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Firing Costs and Inventor Turnover

Emre Ekinci[1]

Abstract: *This paper examines the effect of firing costs on inventor turnover using the patent data provided by the United States Patent and Trademark Office (USPTO) for the 1975-2003 period. The adoption of the wrongful discharge laws in the US is considered as an exogenous increase in firing costs. As states adopt these laws at different dates, a quasi-experimental setting allows us to estimate a casual effect. Using the existing holdup theories investigating the employment relationship, we conjecture that the effect of firing costs on inventor turnover hinges on the extent to which the inventor's knowledge set is transferable to competing firms. We measure knowledge transferability by the number of co-authors an inventor has filed a patent with, his or her specialization across technological classes and reliance on the prior art patented by the current employer. Our analysis shows that these variables alter, as predicted by the theory, how increased firing costs affect inventor turnover.*

Keywords: Patents, Innovation, Wrongful Discharge Laws, Firing Costs, Worker Turnover

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1. Introduction

Worker turnover, an inherent feature of labor markets, is a serious concern for all involved parties. For firms, losing employees with critical knowledge or talent is detrimental to profits (Campbell et al., 2012). For workers, changing jobs is associated with better career outcomes, such as higher wages or promotion prospects (Topel & Ward, 1992; Ghosh, 2007; Neal, 2017). From a policy standpoint, labor mobility offers benefits to the society. While it may be damaging to firms losing critical employees, higher turnover can raise the aggregate economic activity since labor mobility facilitates knowledge spillovers across firms and industries (Cooper, 2001; Song et al., 2003; Møen, 2005; Poole, 2013). Hence, understanding how legal institutions that regulate employment relationships alter turnover dynamics is important.

Firing costs are an important determinant of worker turnover. Thus, their effects on labor markets have attracted significant interest both from researchers and policy makers. Firing costs are determined largely by the set of laws that regulate the employee-employer relationship—generally referred to as job security laws or employment protection laws. Given that many legal jurisdictions (federal states or countries) adopt different protection laws and alter them over time, the question of how these law changes affect labor markets has been studied extensively (e.g., Lazear, 1990; Kahn, 2007, 2010). The major debate in this literature has been whether more stringent protection affects employment adversely. Starting with the seminal work of Lazear (1990), a series of papers have examined how adopting more labor-friendly protection laws affects employment and have found mixed evidence (e.g., Dertouzos & Karoly, 1993; Miles,

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[1] Asst. Prof., PhD., Koc University, Department of Economics, College of Administrative Sciences and Economics, Istanbul, Turkiye, emekinci@ku.edu.tr

2000; Autor et al., 2006). Besides employment level, other economic variables of interest include the demand for temporary-help agency employment (Autor, 2003), re-employment probabilities of currently employed and unemployed workers (Kugler and Saint-Paul, 2004), wages (Autor et al., 2006), firm productivity (Autor et al., 2007), and firm-level innovation (Acharya et al., 2014; Bena et al., 2022).

While the above papers focus on the US labor market, a set of more recent papers employs the changes in the Italian labor law to provide causal estimates regarding the effects of firing costs on labor markets. Boeri and Garibaldi (2019) examine how the 2015 Italian Jobs Act, which raised severance payments, rendered dismissal procedures more labor-friendly and provided hiring subsidies, affects hirings and firings. They find that all firms increased their hirings as a response to the new legislation, whereas firings increased only in large firms. Focusing also on the Italian labor market, Belloc and D'Antoni (2020) follow a different identification strategy. Because labor protection laws are more stringent for firms that have more than 15 employees, they utilize the variation in firm size to explain why labor supply and demand are more responsive to wages when firms are subject to more stringent labor protection laws. To investigate how the employment protection laws alter firms' incentives to provide training, Bratti et al. (2021) use the *Forneo* Law, which was introduced in Italy in 2012 and reduced the firing costs for firms with more than 15 employees. They find that the law increased the number of trained workers, and this increase is driven mostly by lower turnover and less frequent use of temporary contracts. In related work, Lee (2000) considers a reform in South Korea which raised firing costs for temporary workers after a certain period of employment. He finds that increased protection leads firms to improve their screening process and that these efforts result in lower turnover.

The current paper focuses on knowledge workers (i.e., inventors) and studies how the legal changes in the standard for discharging employees affect their turnover. Following the literature (e.g., MacLeod & Nakavachara, 2007; Acharya et al., 2014; Ekinci & Wehrheim, 2022; Bena et al., 2022), we consider the adoption of the wrongful discharge laws (WDLs) (particularly, that of the good faith law) in the US as an increase in firing costs and investigate how they alter inventor turnover.

To guide our empirical analysis, we rely on the holdup models built by Acharya et al. (2014) and Ekinci and Wehrheim (2022). The main feature of these models is that worker effort is a firm-specific investment because the firm can fire the worker before he or she reaps full benefits from effort. The possibility of being fired results in a holdup problem since the worker, anticipating not being able to collect the returns from his or her effort, exerts lower effort in the first place. As a result, the worker's productivity diminishes. Both papers show that increased firing costs raise productivity because they weaken the firm's incentive to fire the inventor, thereby mitigating the holdup problem. Departing from Acharya et al. (2014), Ekinci and Wehrheim (2022) focus on the role of labor mobility on knowledge transfer across firms as a specific mechanism that leads to the holdup problem. They then show that the effect of firing costs on productivity depends on the extent to which the inventor can transfer his or her knowledge stock to competing firms. In particular, the productivity-enhancing effect of increased firing costs is positively related to the degree of knowledge transferability.

