Productivity Gains from Labor Outsourcing: The Role of Trade Secrets

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Abstract: How quickly producers can adjust their workforce with changing demand is important for aggregate productivity. Labor outsourcing allows quick adjustments but potentially exposes sensitive information to outsiders, which may deter producers from outsourcing if the legal system does not adequately protect secret information. I quantify the impact of trade secret protection on labor outsourcing, and consequently, on aggregate productivity. First, using event studies and differences-in-differences around the staggered adoption of the Uniform Trade Secrets Act, I show that better trade secret protection leads to increased outsourcing. Second, to quantify the resulting gains in productivity, I build a structural model of outsourcing and multi-industry dynamics and estimate it with data from the U.S. manufacturing sector. I decompose the cross-state differences in labor outsourcing into differences in firing cost, industry composition, demand volatility, and trade secret protection. Strengthening trade secret protection for all states to match the state with the strictest protection would increase the outsourcing employment by 24% and aggregate output by 1.7%.

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1 Introduction

Producers' demand for workers changes over time due to fluctuations in the demand for goods and the presence of tasks that are not performed frequently. Labor outsourcing allows producers to make quick adjustments to their workforce, bypassing hiring and firing costs. However, many jobs, which could potentially be outsourced, also provide access to sensitive information. For example, accountants might see financial documents, machine operators might see product designs, and security guards might see visitor lists. Sharing such information with outsiders can be problematic if the legal environment does not provide adequate protection for intellectual property. In such cases, producers will be reluctant to use outsourced workers, leading to an inefficiently small outsourcing sector, slower reallocation, and reduced aggregate productivity.

In this paper, I quantify the impact that trade secret protection has on aggregate productivity by affecting the extent of outsourcing in the economy. To show that the legal environment impacts labor outsourcing, I first use the staggered adoption of the Uniform Trade Secrets Act (UTSA) among states of the U.S. Next, I develop and estimate a structural model of industry dynamics in which firms choose whether to use outsourced workers in each task. I use the estimated model to measure the impact of distorted outsourcing decisions on aggregate productivity. I find that if all states of the U.S. could protect trade secrets as well as the 'best' state, the fraction of outsourced workers would increase by 24%, and aggregate output would increase by 1.7%.

The U.S. provides a good laboratory to study this question because it features considerable variation in both trade secret protection and the extent of outsourcing. First, for reasons that were exogenous to outsourcing, the switch to statutory law via the UTSA happened in different states during different years. Second, firms that provide labor-intensive services, which were historically done in-house, employed 11% of the U.S. labor force in 2018, yet this share was just over 3% in 1971. There is also large heterogeneity across states: in 2018, these firms had an employment share of 14.3% in California (90th percentile) but only 7.6% in Wisconsin (10th percentile).

I start by documenting three main stylized facts on the patterns of labor outsourcing in the U.S. First, I show that most U.S. industries enjoyed a growth in labor outsourcing, i.e., the growth in outsourcing was not an artifact of growth in industries that demand outsourcing more than others. Second, the growth in labor outsourcing is not accompanied by a similar 'growth' in the outsourcing of physical goods. Third, the cross-state heterogeneity in outsourcing employment is matched by an equally large heterogeneity in demand for outsourced workers, which does not diminish once I compare more disaggregated industry groups. These facts motivate a state- and time-specific factor that determines the extent of labor outsourcing for all industries.

To understand the role of trade secret protection, I utilize the staggered adoption of the UTSA across U.S. states. First, using historical anecdotes and event studies, I argue that timing of the adoptions was exogenous to outsourcing patterns. Second, using differences-in-differences, I show that trade secret protection has a positive and significant impact on the size of the labor outsourcing sector. Quantitatively, improvements in trade secret law explain 13% of the outsourcing share growth from 1971 to 1997, which added 1.7 million extra jobs to the outsourcing sector. Third, I supplement the relevance of shared information by showing that the impact was not significant for tasks that are (1) unlikely to involve sensitive information or (2) already subject to auxiliary enforcement through professional organizations.

To quantify the aggregate productivity gains, I develop and estimate a structural model of industry dynamics that is based on Hopenhayn (1992). I augment the model in two dimensions. First, I incorporate a task-based production framework in which firms decide whether to use either their employees or outsourced workers for each task. Unlike employees, the number of outsourced workers can be adjusted freely, but their productivity is limited by how much sensitive information is shared. The extent of trade secret protection determines which information can be shared without risking leaks and, thus, the tasks that can be feasibly outsourced. Second, I extend the model to accommodate multiple industries that use different technologies, including different tastes for outsourced labor. In total, the extent of outsourcing can differ *across states* due to differences in four components: (1) employment protection; (2) within-industry firm characteristics; (3) industry compositions; and (4) trade secret protection.

I estimate the model using state-industry-level data from the U.S. manufacturing sector in 2007. I use establishment size distributions and job flows to identify the magnitude of firing costs and the parameters of the idiosyncratic shock process (components (1) and (2)). The fundamental identifying assumption for distinguishing (3) and (4) is that the comparative advantage of outsourced workers (e.g., specialized knowledge) depends on the industry but not on the state. In contrast, the extent of trade secret protection depends on the state, but not on the industry. My identification relies on parameters that are constant across states; hence, it requires estimating all state-industry pairs simultaneously. To make the estimation feasible, I continue in two stages. In the first stage, I use the method of moments to estimate the full model separately for each state under assumptions where the task-based production function simplifies to a CES aggregate of employees and outsourced workers. In the second stage, I treat the estimated factor shares as data and estimate the trade secret protection and outsourcing efficiency parameters using non-linear least squares. The estimated trade secret protection parameters are highly correlated with the UTSA adoption dates. I find the impact of differences in trade secret protection to be considerable. If all states had the trade secret protection of the best state, the cross-state dispersion of outsourcing would decline by 19%.

Using the model estimates, I ask how the extent of outsourcing and aggregate productivity would change if all states enforced trade secret protection as well as the 'best state'. I find that the ratio of purchased outsourcing to payroll expenses would increase by 4.4 pp (from 18.1% to 22.5%), while the aggregate output would go up by 1.7% ($350B in 2018). A large portion of the output growth would come through the entry of new firms, while the size-productivity correlation in the economy would also improve. Since the only productive input in the economy, labor, is fixed, all productivity gains essentially stem from the improved allocation of workers between producers.

My paper is closely related to others that use estimated distortions in firm decisions to analyze the importance of contract enforcement and trust for aggregate productivity. Bloom et al. (2012) find that the regions that have lower trust measures have firms with more centralized structures, slower worker reallocation, and lower productivity. Akcigit et al. (Forthcoming), who quantify the impact of lack of enforcement and the resulting lack of delegation, find that the differences in enforcement can explain 11% of the productivity difference between India and the U.S. Grobovšek (2020) finds similar quantitative effects from lack of enforcement using data from France. The closest paper to mine is Boehm and Oberfield (2020). They study the impact of weak contract enforcement on aggregate productivity through distortions in the choice of intermediate inputs. In particular, in Indian states where courts are more congested, firms move from specialized intermediate inputs towards generic ones to avoid hold-up problems. My empirical strategy is similar to theirs in that I use cross-state variation in wedges to structurally identify distortions. However, there are methodological differences beyond the differences in our questions. Boehm and Oberfield (2020) use firm-level data on intermediate input use, which allows them to control for a larger set of differences across states than mine. At the same time, their model is static, which does not permit analysis of the dynamic flexibility gains from labor outsourcing. While their measure of court congestion is constant over time, I can utilize state-level changes in laws to control for many state-specific covariates through state fixed effects.

My paper is also related to the literature on the cost of employment protection. The patterns and implications of labor flows has been studied extensively,[1] but especially more recently by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009) who showed that input misallocation can explain a large part of cross-country differences in aggregate TFP. Hopenhayn and Rogerson (1993), using a general equilibrium setting, found that a firing cost equal to 1 year of wages can decrease employment by as much as 2.5%.[2] Focusing largely on the fixed-term contracts commonly used in Europe, a branch of the literature asked whether alternative forms of employment can help (Bentolila and Saint-Paul (1992), Cahuc and Postel-Vinay (2002), Caggese and Cuñat (2008), Katz and Krueger (2019)). My contribution here is two-fold. First, I study the importance of a wide range of labor outsourcing practices instead of the fixed-term workers that tend to work in lower-skilled occupations. Second, I allow outsourced workers to be imperfect substitutes to permanent workers and evaluate distortions that limit their utilization.

