3 to 5. The full sample is used in models (1-2), while models (3-6) are split by the average sample ranking of external finance dependent industries following Acharya and Xu (2017) (firms at the average ranking are placed in the low group). Panel B repeats Panel A models (5-6) for various low and high groups. Models (1-2) split the sample by the Garmaise noncompete index, with low employee contract mobility indicating high noncompete law strength (Garmaise >3) for the firm's headquarter state, and high employee contract mobility indicating low noncompete law strength or a ban (Garmaise 0-3). Models (3-4) split the sample into groups by low competition (top tercile) and high competition (bottom two terciles) by the fixed industry classification (FIC) Herfindahl Index of Hoberg and Phillips (2016), while models (5-6) split into low numbers of competitors (bottom tercile) and high numbers of competitors (top two terciles) by the total number of industry competitors in a Hoberg and Phillips (2016) FIC industry. Firm-age observations over 15 years are excluded in Panel B. Variable definitions and scaling are given in Appendix A, and continuous variables are winsorized at the 1% level. Year and firm fixed effects are included, and standard errors are robust to heteroskedasticity and clustered by firm. P-values are given in parentheses. Adjusted r-squared and firm-year observations are also included. *,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Regressions of patents and inventor firm switches on O/K

	Patents		Labor Outflow		Labor Velocity		
	Year (0-2)	Year (3-5)	Year (0-2)		Year (0-2)		
	Full Sample		Low Findep	High Findep	Low Findep		High Findep
Variable	-1	-2	-3	-4	-5		-6
O/K	0.2067***	0.2246***	-2.9769	4.4908**	-2.3227		8.4586***
	-0.001	-0.001	-0.252	-0.03	-0.505		-0.005
Size	0.4180***	0.3860***	-2.9208	3.3029***	-2.6026		4.9676**
	0	0	-0.373	-0.008	-0.546		-0.012
Market / Book	-0.3672***	-0.4110***	12.812	0.309	26.5386**		12.8401
	0	0	-0.198	-0.899	-0.049		-0.114
Momentum	-0.0452*	-0.0133	-1.8107**	-0.9335*	-1.7788**		
	-0.051	-0.618	-0.034	-0.059	-0.001	-0.036	
R&D Intensity	0.1685***	0.1133**	0.2293	2.5831	0.873	2.746	
	0	-0.02	-0.817	-0.138	-0.545	-0.241	
Year & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	
Adj R^2	0.868	0.876	0.493	0.508	0.578	0.596	
No. Obs	7,093	5,702	8,302	5,734	8,302	5,734	

Panel B: Regressions of Inventor Firm Velocity on O/K Given Varying Employee Transferability

	Emp Contract Mobility		HP Competition		HP Competitor Frequency	
	Low	High	Low	High	Low	High
Variable	-1	-2	-3	-4	-5	-6
O/K	0.6692	2.7865*	-2.1525*	3.3344**	0.2545	2.5605*
	-0.517	-0.073	-0.075	-0.018	-0.42	-0.051
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.826	0.505	0.771	0.551	0.603	0.612
No. Obs	3,261	3,222	2,063	4,302	2,130	4,284

Table 4

Inventor Flows and Firm Value. This table examines the impact of inventor flows on firm value using full and matched samples for our firm-year dataset. All models examine the effect of velocity or outflow on Tobin's Q as the dependent variable, adjust for standard errors, and match on R&D Intensity, 12-month prior momentum, and firm size (Model (1) controls for these variables instead of matching). Models (2-6) use 1:1 nearest neighbor matching via propensity score (Model 2) and the Abadie and Imbens method (AIM) in models (3-6), with year and firm fixed effects in Model (2) and an exact match by year and two-digit SIC industry in models (3-6). Model (5) additionally matches on the one-year lag of the dependent variable, and Model (6) additionally matches on the one-year lag of the dependent variable, number of employees, and whether the firm's head-quarter state bans non-compete agreements. Models (4-6) are bias adjusted. Variable definitions and scaling are given in Appendix A, and continuous variables are winsorized at the 1% level. *,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Average treatment effect of risk factors on inventor flows	Full sample	PSM	AIM			
		Simple	Simple	Bias Adj 1	Bias Adj 2	Bias Adj 3
	(1)	(2)	(3)	(4)	(5)	(6)
Velocity	-0.0272***	-0.0249***	-0.0794***	-0.1215***	-0.0906***	-0.0565***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Outflow	-0.0233***	-0.0147*	-0.0618***	-0.0774***	-0.0585***	-0.0220***
	(0.008)	(0.062)	(0.000)	(0.000)	(0.000)	(0.001)

4. Conclusion

Our study tests the *outside option hypothesis* which holds that the risk to a firm from the exit of talented employees is a function of 1) the level of organizational capital (O/K) held by these employees (Eisfeldt and Papanikolaou, 2013), and 2) the ability or willingness of these employees to exit the firm (Donangelo, 2014). We provide direct evidence in support of Eisfeldt and Papanikolaou (2013) and find that higher O/K is associated with higher net flows of inventors out of a firm. This result holds in both our patent-inventor and firm-year datasets. We find that O/K is more strongly associated with inventor exits when employee transferability is high or when the firm is financially constrained; that is, when firms are less able to maintain competitive wages relative to outside firms.