To derive testable predictions regarding turnover, we follow their logic that the effect of firing costs on turnover depends on knowledge transferability. Note that higher degrees of knowledge transferability raise the value of the inventor's outside option, and therefore, result in a higher likelihood of turnover. Thus, when the inventor's productivity increases due to the mitigated holdup problem, the increased productivity is reflected on higher mobility only if the inventor's knowledge stock is transferable. Based on this intuition, we formulate the following two hypotheses: i) the passage of the good faith law increases turnover if the inventor's knowledge stock is sufficiently transferable to competing firms; ii) the positive effect of the good faith law on turnover increases with the degree of knowledge transferability.

For our empirical analysis we construct an inventor-level panel using the patents issued by the United States Patent and Trademark Office (USPTO). More specifically, we merge the disambiguated inventor data (Li et al., 2014) with the National Bureau of Economic Research (NBER) patents file (Hall et al., 2001). The resulting unbalanced panel for the 1975-2003 period allows us to track each inventor's location and employer in every year he or she files a patent. Further, we use the data provided by Autor et al. (2006) to construct variables which indicate the adoption date of each class of WDLs by states. The variation in the adoption dates of WDLs (particularly, that of the good faith law) across states provides a quasi-experimental setting with multiple treatment groups and multiple time periods; thus, we employ a difference-in-differences approach to test our hypotheses.

We take two approaches to measure the degree of knowledge transferability, which, as indicated, determines the effect of increased firing costs on turnover. First, we use the characteristics of the inventor's prior patents, namely the number of the inventor's co-authors in patents filed until the current year and the degree of the inventor's technological specialization. The logic is that the inventor's knowledge stock becomes less firm-specific (i.e., more transferable) with the number of co-authors. Therefore, we expect the effect of the good faith law on turnover to increase with the number of co-authors. By contrast, the same effect is expected to be lower as the inventor specializes in certain technologies. We find that although the total effect of the good faith law on turnover remains negative, it decreases, in absolute value, as the number of co-authors an inventor has increases. In addition, we find that the reduction in turnover probability caused by the passage of the good faith law is lower for inventors who filed patents in diverse technological areas than for those who specialized in certain technological areas. Hence, the results from these tests provide support for the second hypothesis but they are not in line with the first hypothesis.

Next, following Ekinci and Wehrheim (2022), we employ citation-based measures for the degree of knowledge transferability. Specifically, we consider the ratio of self-citations to total citations (i.e., the average of the ratio between citations to patents assigned to the current employer and citations to patents assigned to external firms) and the ratio of unique self-citations to total unique citations (i.e., the ratio between unique citations to patents assigned to the current employer and unique citations to patents assigned to external firms). The intuition behind these two measures is the following. The inventor's knowledge stock becomes more firm-specific (in other words, less transferable) as his or her patents cite more heavily the patents assigned to the current employer rather than the patents assigned to external firms. Thus, we expect the effect of the good faith law on turnover to decrease as the inventor's reliance on the incumbent firm's patents increases. The results from these measures show that the degree of knowledge transferability reduces the negative effect of the good faith law on turnover, but the net effect remains negative for all values of transferability.

The remainder of the paper is organized as follows. In Section 2 we formulate our testable hypotheses. In Section 3 we discuss the wrongful discharge laws in the US and present the data. We present the empirical methodology in Section 4 and discuss the results in Section 5. Lastly, we conclude the paper with some remarks in Section 6.

2. Theoretical Framework

There is a large body of literature that analyzes the effects of firing costs on labor markets. The earlier theoretical work postulates that changes in the legal standard for discharging employees do not affect the efficiency of the markets to the extent that bargaining between the parties and re-contracting is possible (Summers, 1989; Lazear, 1990). Departing from the earlier work, a set of more recent papers takes the incomplete contracting approach to examine how employment relationships are affected by firing costs. MacLeod and Nakavachara (2007) show that because increased firing costs weaken the incentives of both parties to invest in relationship-specific assets, the employer invests more in screening employees. Consequently, better firm-worker matches are formed, and this results in higher productivity.

Following MacLeod and Nakavachara (2007), Acharya et al. (2014) build a holdup model in which the firm decides between investing in a risky project with a high potential return and investing in a safe project with a low return. Given the project's type, the worker's effort choice determines the probability that the project is successfully undertaken, and the surplus generated by the project is shared between the firm and the worker according to their relative bargaining powers. In this setting, exerting effort is potentially a firm-specific investment because the worker cannot reap the returns from the project if he or she is discharged before the project is finalized. Thus, after observing the project's outcome, the firm has an incentive to discharge the worker to increase its share of the surplus. Hence, a holdup problem arises. Anticipating the firm's opportunistic behavior, the worker exerts lower effort, and this results in a lower surplus in the first place. The authors show that increased firing costs curtail the firm's ability to hold up the worker and therefore induce him or her to exert higher effort. Using this intuition, they then derive testable predictions that the adoption of the wrongful discharge laws, which is considered as an increase in firing costs, raises the firm-level innovation output.