My paper is also related to the literature that examines the use of labor outsourcing. The large growth in labor outsourcing practices brought nationwide surveys, as in Harrison and Kelley (1993), Abraham and Taylor (1996) and Houseman (2001). The three biggest reasons managers list for outsourcing are higher flexibility, access to specialized labor, and cost savings. Autor (2001), Houseman et al. (2003) and David and Houseman (2010) analyze how outsourcing allows employers to screen potential hires. Bidwell (2012), using data on outsourcing projects within a single firm, suggests that personal interests also play a role in outsourcing decisions. More recently, Goldschmidt and Schmieder (2017) and Drenik et al. (2020) use microdata on both the employer and client of outsourced workers to confirm the cost saved by outsourcing instead of hiring. Adding to the literature, I proposing and quantify the trade secret protection as a concern in labor outsourcing decisions. My model incorporates an examination of how outsourcing impacts flexibility, access to specialized talent, and cost savings in a simplified way. How-

[1] See Davis and Haltiwanger (1992), Caballero and Hammour (1994), Bartelsman and Doms (2000), Foster et al. (2001), Autor et al. (2007).

[2] Bento and Restuccia (2017) and Da-Rocha et al. (2019) have found the impact of firing costs on employment and productivity becomes even larger once the life-cycle productivity growth of firms is endogenized. The impact of employment protection laws on labor allocation had been an active area, following the early contributions by Lazear (1990) and Bentolila and Bertola (1990).

ever, it does not incorporate the potential benefits through screening or an organizational conflict within the firm.

Last, my paper is related to studies of firm boundaries. Following Coase (1937), Williamson (1975), and Grossman and Hart (1986), the literature analyzes how imperfect contract enforcement impacts the organization of production. The empirical literature has broadly focused on either the make-or-buy decisions for physical inputs by multinationals or the competitive effects of vertical integration.[3] I contribute by showing that intellectual property protection is specifically important for the make-or-buy decision for services.[4]

The rest of the paper is structured as follows. Section 2 summarizes trade secret protection in the U.S. and how it matters for labor outsourcing in particular. Section 3 documents new facts on outsourcing as well as a causal link from trade secret protection that motivates the structural model. Section 4 presents the structural model, while Section 5 presents the estimation strategy and results. Section 6 presents the counterfactual exercise and Section 7 concludes.

2 Background

I start this section by defining trade secrets and discussing their significance for businesses. Second, I discuss the historical development of the trade secret law in the U.S., emphasizing the Uniform Trade Secrets Act (UTSA). Third, I discuss how trade secret law impacts employees and outsourced workers differently.

[3] See Antras (2003), Nunn (2007), Corcos et al. (2013), Antras et al. (2017), and Boehm (Forthcoming) for discussion on multinational organizations. See Alfaro et al. (2016), Crawford et al. (2018), Hansman et al. (2020) for research on competitive effects and Lafontaine and Slade (2007) for a broad review of this literature.

[4] The idea that firms provide a structure that protects secrets has been proposed as early as Alchian and Demsetz (1972) and Liebeskind (1996). See Rajan and Zingales (2001) for a theoretical analysis and Ethier and Markusen (1996), Fosfuri et al. (2001), Bolatto et al. (2017), and Kukharskyy (2020) for the make or buy decision of multinationals in countries with weak IP protection.

2.1 Trade Secrets

The USPTO defines trade secrets as "information that has either actual or potential independent economic value by virtue of not being generally known, has value to others who cannot legitimately obtain the information, and is subject to reasonable efforts to maintain its secrecy". Business information such as customer lists and pricing strategy as well as R&D related information such as manufacturing techniques and designs can be trade secrets.

Trade secrets are arguably the most important form of IP for most businesses. Protecting information on clients and suppliers, pricing strategies, and long-term growth plans have historically been essential for firms. On the other hand, only a fraction of firms engage in formal R&D, and among those that do, a small fraction holds patents. Moreover, trade secrets are still a fundamental part of R&D, even when the ultimate goal is to get a patent.

Trade secrets are understudied compared to other forms of IP, as assigning a dollar value to secrets is hard with the absence of an explicit market.[5] The lack of legal uniformity has also limited statistical research on trade secret protection, even though they are the most litigated form of intellectual property (Lerner, 2006).

2.2 Trade Secret Protection in the U.S.

Before 1979, trade secrets were protected exclusively under common law.[6] This created two main problems. First, as no two cases are the same, there was uncertainty regarding the law's extent.[7] Second, three standard requirements -to declare the act as a trade secret violation- were unfit for outsourcing practices: (1) information had to be illegally appropriated, (2) the accused party had to be in direct competition with the plaintiff, and (3) those who have paid an amount in good faith to purchase the information from the ac-

[5] The 2017 report by the Commission on the Theft of American Intellectual Property estimates the total cost of trade secret theft to the U.S. economy to be between 1% to 3% of GDP, which is somewhere between the yearly outlays to the Dept. of Education and Dept. of Defense.

[6] Common law, as opposed to statutory law, does not rely on a codified set of rules. Instead, it uses previous court decisions to reach new ones.

[7] "... even in states in which there has been significant litigation, there is undue uncertainty concerning the parameters of trade secret protection, and the appropriate remedies for misappropriation of a trade secret.", UTSA Prefatory Note (1985). See Appendix E for details on the legal environment under common law.

cused were not prevented from further use (Lao (1998)). Because the outsourced worker would usually receive the information legally and act only as an intermediary between the client and its competitor, the law did not provide adequate protection for outsourcing relationships.

The Uniform Law Commission has drafted the Uniform Trade Secrets Act (UTSA) in 1979. The UTSA clarified which information constitutes a trade secret, which acts constitute misappropriation, and which are the associated remedies. It broadened the law's scope, e.g., by making misappropriation itself a crime, without the information being used or disclosed. Most importantly, it made third parties liable if they receive this information with a reasonable expectation that it is misappropriated. Each state had to opt-in for the UTSA to be effective in its courts. Minnesota, Idaho, Arkansas, Kansas, and Louisiana were the first states to adopt it in 1980. By 1988, 26 states had already adopted it, and by 2019, all states did.[8]

2.3 Trade Secret Protection and Labor Outsourcing

There are two main reasons why trade secret law is crucial for labor outsourcing. First, although its magnitude varies, all outsourced workers are exposed to some trade secrets. Second, it is harder to prevent outsourced workers from disclosing secrets to third parties compared to employees.

High-skill outsourcing generally provides a personalized solution to the client's problem; hence it is straightforward how an outsourced R&D expert or an accountant would be exposed to secret information. Albeit to a lesser degree, trade secrets are also relevant for the low-skilled. An outsourced machine operator would be exposed to product designs and daily production volumes. An outsourced personal assistant would have access to manager's daily activities, including meetings with other branches and business partners. Furthermore, having access to facilities may enable overhearing the managers' discussions and the rumors circulating among other workers[9]. In short, outsourced work-

[8]There have been two other main developments in trade secrets protection. Economic Espionage Act of 1996 made trade secrets misappropriation that is either interstate or benefits a 'foreign power' a federal crime. The Defend Trade Secrets Act of 2016 (DTSA) allowed any trade secret misappropriation case to be seen in federal courts. Although both are significant developments, they happened at the national level, making it harder to measure their impact.

[9]In SEC v. Steffes, No. 01 Civ. 06266 (N.D. Ill. Sept. 30, 2010), the SEC alleged railroad workers "traded and tipped on observations made on the job, including seeing people in suits tour the rail yards, hearing

ers' regular activities inherently create exposure to firm secrets unless the firm explicitly limits their access, which would reasonably reduce their value.

The data from trade secret litigation confirm the intuition. First, limiting access to certain 'labs' does not protect the business from trade secret misappropriation. Almeling et al. (2010) shows, in their sample of U.S. federal district court cases in 2008, only 35% involved any technical information or know-how. 31% involved customer lists, and 35% involved non-technical business information. Second, the misappropriator is almost always someone who has physical access to the secret: an employee or a business partner in 90% and 93% of the cases for the cases in federal and state appellate courts, respectively (Almeling et al. (2011)). Similarly, the defendant was either a former, current, or an outsourced worker in 76% of the cases tried under the Economic Espionage Act (Searle (2012)).