CRediT authorship contribution statement

Douglas O. Cook: Conceptualization, Methodology, Writing – review & editing. **M. Tony Via:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

None

Data availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2022.103344.

Appendix A: Variable descriptions

Firm characteristics	
O/K	Log of organizational capital. Selling, general, and administrative (SG&A) stock / total assets, adjusted to 2012 dollars using the CPI index, discounted using the perpetual inventory method with a 15% discount rate, as follows: SG&A stock = $SG\&A_t$ + (.85)($SG\&A_{t-1}$) + (.7)($SG\&A_{t-2}$) + (.55)($SG\&A_{t-3}$) + (.4)($SG\&A_{t-4}$). (Based on Eisfeldt and Papanikolaou (2013))
Labor Velocity	(Inventors leaving firm in the prior 1 (3) year period) + (Inventors joining firm in the prior 1 (3) year period). (Source: NBER patent project of Hall, Jaffe, and Trajtenberg (2001), patent dataverse of Li et al. (2014), and the Kogan, Papanikolaou, Seru, and Stoffman (2017) patent data). Based on Hyde (1998).
Labor Outflow	Net number of inventors leaving a firm in the prior 1 (3) year period. (Source: NBER patent data project of Hall, Jaffe, and Trajtenberg (2001), the patent dataverse of Li et al. (2014), and the Kogan, Papanikolaou, Seru, and Stoffman (2017) patent data).
Size	Log of (1 + market capitalization of the firm). (Source: CRSP)
Market/Book	Log of (1 + market capitalization of the firm / book value of assets). (Source: CRSP, Compustat)
Momentum	Prior 12-month return for a firm. (Source: CRSP)
R&D Intensity	Log of (1 + ((R&D spending) / (Total Assets))). (Source: Compustat)
Employees	Log of (1 + number of employees working for the firm). (Source: Compustat)
Garmaise Index	Categorical variable ranging from 0 to 9 based on the state presence of non-compete law provisions, with a higher score indicating stronger non-compete laws, and weaker "outside option" risk. Higher levels indicate lower employee mobility by their noncompete contract. (Source: Garmaise (2011))
Firm Age	Number of years the firm has been publicly traded. (Source: Compustat)
KZ Index	Financial constraints index following (Lamont et al., 2001).
SA Index	Size and age financial constraints index following Hadlock and Pierce (2010).
FinDep Industries	Ranking of industries from 0-100 with higher scores indicating the industry faces more dependence on external financing ability. (Source: Acharya and Xu (2017))
HP Competition	Herfindahl index of Hoberg and Phillips (2016) based on a fixed industry classification (FIC). Ranges from 0 to 10,000.
HP Comp Freq	Count of firms in each fixed industry classification (FIC) of Hoberg and Phillips (2016).
Tobins Q	Annual Tobin's Q (Fiscal year end). (Market value of equity) + (Book value of debt) / (Total assets). (Source: Compustat)

Patent-Inventor Filing Characteristics	
Switch	Patent-inventor level indicator showing a patent filing at a different firm than the inventor's immediate prior patent filing. The prior firm is labeled as a "Switch Out of Firm" while the new firm is labeled as a "Switch Into Firm".
Firm Specificity	Log transformation of firm specificity. The number of internal citations (from future firm patents) divided by the total citations received. (Source: Marx Strumsky, and Fleming (2009), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001)).
Patents per Firm	Log of (1 + number of patents per firm year). The total number of patents filed by the firm during the calendar year. (Source: Marx Strumsky, and Fleming (2009), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001)).
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Patent-Inventor Filing Characteristics	
	Inventor industry concentration of patents across technology classes. Herfindahl type measure of the degree of specialization of an inventor. (Source: Marx, Strumsky, and Fleming (2009)), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001)).
Patents per Inventor	Log of (1 + inventor patent total). Total number of prior patents for the inventor. (Source: Marx Strumsky, and Fleming (2009), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001)).
Time Since Last Patent	TSLP. Total number of years since the last patent filing for the inventor. (Source: Marx, Strumsky, and Fleming (2009), NBER patent data project of Hall, Jaffe, and Trajtenberg (2001))

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