Our empirical analysis is motivated by Ekinci and Wehrheim (2022) who build a holdup model to examine inventor-level productivity. As in Acharya et al. (2014), the firm has an incentive to discharge the inventor even if he or she performs well; however, they focus on the inventor's role in knowledge transfer across firms as a specific mechanism that leads to a holdup problem. Specifically, the inventor gradually acquires knowledge related to the innovation project he or she is working on, and the competing firms gain access to that knowledge only by hiring the inventor (*learning by hiring* as in Song et al. (2003)). To mitigate the risk of losing an inventor, thus valuable information, to a competitor, the firm may discharge the inventor before he or she acquires the full knowledge related to the innovation project. The key aspect of their model is that the severity of the holdup problem depends on the extent to which the inventor can transfer his or her knowledge stock to competing firms. That is, as the inventor's knowledge stock becomes more transferable to competing firms (i.e., as it becomes less firm-specific), the firm's incentive to discharge the inventor gets stronger. Increased firing costs curtail the firm's incentive to discharge the inventor, as in Acharya et al. (2014). Different from their analysis, the magnitude of the effect depends on the degree of knowledge transferability. In particular, they show that higher firing costs raise inventor productivity if the inventor's knowledge stock is sufficiently transferable, and this effect is increasing in the degree of knowledge transferability.

Several recent papers also use the adoption of the WDLs to investigate the effects of increased firing costs on innovation. For example, Bena et al. (2022) distinguish between process innovations (i.e., inventions of a new or an improved method of production) and non-process innovations. They find that firms located in states that adopted the good faith law increase their process innovation by 6.1%-13.4% relative to firms located in non-adopting states. Notably, the adoption of the good faith law does not alter firms' non-process innovation. In a related paper, Keum (2020) focuses on firms' competitive positions in investigating firm innovation. He finds that increased labor protection raises innovative output of leading firms (i.e., firms with a strong competitive position in the product market) while reducing innovation made by lagging firms.

We use Ekinci and Wehrheim's (2022) theory to guide our analysis on inventor turnover. As noted, while increased firing costs raise inventor productivity, how such productivity increases alter turnover is subtle as it depends on the characteristics of the inventor's knowledge set. In particular, higher degrees of knowledge transferability alter the effect of firing costs on turnover through two channels. First, even in the absence of a holdup problem, the inventor becomes more likely to switch firms because his or her outside option becomes more attractive as he or she can transfer a higher portion of his or her knowledge stock to competing firms. Second, as the inventor's productivity goes up due to the mitigated holdup problem, he or she becomes more valuable in the labor market. Moreover, the increase in effort incentives caused by higher firing costs is greater when the inventor's knowledge stock is more portable (Ekinci & Wehrheim, 2022). Thus, as knowledge transferability increases, higher firing costs result in even a higher productivity increase. However, increased productivity translates into a higher turnover propensity only if the inventor's knowledge stock is transferable to competing firms. Using this rationale, we make the following conjectures. First, the probability of turnover increases with firing costs if the inventor's knowledge stock is sufficiently transferable. Second, the effect of firing costs on turnover hinges on the degree to which the inventor's knowledge stock is transferable to competing firms.

Following the literature, we consider the passage of the wrongful discharge laws, and particularly that of the good faith law, as an increase in firing costs borne by the firm (e.g., MacLeod & Nakavachara, 2007; Acharya et al., 2014; Keum, 2020; Ekinci & Wehrheim, 2022; Bena et al., 2022). Thus, our conjectures lead to the following two hypotheses we test in the following sections: i) the passage of the good faith law increases turnover if the inventor's knowledge stock is sufficiently transferable to competing firms; ii) the positive effect of the good faith law on turnover increases with the degree of knowledge transferability.

3. Data

3.1. Wrongful Discharge Laws in the US

In early 1970s the US began implementing major changes in its labor laws that concern employment protection. In particular, a gradual shift occurred from the common law doctrine of *employment at will*, which allowed the employer to terminate employment for "good cause, bad cause, or no cause at all", to a regime characterized by common law exceptions to employment at will. These exceptions are composed of three broad categories: public policy, implied contract, and good faith (Morris, 1994; Muhl, 2001; Bird, 2004). We use the classification of legal doctrines developed by Autor et al. (2006) for the adoption of WDLs by each state (other studies using the same classification include Autor et al. (2007), MacLeod & Nakavachara (2007), Acharya et al. (2014), and Ekinci & Wehrheim (2022)). Table 1 presents the adoption date of each doctrine across states.

Table 1. Adoption Dates of Wrongful Discharge Laws

State	Implied Contract	Public Policy	Good Faith
Alabama	1987		
Alaska	1983	1986	1983
Arizona	1983	1985	1985
Arkansas	1984	1980	
California	1972	1959	1980
Colorado	1983	1985	
Connecticut	1985	1980	1980
Delaware		1992	1992
Florida			
Georgia			
Hawaii	1986	1982	
Idaho	1977	1977	1989
Illinois	1974	1978	
Indiana	1987	1973	
Iowa	1987	1985	
Kansas	1984	1981	
Kentucky	1983	1983	
Louisiana			1998
Maine	1977		
Maryland	1985	1981	
Massachusetts	1988	1980	1977
Michigan	1980	1976	
Minnesota	1983	1986	
Mississippi	1992	1987	
Missouri	1983	1985	
Montana	1987	1980	1982
Nebraska	1983	1987	
Nevada	1983	1984	1987
New Hampshire	1988	1974	1974
New Jersey	1985	1980	
New Mexico	1980	1983	
New York	1982		
North Carolina		1985	
North Dakota	1984	1987	

Table 1. Adoption Dates of Wrongful Discharge Laws (Continue)

State	Implied Contract	Public Policy	Good Faith
Ohio	1982	1990	
Oklahoma	1976	1989	1985
Oregon	1978	1975	
Pennsylvania		1974	
Rhode Island			
South Carolina	1987	1985	
South Dakota	1983	1988	
Tennessee	1981	1984	
Texas	1985	1984	
Utah	1986	1989	
Vermont	1985	1986	
Virginia	1983	1985	
Washington	1977	1984	
West Virginia	1986	1978	
Wisconsin	1985	1980	
Wyoming	1985	1989	1994

Note: This table displays the adoption dates of WDLs by each state. Data are retrieved from Autor et al. (2006). The adoption of the good faith law was reversed by New Hampshire in 1980 and by Oklahoma in 1987, and Missouri reversed its decision to adopt the implied contract law in 1988.