Employees are less susceptible to these concerns than outsourced workers for two main reasons. First, voluntary disclosure of secrets is less likely for employees. Because the employment relationship is generally of longer-term[10], it allows the design of better incentives for the employee to work in the best interest of the employer (Liebeskind (1996), Gibbons et al. (2013)). Second, inevitable disclosure is less likely for employees. While covenant not to compete (CNC) agreements[11] are ubiquitous among employees that work with sensitive data (Jeffers, 2018), they are not common in outsourcing agreements, being directly at odds with the business model of most outsourcing firms.[12] Lastly, signing a non-disclosure agreement helps, but how its enforcement is largely determined by the trade secret law (See Appendix E.2).

In short, firms have reason to avoid labor outsourcing to limit the risks of losing trade secrets. The next section tests and confirms this hypothesis using the cross-state legal variation across the U.S. The modeling choices in Section 4 are based on the frictions discussed here.

coworkers discuss the possible sale of their company, and being asked to prepare asset valuations."Cohen and Dunning (2010)

[10]There is no legal constraint on how long an outsourcing relationship lasts. However, longer relationships make it more likely that the courts will interpret it as a de facto employment relationship in case of a dispute, especially upon termination. Amarnare v. Merrill Lynch, Pierce, Fenner & Smith Inc., (611 F. Supp. 344 S.D.N.Y. 1984).

[11]CNC agreements designate a period for which the employee cannot work in the same industry with the previous employer upon termination of the employment contract.

[12]"Firms regularly hire consultants to advise on sensitive business problems, and one of the important qualifications of the consultants seems to be that they know the industry well-they have offered similar consulting services to the competitors." Kitch (1980)

3 Empirical Analysis

In the first half of this section (3.1), I document two broad facts on domestic[13] labor outsourcing in the U.S, focusing on its growth and cross-state heterogeneity. In the second half (3.2), I argue the trade secret laws in the U.S. help explain the two facts.

I define labor outsourcing as the purchase of labor-intensive services that can otherwise be done in-house. My definition is far from being arbitrary. The businesses that provide outsourcing as I define it are conveniently classified into two 2-digit NAICS sectors.[14] NAICS 54 (The Professional, Scientific, and Technical Services) principally employs high-skill occupations such as consultants, accountants, and data analysts. NAICS 56 (The Administrative and Support and Waste Management and Remediation Services) principally employs lower-skilled occupations such as machine operators, security guards, and janitors. The output of both sectors is mainly used as an intermediate input by other sectors. The set of industries in this definition is similar to Berlingieri (2013), but more extensive than Autor (2003) and Katz and Krueger (2019) who prioritize temp agencies.

Throughout the paper, I refer to the firms and the industries that supply labor outsourcing services as the outsourcing firms and the outsourcing sector for brevity.

3.1 Facts on Domestic Labor Outsourcing

Fact 1: The outsourcing sector's employment share has tripled since the 70s.

The outsourcing sector's employment share increased from 3% in 1971 to 11% in 2019. The left-hand side panel in Figure 1 depicts the normalized non-farm employment, service employment, and employment in the outsourcing sector. The average growth in the outsourcing sector far exceeds the US non-farm and services employment. The right-hand side panel shows the large growth was evident for both skill groups. So, the underlying reasons cannot be exclusively based on the skill level.

[13] I abstract from foreign outsourcing (e.g., call centers abroad) because it constitutes a relatively small fraction (3.5% in 2004) of total labor outsourcing practices (Amiti and Wei (2005)). See Appendix C for the cross-country evidence on the relationship between outsourcing and trade secret protection. The cross-country evidence broadly supports the analysis within the U.S.

[14] See Appendix B for the few exceptions, the details of the selection of industries, and how I map different classifications to one another.

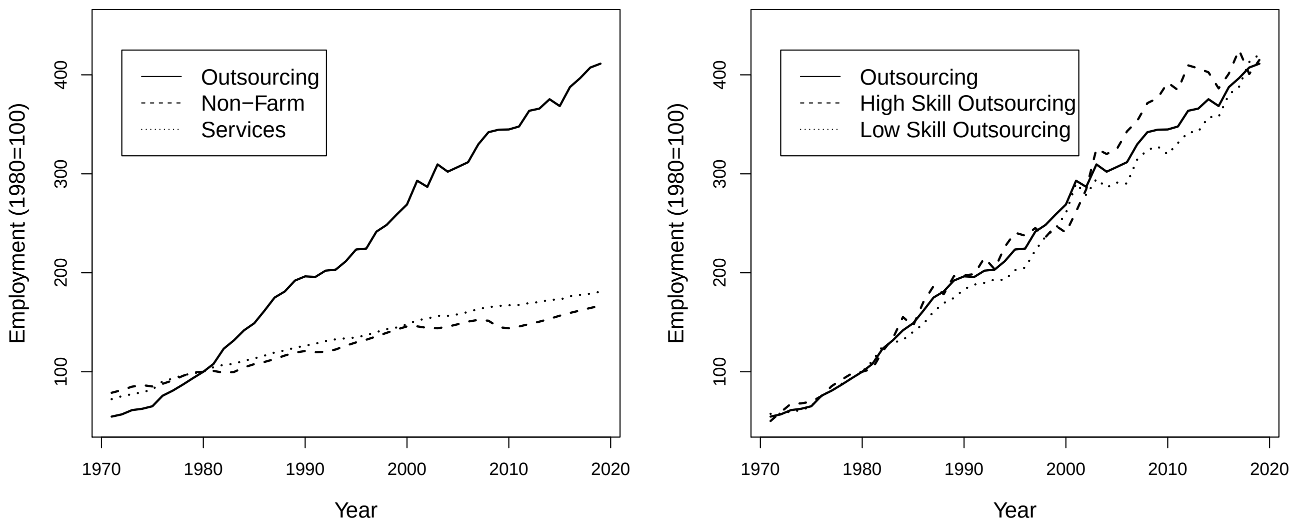


Figure 1: Employment Trends in Multiple Industry Groups (1971-2019) Notes: See Appendix B and Table 7 for details on how I pick and classify sectors into low and high skill outsourcing. Service Employment in the left panel consists of all U.S. Census 1990 3-digit industry groups from 400 to 892. Sector level employment is from the Annual Social and Economic Supplement (ASEC) of IPUMS-CPS. Total Non-farm employment is published by the Bureau of Labor Statistics (BLS).

The growth in outsourcing was also not an artifact of (1) the growth in industries that historically had above-average demand for outsourcing or (2) the growth in demand for occupations that historically had been outsourced more than others. I use the BEA Integrated Production Account and find the aggregate ratio of purchased services to value-added has increased from 0.25 in 1963 to 0.44 in 2018. Using the time series for 63 industries, I compute the counterfactual growth if each industry's purchased services ratio remained constant while the output shares changed as they did (between-industry), and if the output shares remained constant while the purchased services ratios changed as did (within-industry). I find that 84% of the growth is within-industry, i.e., would still happen with no structural change. I further check whether the growth in services outsourcing is part of a broader trend of shrinking firm boundaries. On the contrary, the ratio of all intermediate inputs to value-added has decreased from 0.83 to 0.76 during the same period. Although each industry uses more intermediate inputs on average, the structural shift from manufacturing to services more than canceled the growth. Berlingieri (2013) does a similar test for occupations. He picks occupations that are predominantly employed in outsourcing sectors and tracks their employment share over time. He finds that this share shows no trend after 1970, where most of the outsourcing growth happens.

Fact 2: The supply of and demand for outsourcing is heterogeneous across states.

To measure the supply of outsourcing, I use the American Community Survey from the IPUMS USA database to get employment shares for outsourcing providing sectors. Figure 2a presents the shares across the states of the U.S. First, there is considerable heterogeneity: the state at the 90th percentile has a share of 14.3% while the 10th has 7.6%. Second, a large part of the heterogeneity comes from high-skill outsourcing: the outsourcing employment share and high skill ratio have a correlation of 0.6.