While each exception captures a different aspect of the employment relationships, they all raise the level of justification before the employer can discharge an employee without facing any legal remedies (Miles, 2000; Autor et al., 2006; MacLeod & Nakavachara, 2007). Under the public policy exception, it is wrongful to discharge an employee who refuses to violate the principles of public policy. For example, this law ensures that the employer cannot force the employee to commit an illegal act such as price-fixing or that it cannot prevent the employee's whistleblowing (Miles, 2000; Autor et al., 2006). Under the implied contract exception, courts may infer (using, for example, personnel manuals) that the employment relationship is governed by a contract which stipulates that termination is possible only if "good cause" is provided by the employer (Miles, 2000; Autor et al., 2006). Finally, the good faith exception deals with the cases in which the employer has an opportunistic motive for discharge. In particular, if the termination decision is not based on "just cause", then the motive for discharge can be deemed bad faith and the court may decide for wrongful discharge. For example, discharging an employee before he or she becomes entitled to employment benefits such as retirement benefits or bonuses violates the good faith exception (Miles, 2000; Autor et al., 2006).

Following Acharya et al. (2014) and Ekinci and Wehrheim (2022), we examine the effect of the good faith law while controlling for the adoption of the public policy and implied contract exceptions. The main reason for taking this approach is that the intuition behind this law is consistent with the theory proposed by Ekinci and Wehrheim (2022). As discussed above, the firm has an incentive to discharge an inventor before he or she acquires valuable information in order to mitigate the risk of losing him or her to competitors. Thus, the decision to discharge before the inventor reaps the returns from his or her effort in the innovation process may be considered within the scope of the good faith law.

3.2. Patent Data

To construct an inventor-level (unbalanced) panel data, we use patents filed at the USPTO. More specifically, we merge the disambiguated inventor data provided by Li et al. (2014) with the NBER patents file (Hall et al., 2001).

Variables crucial to our empirical analysis are inventors' locations in the year they file a patent application and whether or not they have changed employer in that year. We derive the inventor's location using his or her residential address provided on the patent document. Because the theory we are testing does not apply to cases in which inventors move from self-employment to employment, we use assignee names to construct a variable for turnover. In particular, we construct this variable under the assumption that inventors whose successive patents have different assignees have switched employers between the application dates of those two patents. More specifically, we use the midpoint of application dates of a given pair of successive patents, and our dependent variable equals one if the inventor has changed his or her employer between those dates and it equals zero if otherwise. To screen out false positives due to collaborative R&D, mergers and acquisitions, and organizational name changes, we infer an employer change from a given pair of successive patents if the following three conditions are satisfied. First, there must be no patent assigned to the previous assignee up to 360 days after the second patent application. Second, there must be no patent assigned to the new assignee up to 360 days before the previous patent application. Third, we rely on the NBER Patent Database to exclude differences in assignee names due to mergers and acquisitions.

Although the patent data are widely used in the literature to analyze inventor mobility (e.g., Song et al., 2003; Marx et al., 2009; Akcigit et al., 2016), this approach poses some challenges. First, we fail to detect any location or employer changes in years the inventor does not file a patent. Second, since we detect a change in location or employer using two consecutive patents filed by an inventor, we do not observe the exact date of either change. Third, we do not observe whether turnover is voluntary.

Our working sample covers the period between 1975 and 2003 since our data on the adoption of the WDLs end in early 1990s. This sampling approach is consistent with the earlier studies using the same datasets. For example, Acharya et al. (2014) focus on the years 1971-1999 while Ekinci and Wehrheim (2022) use data for the period between 1975 and 2003. This leaves us with a sample consisting of 2,746,877 worker-years and 1,106,616 unique patents. Summary statistics are presented in Table 2.

Table 2. Summary Statistics

	Mean	S.D.	Min	p.25	Median	p.75	Max
Good faith	0.25	0.43	0.00	0.00	0.00	1.00	1.00
Public policy	0.58	0.49	0.00	0.00	1.00	1.00	1.00
Implied contract	0.75	0.43	0.00	1.00	1.00	1.00	1.00
Turnover	0.09	0.28	0.00	0.00	0.00	0.00	1.00
Labor market experience	7.26	5.98	1.00	3.00	6.00	10.00	25.2
Tenure at firm	5.05	4.38	0.00	2.00	4.00	7.00	28.00
# of co-authors	4.47	6.18	0.00	1.00	3.00	5.00	362.00
Average team size	1.71	1.65	0.00	0.75	1.33	2.20	50.00
Knowledge concentration	0.57	0.35	0.01	0.25	0.50	1.00	1.00
Inventor quality	90.53	41.75	0.00	11.86	31.86	85.63	35364.3
% change in GDP	6.47	3.17	-26.6	4.30	6.20	8.4	42.8
Average self-citation ratio	0.14	0.22	0.00	0.00	0.00	0.20	1.00
Unique self-citation ratio	0.13	0.21	0.00	0.00	0.00	0.19	1.00
Technology classes							
Chemicals	0.20	0.40					
Computers and communications	0.17	0.37					
Medical (excluding drugs)	0.05	0.21					
Electrical and electronic (excluding semiconductors)	0.16	0.37					
Mechanical	0.16	0.37					
Other technologies	0.17	0.37					
Drugs	0.07	0.26					
Semiconductors	0.03	0.16					
Number of inventor-years				2,746,877			
Number of patents				1,106,616			