To measure the demand for outsourcing, I use the 2017 Census of Manufactures in Figure 2b, which provides estimates of expense items for employer establishments. Specifically, it gives expense estimates for Temporary Staff and Employee, Data Processing Services, Advertising and Promotional Services, and Professional and Technical Services. For each state, I plot the ratio of these to the Annual Payroll. First, the state-level heterogeneity is comparable to the heterogeneity in supply. The state in the 90th percentile has a ratio of 0.18, while the 10th has 0.1. Second, heterogeneity does not concentrate on one of the four types of outsourcing expenses. Third, it does not disappear at more disaggregated levels. Both the Plastics and Rubber Products Manufacturing and the Machinery Manufacturing exhibit similar degrees of heterogeneity in outsourcing expenses, although their composition is very different.[15]

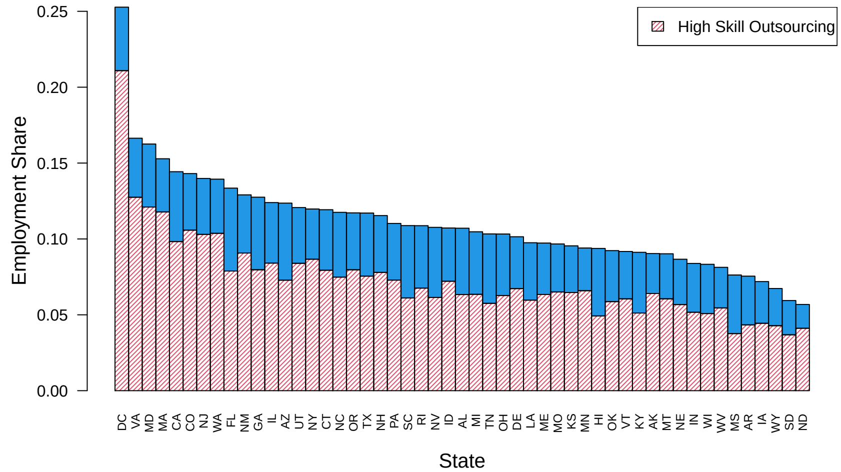
3.2 Evidence on the Effect of Trade Secret Laws

The previous facts presented a considerable heterogeneity in labor outsourcing both across states and over time that was not explained by differences in skill levels, industries, and occupations. Here, I test whether the differences in trade secret protection over time and across states played a role.

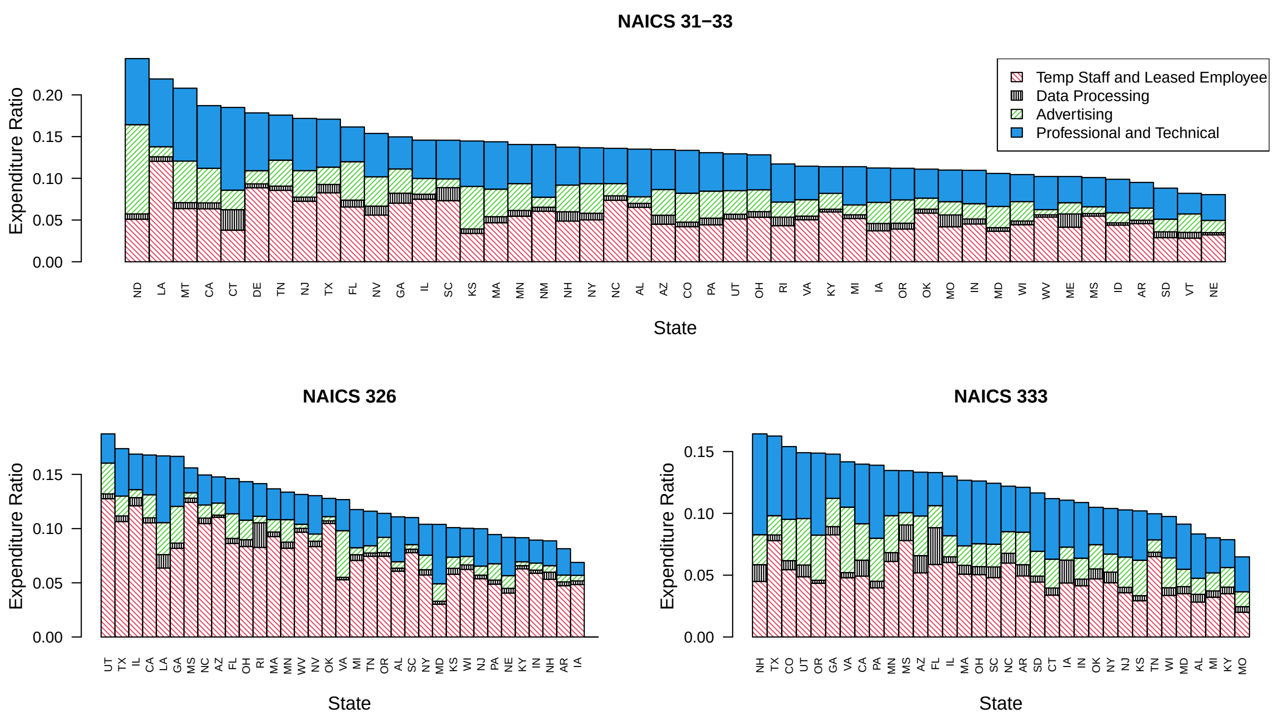
Data and the Estimation Method

Testing the impact of trade secret protection is not straightforward for a few reasons. First, the legal frameworks differ across states in clarity and scope, which are hard to quantify.

[15]The degree of heterogeneity also persists at the 6-digit industry level; however, the data is censored for most state-industry pairs to ensure the confidentiality of firm data. For example, the 10th and the 90th percentiles are 9% and 18% in the Plastics Pipe and Pipe Fitting Manufacturing (NAICS 326122).



(a) Employment Share of Outsourcing Sectors (2017) Notes: The full length of the bar designates the employment share of outsourcing, while the shaded length (in red) designates the portion that is in high skill outsourcing sectors. The data is from IPUMS USA. See Figure 1 for details on which industries are included.



(b) Ratio of Outsourcing Expenses to Annual Payroll in Manufacturing Sectors (2017) Notes: The top panel provides estimates for all NAICS manufacturing sectors (31-33), the bottom left panel for Plastics and Rubber Products Manufacturing (326), and the bottom right panel for Machinery Manufacturing (333). In each panel, only the states with complete data on each of the four outsourcing expenses are included. All panels use data from the 2017 Census of Manufactures.

Figure 2: The Cross-state Supply of and Demand for Labor Outsourcing Notes: The details on the data sources and the state abbreviations are available in Appendix B.

I use two measures in this section, namely, adoption of the Uniform Trade Secrets Act (UTSA) and the trade secret protection index (TSP index henceforth) constructed by Png (2017a) and Png (2017b). The adoption of the UTSA was essential both for reducing the uncertainty about the trade secret protection and extending its coverage, particularly for labor outsourcing relationships. The TSP index evaluates whether states had certain types of protections in a given year and assigns a score ranging from 0 to 1 (See Appendix B for details). I use the two measures separately and together in my analysis.

Second, I need a measure of the extent of outsourcing. Unfortunately, comprehensive data on demand for labor outsourcing does not exist before 2007. Thus, I use the supply of labor outsourcing as my measure.[16] I use the state-year level employment shares of the outsourcing sector from the ASEC samples. In total, I have an unbalanced panel of 50 states and the District of Columbia from 1970 to 1997.

Last, to measure the causal link, I need exogenous variation in protection. The UTSA provides precisely that. After being drafted, each state had to opt-in to start using it. The adoption times differed significantly (See Figure 16), creating cross-sectional variation in trade secret protection on top of the time-series variation. After arguing its exogeneity, I use the staggered adoption of the UTSA as my exogenous variation for trade secret protection.

The staggered adoption of the UTSA allows aggregating the information from differences-in-differences (DiD) comparisons across multiple pairs of states over many periods. The Two-Way Fixed Effects (TWFE) estimator provides an intuitive tool and is widely used in studies with staggered adoptions. However, the recent work following Goodman-Bacon (2018) has shown TWFE may fail to give (1) consistent test statistics for pre-trends and (2) intuitive measures of treatment effects without strong assumptions (Appendix F for details). In my analysis, I primarily yield to the historical setting to argue for the exogeneity of the UTSA adoptions, together with statistical tests for pre-trends. I then provide estimates from both the TWFE estimator and the estimator proposed by Callaway and Sant'Anna (2019), which provides a consistent estimate under multiple dimensions of treatment heterogeneity and selection into treatment based on covariates.