We use the following control variables in regressions: labor market experience (the difference between the current year and the year of the first patent filed by the inventor), tenure at the current firm, number of (unique) co-authors before the current year, the average team size in patents filed before the current year, knowledge concentration (the Herfindahl index of distribution across technology classes for all patents filed before the current year), technology classes (as defined in Hall et al. (2001)). Note that we include the squared terms of experience and tenure, and apply a log transformation to the variables concerning the number of co-authors and team size (that is, we define $\hat{x} = \log(1 + x)$, where x is the variable being transformed). Additionally, we include the percent change in the state-level GDP from the previous year (retrieved from the Bureau of Economic Analysis (BEA) website) to address the correlation between the state-level economic activity and the decision to adopt WDLs. Note that because we construct a panel of inventors using patent documents, we do not include any firm-level control variables in our regressions (see Acharya et al. (2014), who use the *Compustat* database to retrieve firm-level control variables).

4. Empirical Methodology

To examine the effect of the good faith law on inventor turnover, we use the variation in the adoption of the WDLs in the US. Because states adopt these doctrines at different dates, we have a quasi-experimental setting. Thus, we employ a difference-in-differences approach by estimating the following two-way fixed effects model:

$$y_{ist} = \alpha_o GF_{st} + \alpha_1 V_{ist} GF_{st} + \gamma IC_{st} + \delta PP_{st} + \mu_t + \theta_s + \beta X_{ist} + \epsilon_{ist}, \quad (1)$$

where i, s and t denote inventor, state, and year, respectively, y_{ist} is a binary indicator which takes a value of one if inventor i has switched employer in year t, X_{ist} is the vector of observable characteristics of inventor i, V_{ist} is the degree of transferability of inventor i's knowledge stock, μ_t and θ_s are year and state fixed effects, respectively, ϵ_{ist} is the disturbance term, and finally, GF_{st}, $IC_{st}$and PP_{st} are binary variables indicating whether the corresponding doctrine is effective in state s in year t.

In equation (1), the coefficients of interest are α_o and α_1. Note that the passage of the good faith law changes the propensity to turnover by $\alpha_o + \alpha_1 V_{ist}$. Hence, assuming higher values of V_{ist} indicate higher degrees of knowledge transferability, the first hypothesis implies that this term should be positive when V_{ist} is sufficiently large. The second hypothesis implies that α_1 should be positive.

Next, as in Autor et al. (2007), Acharya et al. (2014), and Ekinci and Wehrheim (2022), we estimate the following dynamic specification to probe whether our estimates from equation (1) are consistent with a causal interpretation:

$$y_{ist} = \sum_{k=-3}^{2} \alpha_{t+k} \Delta GF_{st+k} + \gamma_{t+k} \Delta IC_{st+k} + \delta_{t+k} \Delta PP_{st+k} + \tilde{\alpha} GF_{st-4} + \tilde{\gamma} IC_{st-4} + \tilde{\delta} PP_{st-4} + \mu_t + \theta_s + \beta X_{ist} + \epsilon_{ist}, \quad (2)$$

where ΔGF_{st+k}, ΔIC_{st+k} and ΔPP_{st+k} are binary variables indicating whether the corresponding doctrine was adopted by state s in year $t + k$, and GF_{st-4}, IC_{st-4} and PP_{st-4} are binary variables taking a value of one in every year beginning with the fourth year after the adoption of the corresponding doctrine. If the results concerning the effect of the good faith law are consistent with a casual interpretation (i.e., there is no anticipation of the law change leading to a behavioral change), the coefficients on the leads of this law should be zero (i.e., $\alpha_{t+1} + \alpha_{t+2} = 0$). Also, coefficient $\tilde{\alpha}$ captures the long-run effect of the good faith exception on inventor turnover. A similar interpretation applies to the coefficients on the adoption of the implied contract and public policy exceptions.

5. Empirical Results and Discussion

We begin our analysis estimating the direct effect of each class of WDLs on turnover. As discussed, how the passage of these laws alters turnover is ambiguous since the effect of increased firing costs on turnover depends on the degree to which the inventor's knowledge stock is transferable to competing firms. As a benchmark, we first look at the direct effect that these laws may have on turnover and then formally test the two hypotheses discussed above. To this end, we estimate equation (1) under the assumption that the effect of the good faith law on turnover does not depend on knowledge transferability, i.e., $\alpha_1 = 0$.

The results are reported in Table 3. In columns 1 through 3 we include, respectively, state-specific trends, a time trend that varies with the adoption of the good faith law, and state-specific trends that vary with the adoption of the good faith law.