[16] Although there was no definitive procedure, the governing law was of the state where the misappropriation happened in a large majority of cases (See Appendix E.3). This state would generally be the one where the client operates, especially in the 80s and 90s. As long as outsourcing firms are more likely to serve clients in their states, my mechanism predicts a positive relationship between the strength of trade secret protection and the employment share of the outsourcing sector in that state.

Exogeneity of the UTSA Adoption

I start by confirming that the adoption of the UTSA did not coincide with the adoption of other major state-level laws. The adoption time of the UTSA has a weak correlation with the adoption of other commercial uniform laws (0.13) and employment protection laws ($<$0.04) across states.

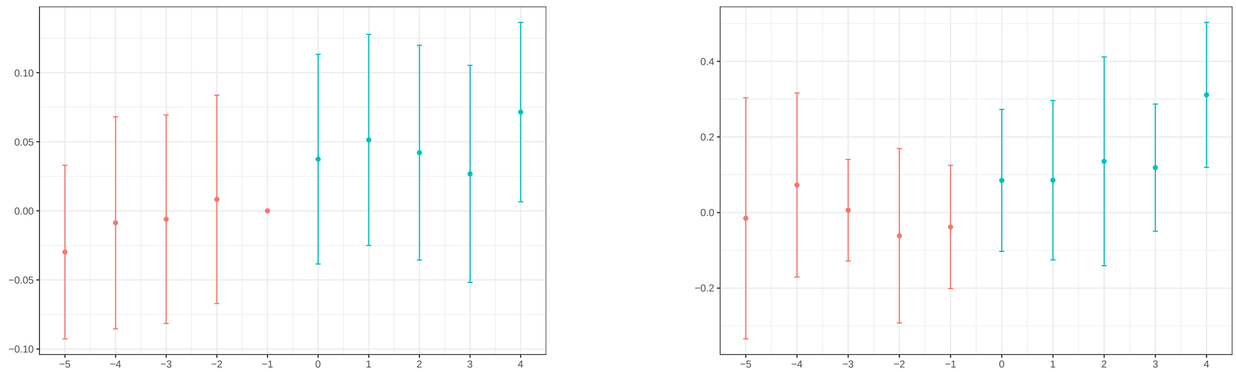
The adoptions' history suggests the timing choices of states were less about economic concerns and more about differences in legal structures and opinions. First, Ribstein and Kobayashi (1996) shows the basic economic characteristics like size, population density, and state expenditures were irrelevant in explaining the adoption of any uniform law. The structure of the state legislatures (e.g., size of chambers), on the other hand, had predictive power on the adoption dates. Second, in the case of the UTSA, Sandeen (2010) documents, many states postponed their adoption to after 1985 due to the opposition organized by a single attorney who argued certain clauses could be misinterpreted. Last, Png (2017a) discusses how UTSA was adopted in California only when proposed a second time and rejected in New York for reasons unrelated to the intended coverage of the UTSA. The opposition came from farmworkers in California and trial lawyers in New York. They were concerned that the law can be used to hide information about pesticides and trial evidence, respectively. The convergence also supports the argument for differences in legal opinions as all states adopted a version of the UTSA eventually.

The quantitative tests do not suggest the presence of pre-trends either.[17] First, I run the classical event study regression with the leads and lags of the treatment in a TWFE setting

$$y_{it} = \sum_{l \in \{-4,-3,-2,0,1,2,3\}} \delta_l A_{itl} + \delta_4 A_{it,l\geq 4} + \delta_{-5} A_{it,l\leq -5} + \beta x_{it} + \alpha_i + \gamma_t + \epsilon_{it} \tag{1}$$

where y_{it} is the log employment share of outsourcing sectors, A_{itl} is equal to 1 if for state i, year t is l years after the adoption of the UTSA. The coefficient estimates are in Figure 3a. There are no signs of a pre-trend, i.e., the states that are closer to adoption have comparable outsourcing shares to others. However, the plot also hints at dynamic treatment effects: it takes a few years for the treatment to have full effect. Thus, the pre-trend test likely suffers from the bias suggested by Abraham and Sun (2018). Thus, I supplement

[17] Png (2017a) and Klasa et al. (2018) provide several tests and conclude variables used in their analysis including R&D expenditures and capital structures of firms do not predict the adoption of the UTSA.



(a) Two-way Fixed Effects (1977-1997)

(b) Group-Time ATT (1977-1987)

Figure 3: Event Study Estimates for the UTSA Adoption Notes: The X-axis refers to l in (1) for the left panel and $t-g$ in (3) for the right panel. Y-axis provides the corresponding estimates with 95% confidence intervals constructed from standard errors clustered at the state level. I use the doubly-robust balancing procedure in the right panel. The outsourcing shares and employment series are from the IPUMS-CPS database. The controls are population, GDP, manufacturing GDP, manufacturing employment, unionization rate, high school and college shares, and adoption of exceptions to at-will employment. Since the CS estimator relies on propensity score matching, the control group must be sufficiently large for estimation. Hence, the estimation only runs for adoptions until 1987. See Figure 1 for details on included industries.

the analysis by using the estimator by Callaway and Sant'Anna (2019) (CS henceforth).

CS starts with the concept of group-time average treatment effects on the treated:

$$ATT(g,t) = E[Y_t(g) - Y_t(0)|G = g] \tag{2}$$

where g denotes group index (the adoption time), G_i denotes the group of unit i, $Y_t(g)$ ($Y_t(0)$) denotes the outcome variable at time t conditional on being treated at time g (never being treated). Thus, $ATT(g,t)$ denotes the effect of being treated at time g that is measured in time t, thus allows heterogeneity across groups and dynamic treatment effects. Furthermore, by conditioning on being treated, it controls for selection into treatment.[18] After identifying $ATT(g,t)$, CS aggregates them over t to get average dynamic effects:

$$\theta_D(e) := \sum_{g=2}^{\mathcal{T}} \mathbf{1}\{g + e \leq \mathcal{T}\} ATT(g, g+e) P(G = g | G + e \leq \mathcal{T}) \tag{3}$$

where e denotes the exposure time and $\theta_D(e)$ are the counterparts of the event study

[18] CS identifies ATT(g,t) under the assumptions of parallel trends (conditional on observables) and absorbing treatment. In particular, to avoid the bias generated by dynamic treatment effects, CS only uses units that are not yet treated in the control group and uses propensity score matching to balance the two groups on relevant observables to take potential selection into treatment into account.

estimates of the classical DiD under homogenous treatment. Lastly, $ATT(g,t)$ can be aggregated over both g and t to get an overall treatment effect:

$$\theta_S^O := \sum_{g=2}^{\mathcal{T}} \theta_S(g) P(G=g) \tag{4}$$

Figure 3b plots the event study estimates from (3), which confirm the findings with the TWFE: there are no apparent pre-trends, and the full effect is realized only a few years after the adoption.

The Impact of Trade Secrets Laws

Having established a case for the exogeneity of the UTSA adoption, I use the variation it created to estimate the impact on outsourcing employment.

I have so far ignored that trade secret protection may have differed both pre- and post-adoption across states. I use the TSP index as the main regressor in the main specification below, instrumented by the adoption dummy in a TWFE model. Therefore, I measure the impact through an index that quantifies this heterogeneity while restricting attention to changes through the UTSA. To test the results' robustness, I also use the CS estimator to take selection into treatment, dynamic treatment effects, and treatment heterogeneity over time of adoption into account. In the main specification, I estimate a TWFE-IV model of the form:

$$y_{it} = \beta tsp_{it} + \tilde{\beta} x_{it} + \alpha_i + \gamma_t + \epsilon_{it} \tag{5}$$

where y_{it} is the log employment share of outsourcing sectors, tsp_{it} is the TSP index, x_{it} is the vector of controls, α_i and γ_t are the state and year fixed-effects. α_i helps control for state-specific factors that remain constant over time, such as persistent differences in state subsidies and the availability of natural resources. γ_t provides a non-parametric time trend, controlling for broad trends in the economy, such as the growth in information technology and changes in the federal subsidies. I instrument the TSP index with the adoption dummy for the UTSA and use White standard errors clustered at the state level.