Table 3. Effects of WDLs on Turnover

	(1)	(2)	(3)
Good faith (GF)	-0.0002	-0.0099**	-0.0124**
	(0.003)	(0.004)	(0.006)
Public policy	0.0006	0.0036	-0.0004
	(0.002)	(0.0023)	(0.002)
Implied contract	0.0013	0.0002	0.0006
	(0.002)	(0.003)	(0.002)
Experience	0.0071***	0.0072***	0.0071***
	(0.0004)	(0.0004)	(0.0004)
Experience^2	-0.0119***	-0.0119***	-0.0119***
	(0.002)	(0.002)	(0.002)
Tenure	-0.0008	-0.0009*	-0.0008
	(0.001)	(0.001)	(0.001)
Tenure^2	-0.0081***	-0.0079***	-0.0081***
	(0.002)	(0.002)	(0.002)
# of co-authors	-0.0129***	-0.0130***	-0.0130***
	(0.001)	(0.001)	(0.001)
Knowledge concentration	0.0226***	0.0229***	0.0226***
	(0.002)	(0.002)	(0.002)
Technology classes	Yes	Yes	Yes
State-specific trends	Yes		
GF adoption trends		Yes	
GF adoption x State-specific trends			Yes
Number of observations		2,746,877	
R^2	0.024	0.024	0.024

Note: This table reports the results from estimating equation (1) when α_1 is set to zero. Each specification includes controls for labor market experience, tenure at the current firm, number of co-authors before the current year, average team size in patents filed before the current year, and knowledge concentration. Robust standard errors (reported in parentheses) are clustered at state level. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

The results show that the effect of the good faith law on turnover is negative and statistically significant (except in column 1), whereas the coefficients of the implied contract and public policy exceptions are close to zero and not significant. Focusing on the good faith law, we observe that its passage has no impact on turnover when state-specific trends are included since the corresponding coefficient is negative but small and not precise (column 1). By contrast, the effect becomes more substantial in magnitude and statistically significant when time trends are interacted with the adoption of this class of exception. In particular, the probability of turnover decreases by 0.99 percent when a linear time trend varies with the adoption of the good faith law (column 2) and by 1.24 percent when state-specific time trends are allowed to vary with the adoption of the good faith law (column 3).

Next, we turn to equation (2) and augment the specifications in Table 3 with the leads and lags of each class of exceptions to address concerns about reverse causality and examine dynamic effects. The results are reported in Table 4. Importantly, the coefficients on the lead indicators for the good faith law are close to zero and statistically not significant. This means that the effect of the good faith law on turnover is not observed prior to its adoption, thereby showing no evidence for reverse causality. Although all coefficients on the lag indicators for this law are negative, only some of those reported in column 3 are statistically significant. According to these estimates, the probability of turnover decreases by 0.85 percent in the first year the good faith law is adopted and by 1.18 percent in the long run (i.e., after the fourth year of its adoption).

Table 4. Dynamic Effects of WDLs on Turnover

	(1)	(2)	(3)
Good faith (t-2)	-0.0027	0.0025	-0.0007
	(0.004)	(0.005)	(0.004)
Good faith (t-1)	-0.0007	0.0038	0.0022
	(0.006)	(0.007)	(0.005)
Good faith (t)	-0.0048	0.0002	-0.0010
	(0.004)	(0.005)	(0.004)
Good faith (t+1)	-0.0008	-0.0024	-0.0085*
	(0.003)	(0.005)	(0.005)
Good faith (t+2)	-0.0000	-0.0017	-0.0079
	(0.0077)	(0.008)	(0.007)
Good faith (t+3)	-0.0027	-0.0047	-0.0108
	(0.006)	(0.007)	(0.007)
Good faith (t+4)	-0.0041	-0.0082	-0.0118*
	(0.006)	(0.008)	(0.007)
Implied contract (t-2)	0.0013	0.0028*	0.0003
	(0.002)	(0.002)	(0.002)
Implied contract (t-1)	0.0027	0.0039*	0.0015
	(0.002)	(0.002)	(0.002)
Implied contract (t)	0.0024	0.0035*	0.0010
	(0.002)	(0.002)	(0.002)
Implied contract (t+1)	0.0004	0.0014	-0.0012
	(0.003)	(0.003)	(0.003)
Implied contract (t+2)	0.0027	0.0035*	0.0009
	(0.003)	(0.002)	(0.003)
Implied contract (t+3)	0.0032	0.0037	0.0013
	(0.003)	(0.003)	(0.003)
Implied contract (t+4)	0.0042	0.0024	0.0020
	(0.004)	(0.004)	(0.004)
Public policy (t-2)	0.0003	-0.0015	0.0009
	(0.002)	(0.003)	(0.002)
Public policy (t-1)	0.0024	0.0006	0.0031
	(0.002)	(0.002)	(0.002)
Public policy (t)	-0.0002	-0.0012	0.0006
	(0.003)	(0.003)	(0.003)
Public policy (t+1)	0.0009	0.0001	0.0007
	(0.003)	(0.0027)	(0.003)
Public policy (t+2)	-0.0003	-0.0011	-0.0004
	(0.003)	(0.004)	(0.003)
Public policy (t+3)	0.0005	-0.0005	0.0006
	(0.004)	(0.004)	(0.004)

Table 4. Dynamic Effects of WDLs on Turnover (Continue)

	(1)	(2)	(3)
Public policy (t+4)	0.0002	0.0009	0.0001
	(0.005)	(0.005)	(0.005)
Technology Classes	yes	yes	yes
State-specific trends	yes		
GF adoption trends		yes	
GF adoption x State-specific trends			yes
Number of observations		2,746,877	
R^2	0.024	0.024	0.024

Note: This table reports the results from estimating equation (2). Each specification includes the controls for the labor market experience, tenure at the current firm, the number of co-authors an inventor has before the current year, the average team size in patents filed before the current year, and knowledge concentration. Robust standard errors (reported in parentheses) are clustered at state level. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

This set of results also reveals interesting patterns concerning the dynamic effects of the implied contract exception. We observe that most lag indicators are positive (11 out of 12 cases), but only one of them is statistically significant (column 2). In the same specification, the coefficient on the adoption year is also positive and significant (at the ten percent level). However, the lead indicators are positive and statistically significant (at the ten percent level), casting doubts over any casual interpretation regarding the effect of this law on turnover. Finally, we observe that all lead and lag indicators for the public policy exception are close to zero and not significant.

We now turn to the two hypotheses that concern how firing costs alter turnover. To this end, we include an interaction term between the transferability of the inventor's knowledge stock and the adoption of the good faith law (i.e., α_1 is estimated along with α_0). We use four variables to measure knowledge transferability. Our first two measures are based on the characteristics of the inventor's earlier patented inventions. First, we compute the number of (unique) co-authors each inventor has in patents filed until the current year. Our conjecture is that as an inventor's patents are co-authored by more inventors, his or her knowledge stock becomes less firm-specific (i.e., more transferable). Hence, we expect the effect of the good faith law on turnover to increase with the number of co-authors an inventor has (i.e., we expect $\alpha_1 > 0$). Second, we use the inventor's knowledge concentration. Specifically, we compute the inventor's degree of technology specialization by calculating the Herfindahl index of distribution of all patents he or she filed until the current year. Our conjecture is that an inventor who is a technology generalist has a higher number of potential firms to move to, and therefore, his or her knowledge set is more transferable. With this interpretation, we expect the effect of the good faith law on turnover to decrease with the degree of technology specialization (i.e., we expect $\alpha_1 < 0$). Note that technology concentration is bounded, by construction, between 0 and 1, and a worker's knowledge stock becomes less diverse (more concentrated) as it approaches to 1.

The results are reported in Table 5. Columns 1 through 3 display the results when the degree of transferability is measured by the number of co-authors. We observe that the coefficient on the good faith law is negative in all specifications but significant (at the five percent level) in columns 2 and 3. More importantly, the coefficient on the interaction between the good faith law and the number of co-authors is positive and significant (at the five percent level in columns 1 and 2 and at the ten percent level in column 3). To get a sense of the magnitude of these effects, consider the results in column 3 in which state-specific time trends are allowed to vary with the passage of the good faith law. Accordingly, the passage of the good faith law reduces the probability of turnover by 1.33 percent if the worker's all prior patents have been solo-authored; however, the negative effect decreases by 0.27 percent for a unit-increase in the number of unique co-authors. Note that the total effect turns positive at approximately 137 co-inventors, i.e., $\exp(0.0133/0.0027) - 1 \approx 137$. In practice, however, this is not likely to be observed because in our sample workers in the top 1 percentile have 29 co-authors (although there are some outliers with more than 137 co-authors).

Table 5. Effects of Good Faith Law and Knowledge Transferability on Turnover (I)

	(1)	(2)	(3)	(4)	(5)	(6)
Good faith (GF)	-0.0023	-0.0116**	-0.0133**	0.0021	-0.0079*	-0.0099*
	(0.004)	(0.005)	(0.007)	(0.003)	(0.004)	(0.006)
# of co-authors	-0.0144***	-0.0144***	-0.0143***	-0.0136***	-0.0137***	-0.0136***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# of co-authors x GF	0.0029**	0.0029**	0.0027*			
	(0.001)	(0.001)	(0.0014)			
Knowledge concentration	0.0230***	0.0233***	0.0230***	0.0239***	0.0242***	0.0239***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Knowledge concentration x GF				-0.0034*	-0.0034*	-0.0032*
				(0.002)	(0.002)	(0.002)
Public policy	0.0003	0.0037	-0.0006	0.0004	0.0038	-0.0006
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Implied contract	0.0012	0.0001	0.0005	0.0013	0.0001	0.0006
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Technology Classes	yes	yes	yes	yes	yes	yes
State-specific trends	yes			yes		
GF adoption trends		yes			yes	
GF adoption x State-specific trends			yes			yes
Number of observations	2,746,877					
R^2	0.024	0.023	0.024	0.024	0.023	0.024

Note: This table reports the results from estimating equation (1). Each specification includes controls for labor market experience, tenure at the current firm, number of co-authors before the current year, average team size in patents filed before the current year, and knowledge concentration. Robust standard errors (reported in parentheses) are clustered at state level. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

Columns 4 through 6 report the results when knowledge concentration is used to measure the extent to which the inventor's knowledge stock is transferable to competing firms. We observe that the coefficient on the good faith law is positive but not significant in column 1, whereas it is negative and significant (at the 10 percent level) in columns 5 and 6. Consistent with the second hypothesis, the coefficient on the interaction between the good faith law and knowledge concentration is negative and statistically significant (at the ten percent level). Since the coefficient of the good faith law is always negative, the total effect of this law remains negative for all values of knowledge concentration. For example, the results in column 6 imply that the passage of the good faith law reduces the probability of turnover by 0.99 percent if the worker is a generalist (i.e., knowledge concentration approaches to 0) and by 1.31 percent if the worker is a specialist (i.e., knowledge concentration approaches to 1).