Table 1 presents the regression results. Trade secret protection has a positive and statistically significant effect at 5% level, in line with my hypothesis. Moreover, the quantitative estimates are similar across specifications without controls or instrumentation. Using the

Table 1: Two-way Fixed Effects Estimation

	TSA Adoption	TSP Index	IV	TSA Adoption	TSP Index	IV
	(1)	(2)	(3)	(4)	(5)	(6)
TS Protection	0.05*	0.12*	0.12*	0.06**	0.13**	0.13**
	(0.03)	(0.06)	(0.06)	(0.03)	(0.05)	(0.06)
Demographics				Yes	Yes	Yes
Ind Composition				Yes	Yes	Yes
Union				Yes	Yes	Yes
WDL				Yes	Yes	Yes
State & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Range	1970-1997	1970-1997	1970-1997	1970-1997	1970-1997	1970-1997
Observations	1,180	1,180	1,180	1,180	1,180	1,180

Notes: The dep. variable is the log outsourcing sector share of employment. The employment series are from IPUMS-CPS. See Figure 1 for details on included industries. The main variable of interest is the UTSA adoption dummy in columns (1) and (4), and the TSP index in others. Columns (2) and (4) present OLS estimates while (3) and (6) present IV estimates. Columns (4)-(6) controls for unionization rate, the share of college and high school graduates, the exceptions (good faith, implied contract, public policy) to the at-will employment as well as logged population, GDP, manufacturing GDP, and manufacturing employment. See Appendix B for details on how each variable is constructed. I cluster the standard errors at the state level. *p<0.1; **p<0.05; ***p<0.01

estimates, I find the outsourcing sector would be 13% smaller had all the controls changed as they did, but the TSP indices remained the same as the 1970 levels, translating to 1.7M jobs.

I also use the CS estimator's overall treatment effect in Equation (4), which gives comparable results.[19] The CS estimates are qualitatively in line with the TWFE estimates, although their magnitude is larger. The difference in magnitudes may indicate large dynamic treatment effects, as suggested by the event study estimates in Figure 3.

Two additional concerns bias the estimates towards 0 and cannot be resolved without additional data. First, the treatment also impacts the control group. Once a state adopts the UTSA, its subsequent decisions may affect the others that are yet to adopt. As the

[19]Since CS takes potential selection into treatment based on observable covariates into account, it requires a large enough control group for balancing the treatment and the control groups. A larger estimation period allows using more pairwise DiD estimates to incorporate in the estimation. However, as the estimation horizon grows, the control group's size gets smaller, and the balancing becomes less precise and eventually infeasible. Lastly, the CS estimator requires a balanced panel; hence the longest estimation period I can use is from 1977 to 1987. I also present results from smaller horizons where the balancing is more precise.

Table 2: Overall Treatment Effect via Group-Time ATT Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
UTSA Adoption	0.20	0.13	0.16	0.16	0.11	0.16
	(0.077)	(0.076)	(0.065)	(0.057)	(0.047)	(0.051)
Range	1977-1982	1977-1983	1977-1984	1977-1985	1977-1986	1977-1987
Number of Adopted States	6	9	11	11	13	19

Notes: The estimates correspond to Callaway and Sant'Anna (2019) group-time att estimates integrated over time of adoption and the length of exposure to treatment using (4). The dependent variable is the log outsourcing sector share of employment, and the treatment is the adoption of the UTSA. The control group consists of states that are not-yet-treated, and the balancing is done via the doubly-robust estimation method by Sant'Anna and Zhao (2020). See the notes for Table 1 for a list of control variables included and details on the variables.

extent of cross-state citations increases, my estimates' bias would be greater. Second, the data available for this period is on the supply side, while the adoption most likely impacts the demand. As the extent of cross-state trade of outsourcing services increases, my estimates' bias would be greater. The structural model in Section 4 uses demand-side data to circumvent the second problem, while the first problem requires measuring the extent of cross-state legal influence.

Placebo Regressions

If trade secret protection is indeed important, the effect of laws should be greater for high-skill outsourcing, where the exposure to trade secrets is arguably higher. In columns 2 and 3 of Table 1, I estimate Equation (5) for high-skill and low-skill outsourcing sectors separately. In line with the theory, the impact on high skill outsourcing is greater. In column 4, I address 3-digit sectors 841 and 890, which mainly employ lawyers and accountants subject to client privilege codes: her association would disbar an accountant or lawyer that discloses her client's information to 3rd parties.[20] Hence, these two sectors should be affected to a lesser extent. The estimate confirms this, where the estimate is both quantitatively smaller and not different from 0 at a 10% significance level. Lastly, in column (5), I re-run column (1) excluding subsector 732 (Computer and data processing services) and confirm that the concurrent growth of the role of computers in businesses does not drive the results.

[20] See the American Institute of Certified Public Accountants' Trust Services Criteria and the American Bar Association's Model Rules of Professional Conduct.

Table 3: Placebo Regressions

	Outsourcing Share	High-Skill	Low-Skill	Leg-Acct	Except Comp
	(1)	(2)	(3)	(4)	(5)
TSP Index	0.13**	0.18**	0.12	0.13	0.13*
	(0.06)	(0.09)	(0.08)	(0.11)	(0.07)
Range	1970-1997	1970-1997	1970-1997	1970-1997	1970-1997
Observations	1,180	1,174	1,175	1,177	1,180

Notes: The outsourcing shares and employment series are from the IPUMS-CPS database. See Figure 1 for details on included industries and their assignment into skill bins. The fourth column is the total employment in 3-digit 1990 U.S. Census sectors 841 (Legal services) and 890 (Accounting, auditing, and bookkeeping services). The fifth column is all 3-digit high skill outsourcing sectors except for 732 (Computer and data processing services). Standard errors are clustered at the state level. See Table 1 for details on the controls. *p<0.1; **p<0.05; ***p<0.01

4 A Model of Outsourcing and Trade Secret Protection

In this section, I construct a multi-industry firm dynamics model based on Hopenhayn (1992), where firms decide whether to use in-house or outsourced workers for various tasks. Outsourced workers are more productive in certain tasks and are easier to adjust, but need firm-specific information to perform. The effective trade secret protection determines what amount is safe to share, i.e., the size of the *enforcement friction*.

The model provides three main inputs that allow quantifying the output cost of enforcement frictions using the observed cross-state heterogeneity in outsourcing use. First, it provides a mapping between observables such as firm size distribution and job destruction rates and structural parameters such as demand persistence and labor adjustment costs. Second, it provides an intuitive restriction: the productivity advantage of outsourced workers depends on the industry but not on the state. In contrast, the strength of trade secret protection depends on the state but not on the industry. Third, it maps estimated firm-level distortions to aggregate productivity by taking general equilibrium effects through product and labor markets into account, providing the final piece.

.

4.1 Environment

4.1.1 Agents and Preferences

The economy consists of (1) a DRS intermediate goods sector with K industries, (2) a CRS final good sector, (3) a CRS outsourcing sector, and (4) a unit measure of workers. Each K industries in the intermediate sector have a continuum of firms and a large pool of potential entrants. All firms maximize expected discounted profits. Each worker inelastically supplies one unit of labor and is indifferent between being a permanent or outsourced worker.

4.1.2 Technology

The Final Good and Outsourcing Sectors

All the action in the model is in the intermediate goods sector, so I quickly discuss the other two sectors here. The final goods sector produces the final good by aggregating the intermediate goods, solving:

$$\max_{\{Y_k\}_{k=1}^{K}} Y = \left(\sum_{k=1}^{K} Y_k^{\omega} \right)^{\frac{1}{\omega}} - \sum_{k=1}^{K} P_k Y_k \tag{6}$$

where $1/(1-\omega)$ is the elasticity of substitution across intermediate goods.[21] The outsourcing sector transforms each worker into an outsourced worker. Since both sectors make 0 profits, firms' ownership and size are irrelevant.

The Intermediate Goods Sector

The intermediate goods sector consists of K industries. To simplify the notation, I avoid the industry subscript whenever possible. The structure of the environment is the same across all industries; only the parameter values potentially differ.

The production of each firm is a CES aggregate of production in individual tasks that

[21] I do not model demand shares for intermediate goods explicitly, since it is not possible to distinguish them from intermediate goods prices without data on quantities.

are indexed by $i \in [0, 1]$:

$$y = \left(\int_0^1 y(i)^\gamma di \right)^{\frac{\theta}{\gamma}} \tag{7}$$

where $\theta < 1$ controls returns to scale and $1/1 - \gamma$ is the elasticity of substitution across tasks. Each task i can be done with **permanent** or **outsourced** workers:

y(i) = g(i)n(i)+1$_{\{z \geq \zeta(i)\}}\delta r(i)$where $n(i)$ and $r(i)$ denote the number of permanent and outsourced workers assigned to task i, $g(i)$ denotes the marginal product of permanent workers in task i, δ denotes the marginal product of rented workers, and z denotes the amount of firm-specific knowledge shared with each outsourced worker. $\zeta(i)$ denotes the minimum amount of information that must be shared to outsource task i. The relative sizes of $g(i)$ and δ determine gains from outsourcing a task, while $\zeta(i)$ puts a hard constraint on which tasks are feasible to be outsourced.[22]

I assume $g(i)$ is strictly increasing, i.e. (1) the tasks are ordered by how suitable they are to outsourcing, which is without loss of generality, and (2) there is a strict ordering of their suitability. The next assumption is less innocuous.

Assumption 1. $\zeta(i)$ *is strictly increasing.*

Assumption 1 implies that the gains from outsourcing ($g(i)$) strictly decreases with the required amount of information for the task to be outsourced. This assumption can be micro-founded with a model with communication costs. Relaxing it requires a two-dimensional task space, which is mathematically straightforward but complicates the notation and is hard to take to data. Nevertheless, this assumption is rather conservative for the impact of trade secret laws. The tasks that would provide the highest marginal gain once outsourced are assumed to be the ones that are already outsourced.

To make the structure more concrete, imagine SD, a software design firm whose tasks can be grouped into office security, testing, and design. The left-hand side panel in Figure 4 places the tasks in the x axis, where the increasing and flat lines represent the marginal product of permanent and outsourced agents respectively in each task i. Design tasks are the firm's core functions and require knowing the specifications of clients, how the

[22] I abstract from capital as an additional input in the production process. Veracierto (2001) has previously shown that explicitly modeling capital does not impact the quantitative inference on steady-state labor flows in industry dynamics models.

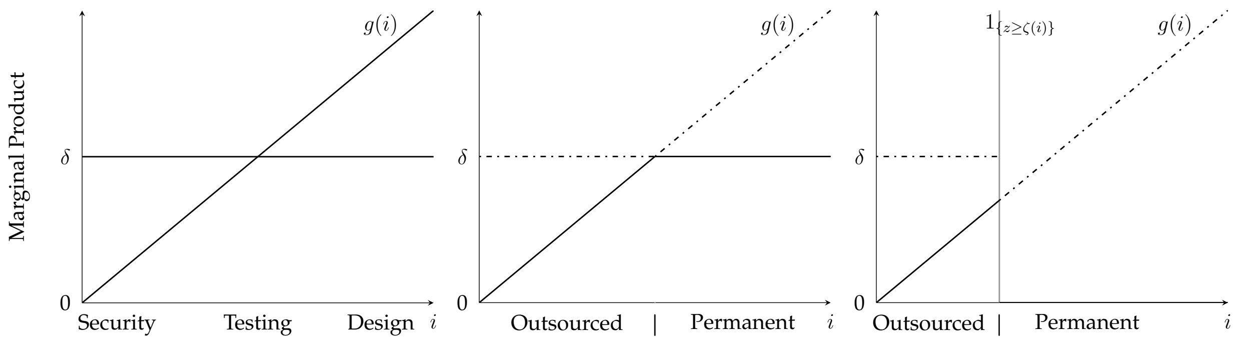


Figure 4: The Task Allocation Problem of a Software Design Firm Notes: The dashed line pieces denote the upper-envelope of the two lines.

data is organized, etc. The extent of information required would make it more efficient to use a permanent worker. On the other hand, office security requires little firm-specific knowledge; it could be even more required productive once outsourced from a security company with better training material. Testing would be in the middle, requiring some firm-specific knowledge, such as the designed software's potential flaws, but not as much as required by the designers. First, suppose the information-sharing constraint ($z > \zeta(i)$) was not present. Assuming the marginal costs are constant and equal, SD would choose to use permanent workers for design and some testing functions and outsource the rest as in the middle panel of 4. However, when the information-sharing constraint is binding, as in the right-hand side panel, the outsourced' effective marginal product becomes zero for the tasks that do not satisfy the constraint. Hence, SD would be forced to outsource a smaller set of tasks.

Why does SD not share as much information as possible then, i.e., maximize z? If SD shares too much, the outsourced would find it more profitable to steal the knowledge, risking a potential lawsuit. Instead of explicitly modeling the 'trade secret theft' and its aftermath, which is not the focus of the current paper (See Section 4.4), I simplify it into a hard constraint: the firm only shares an amount that does not induce the outsourced worker to steal. How much information is 'too much' is determined by π, which I introduce next, which represents the trade secret protection provided by the courts.

The Intermediate Firm's Static Allocation Problem

Before completing the description of the environment, I first characterize the firm's static task allocation problem with a given number of workers. I then use the solution to this problem later, which simplifies describing the rest of the environment. The firm with n permanent and r outsourced workers chooses how many to allocate each task $(n(i), r(i))$, and how much information to share with the outsourced (z) to solve:

$$
\begin{aligned}
F(n,r) = \max_{n(i),r(i),z} \quad & \left(\int_0^1 y(i)^\gamma di \right)^{\frac{\theta}{\gamma}} \\
\text{(Task production)} \quad & y(i) = g(i)n(i) + 1_{\{z \geq \zeta(i)\}} \delta r(i) \\
\text{(Resource Constraints)} \quad & \int_0^1 r(i)di = r, \ \int_0^1 n(i)di = n \\
\text{(Information-Sharing)} \quad & z \leq \pi
\end{aligned}
\tag{8}
$$

The last constraint represents the legal friction: with perfect enforcement, π would equal one and the information-sharing constraint would be redundant. Given the assumptions on $g(i)$ and $\zeta(i)$, the problem simplifies substantially:

Lemma 1. *Let $n, r, \pi > 0$, $\gamma < 1$. For $g(i), \zeta(i)$ strictly increasing, $\exists$ a unique $0 \leq \bar{z} \leq \zeta^{-1}(z)$ s.t. tasks $i \leq \bar{z}$ only use outsourced and tasks $i > \bar{z}$ only use permanent workers.*

Proof. See Appendix A for all proofs. □

Thus, the problem of choosing $n(i), r(i)$ boils down to choosing the threshold $\bar{z}$. The model does not allow identifying the level of $g(i)$ from δ. Although the shape of the $g(i)$ is still important, it matters mainly for counterfactuals that extrapolate from the range of data. Since I do have task-level data that helps me identify its shape, I go ahead and assume $g(i) = i$ and stick to counterfactuals within the range of my data. Lastly, it is neither possible nor necessary to identify $\zeta()$ and π separately. Thus, I normalize $\zeta^{-1}(\pi) = \pi$. These provide a simple characterization of $F(n,r)$, the maximum production that can be achieved with n and r:

Assumption 2. $g(i) = i$.

Proposition 1. *The solution to (8) can be written as*

$$
F(n,r) = \Big(\underbrace{\left((1-\gamma)(1-\bar{z}^{\frac{1}{1-\gamma}})\right)^{1-\gamma}}_{\alpha_n(n,r)} n^\gamma + \underbrace{\bar{z}^{1-\gamma}\delta^\gamma}_{\alpha_r(n,r)} r^\gamma \Big)^{\frac{\theta}{\gamma}}
\tag{9}
$$

where $\bar{z}$ is a known function of π, n, and r.

Although (9) looks like a Constant Elasticity of Substitution (CES) function in permanent and outsourced workers, $\bar{z}$ being a function of n and r complicates things. The next assumption is not required for solving the model but makes the estimation procedure feasible.[23]

Assumption 3. *The information-sharing constraint is binding.*

Corollary 1. *Under Assumption 3, $\bar{z} = \pi$. Thus, the solution to (8) can be written as*

$$F(n, r) = A(\pi, \delta)\big(\alpha(\pi, \delta)n^{\gamma} + (1 - \alpha(\pi, \delta))r^{\gamma}\big)^{\frac{\theta}{\gamma}} \tag{10}$$

To sum up, under certain assumptions, the solution to the task allocation problem boils down to a CES, where the factor shares are determined both by the marginal product of outsourced workers (δ) and the strength of trade secret protection (π). Specifically, stronger protection has two effects on F: (1) the factor share of permanent workers $\alpha(\pi, \delta)$ go down, and (2) the productivity multiplier $A(\pi, \delta)$ goes up. The first effect derives since a smaller share of tasks use permanent workers while the second effect follows from a larger choice set. Lastly, the parameter that determines the substitution elasticity across tasks (γ) is inherited in the CES form to determine the elasticity of substitution between permanent and outsourced workers.