Next, we turn to our citation-based measures to examine how the effect of the good faith law on turnover changes with the reliance of the inventor's patented innovations to prior art patented by his or her current employer. Following Ekinci and Wehrheim (2022), for each patent we calculate the ratio of backward self-citations (i.e., citations to the patents assigned to the inventor's current employer) to total backwards citations and then take the average of this ratio for all patents filed by the inventor at the current firm until the current year. Second, we consider unique citations to prior work. Accordingly, we compute the ratio of backward self-citations to total backward citations for all patents filed by the inventor at the current firm until the current year. The intuition behind these two measures is the same: an inventor's knowledge stock becomes more firm-specific (in other words, less transferable) as his or her patents cite more heavily the patents previously assigned to the current employer than the patents assigned to external firms. Hence, we expect that the effect of the good faith exception on turnover will decrease with the share of backward self-citations (that is, we expect $\alpha_1 < 0$).

Table 6. Effects of Good Faith Law and Knowledge Transferability on Turnover (II)

	(1)	(2)	(3)	(4)	(5)	(6)
Good faith (GF)	0.0021	-0.0080	-0.0014	0.0022	-0.0080	-0.0014
	(0.003)	(0.005)	(0.011)	(0.003)	(0.005)	(0.011)
Av. self-citation ratio	-0.0389***	-0.0397***	-0.0389***			
	(0.004)	(0.004)	(0.004)			
Av. self-citation ratio x GF	-0.0174***	-0.0167***	-0.0173***			
	(0.006)	(0.006)	(0.006)			
Unique self-citation ratio				-0.0391***	-0.0400***	-0.0392***
				(0.004)	(0.004)	(0.004)
Unique self-citation ratio x GF				-0.0185***	-0.0179***	-0.0184***
				(0.006)	(0.006)	(0.006)
Public policy	0.0014	0.0031	0.0004	0.0014	0.0032	0.0004
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Implied contract	0.0013	0.0019	0.0007	0.0013	0.0019	0.0008
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Technology Classes	Yes	yes	yes	yes	yes	yes
State-specific trends	Yes			yes		
GF adoption trends		yes			yes	
GF adoption x State-specific trends			yes			yes
Number of observations	2,274,181					
R^2	0.025	0.024	0.025	0.025	0.024	0.025

Note: This table reports the results from estimating equation (1). Each specification includes controls for labor market experience, tenure at the current firm, number of co-authors before the current year, average team size in patents filed before the current year, and knowledge concentration. Robust standard errors (reported in parentheses) are clustered at state level. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

This set of results are presented in Table 6. Columns 1 through 3 report the results when the degree of knowledge specificity is measured by the average ratio of self-citations to total citations. As observed in the previous set of results, the coefficient of the good faith exception is positive controlling for state-specific trends (column 1) but is negative controlling for adoption-specific trends and controlling for state-specific trends that vary with the adoption of this law (columns 2 and 3, respectively). Even though the magnitudes of these coefficients are similar to those observed in the previous specifications (e.g., compare column 1 in Table 6 with columns 1 and 4 in Table 5, and column 2 in Table 6 with column 5 in Table 5), none of them is statistically significant. Consistent with the second hypothesis, the coefficient of the interaction between the good faith exception and the average ratio of self-citations to total citations is negative and statistically significant (at the one percent level) in all specifications. Specifically, the passage of the good faith exception reduces the probability of turnover by approximately 1.7 percent more if the inventor's knowledge set is purely firm-specific as opposed to being general (i.e., the average of self-citations-total citations ratio increases from 0 to 1). Further, the total effect of the good faith law on turnover does not turn positive.

The next set of results, reported in columns 4 through 6, uses the ratio of unique self- citations to total unique citations to measure the specificity of the inventor's knowledge stock. We observe that the results are qualitatively the same as those in columns 1 through 3, and therefore, provide supporting evidence for the second hypothesis. Accordingly, the coefficient of the good faith exception is small and not significant, and its sign depends on the specification. By contrast, the estimated negative interaction effect is substantial and statistically significant at the one percent level in each specification. Specifically, the effect of good faith law on turnover decreases by around 1.8 percent as the ratio of self-citations to total citations increases by one unit.

6. Conclusion

This paper provides an empirical analysis of how firing costs affect inventor turnover. Our analysis is motivated by the existing holdup theories which show that increased firing costs curtail the firm's ability to hold up the worker, thereby leading to an increase in productivity (Acharya et al., 2014; Ekinci & Wehrheim, 2022). In particular, Ekinci and Wehrheim (2022) focus on inventor productivity and show that such a productivity-enhancing effect depends on the extent to which the inventor's knowledge stock is transferable to competing firms. Using their rationale, we posit that increased firing costs raise the probability of turnover if the inventor's knowledge stock is sufficiently transferable and that the positive effect is increasing in the degree of knowledge transferability.

To test these two hypotheses, we employ adoption of the WDLs in the US (particularly, the adoption of the good faith law) as an increase in firing cost and use the patent data to derive inventor turnover. The results provide strong support for the second hypothesis. Specifically, we use several measures for knowledge transferability (the inventor's number of co-authors, knowledge concentration and reliance on the prior art patented by the current firm) and find that the effect of the passage of the good faith law on turnover increases with the degree of knowledge transferability. By contrast, the results concerning the total effect of the good faith are not consistent with the first hypothesis.

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