Intermediate Goods Sector - Dynamics Elements

The firms are ex-ante identical, but they are subject to idiosyncratic demand shocks s that follow an AR(1) process $s' = \rho s + \epsilon$ where $\epsilon \sim N(0, \sigma^2)$ and shocks are independent across firms.[24] Adjusting the stock of permanent workers has a cost of $\tau \max\{0, n_{-} - n\}$, where n_{-} is the stock of workers that were under contract, n is the new stock of workers, and τ is a per-worker firing cost. The incumbent firms have to pay a fixed cost of operating c every period or exit and pay a one-time cost of τn_{-}.[25] The entrants have to

[23]Specifically, it allows estimating the model for each state of the U.S. separately. Assumption 3 is not on parameters, but on equilibrium outcomes. After estimation, confirm that this assumption is satisfied for the vast majority of the firms under the estimated parameters. I discuss its benefits and caveats in detail in Section 5.

[24]I use revenues to discipline the production function; hence s may represent fluctuations in both prices and quantities. I will call s demand shocks for brevity.

[25]I use the specification here following the empirical evidence in Bottasso et al. (2017) that countries with

pay a cost of entry c^E before drawing a shock from the distribution $\phi(.)$. Both the fixed cost of operating and the entry cost are paid in the units of final goods.

4.1.3 Timing

The timing of events in a given period is as follows:

1. Entry decisions are made
2. Intermediate firms learn their productivity shocks and decide whether to stay or exit.
3. Intermediate firms make hiring/firing and outsourcing decisions and produce
4. Final good sector produces

4.2 Intermediate Firm's Dynamic Problem

I restrict attention to the steady-state, where firms' distribution across state variables stays constant for all industries. I denote the steady-state value function of the intermediate firm with V:

$$V(s, n_{-}) = max\{\underbrace{\max_{n,r} \; p_k sF(n, r) - n - r - \tau \max\{0, n_{-} - n\} - Pc + \beta EV(s', n)}_{stay}, \underbrace{\tau n_{-}}_{exit}\} \tag{11}$$

where $F(n, r)$ is given in (10). p_k and P refer to the intermediate and final good prices, and the wage is normalized to 1. There is a single market wage for the hired and outsourced since outsourcing is provided competitively, and workers are indifferent.[26] The firm compares the exit cost to the expected discounted value of profits to decide whether to stay in business. The decision to use permanent versus outsourced workers depends both on the structure of $F(n, r)$, and the firing cost τ (See Section 4.5). Lastly, potential entrants compare the cost of entry to the expected future discounted profits to decide whether to enter

higher firing costs also have lower firm exit rates. If I modeled the exit cost as a fixed number, my model would generate the opposite pattern.

[26] I only have data on outsourcing expenditures, instead of the number of outsourced workers. Hence, the differences in input prices and factor shares are not separately identified. The model captures any cost savings or markups attached to outsourced workers with the factor share (α).

or not. Since the product prices are determined in equilibrium, increased entry moves prices down, depressing the profits firms make, thus feeding back to slow entry.

4.3 Equilibrium

A steady-state equilibrium consists of the final good producer's demand for intermediate goods $\{Y_k\}_{k=1}^{K}$, value and policy functions of the intermediate firms $\{V_k, n_k, r_k\}_{k=1}^{K}$, the intermediate good prices $\{p_k\}_{k=1}^{K}$, the final good price P, the measure of entrants in each industry $\{\mu_k\}_{k=1}^{K}$, and the steady-state distribution of intermediate firms $\{\psi_k\}_{k=1}^{K}$ that solve

1. $V_k(s, n_-) = max\{\max_{n,r} p_k s F_k(n, r) - n - r - \tau \max\{0, n_- - n\} - P c_k + \beta EV(s', n), \tau n_-\} \forall k \in K$ (Intermediate Problem)
2. $EV_k(s, 0) = P c_k^E \quad \forall k \in K$ (Free Entry)
3. $\sum_k \int [n_k(s, n_-) + r_k(s, n_-)] d\psi_k(s, n_-) = L^s$ (Labor Market Clearing)
4. $\psi_k(s, n_-) = T(\psi_k(s, n_-), \mu_k) \quad \forall k \in K$ (Stationary Dist)
5. $\frac{Y_k}{Y_j} = \left(\frac{P_k}{P_j}\right)^{\frac{1}{\omega-1}} \quad \forall k, j \in K$ (Intermediate Good Demand)
6. $P = \left(\sum_k p_k^{\frac{\omega}{\omega-1}}\right)^{\frac{\omega-1}{\omega}}$ (Final Good Price)

4.4 Discussion of the Model Elements

The equilibrium defined in 4.3 describes the economy of a single state. The model allows four possible channels to explain the state-level differences in outsourcing use: differences in (1) cost of firing, (2) within-industry firm dynamics, (3) industry compositions, and (4) trade secret protection. In this subsection, I discuss how the model generates and quantitatively disciplines each channel.

Since each state recognizes different exceptions to at-will employment, effective firing costs potentially differ across states. The firing costs only apply to the permanent workers in the model, thus, incentivize outsourcing. The model allows industries to differ in almost all dimensions, including the relative average productivity of outsourcing δ_k. Since industry compositions are available in the data, the model allows controlling for 'industry fixed-effects' that would lead to different outsourcing choices across industries.

When the same industry has different outsourcing levels across states, the model does not automatically assign the differences to state policies. Instead, it takes into account that firms that belong to the same industry may be fundamentally different across states and face different operating costs or demand fluctuations. Only when firms in the same industry have different outsourcing behavior across states that cannot be explained by differences in firm characteristics or the firing costs, the model will assign this to differences in the extent of enforcement friction. Thus, there is a natural link from the enforcement frictions to labor allocation and aggregate output.

Lastly, I model trade secret theft only as a threat, which never happens in equilibrium. Thus, the model assumes a lack of trade secret protection is unequivocally inefficient, which does not have to be true. The unregulated transmission of secrets in the economy can theoretically be welfare improving. On top of reduced incentives to innovate (Samaniego (2013)), there are two additional barriers against this free flow of ideas. First, when the legal protection is lacking, companies invest in costly physical barriers to prevent theft[27] Second, in business partnerships, the sides become more hesitant to share information, which is the main idea of this paper.[28] I assume these three effects dominate the gains from the chaotic flow of ideas through theft; i.e., the current level of trade secret protection is below the socially optimal level. The strong correlation between trade secret protection and GDP per capita across countries is consistent with this idea.[29]

[27]Risch (2007) documents how a client boasted about introducing to the workplace "fingerprint scanners, almost no Internet access, expensive network filtering appliances to scan outgoing email, special locks on the computers, disabled CD-ROM drives, and portable drives, extensive physical security, and so forth." to avoid trade secret theft.

[28]Increasing collaboration in innovative activities was one of the main aims behind the EU legislation that introduced a uniform trade secret law across the EU in 2016 (Directive on the Protection of Trade Secrets). https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=SWD:2013:0471:FIN:EN:PDF

[29]See Figure 13 in Appendix C. See Ottoz and Cugno (2011) and Acemoglu and Akcigit (2012) for theoretical analyses of the optimal scope of trade secret protection.

4.5 Outsourcing Choice

Characterizing firms' policy functions is difficult in the full model due to discrete exit choice and non-convex adjustment cost. Ignoring entry and exit, assuming a differentiable adjustment cost function $\Phi(n_-, n)$, and a binding information-sharing constraint gives a formula that carries the full model's intuition and allows a simple characterization of the forces at work. The problem of the firm in industry k would simplify to

$$\begin{aligned} V_k(s, n_-) = \max_{n,r} \ & p_k s A(\pi, \delta_k) \left(\alpha(\pi, \delta_k) n^{\gamma_k} + (1 - \alpha(\pi, \delta_k)) r^{\gamma_k}\right)^{\frac{\theta_k}{\gamma_k}} \\ & - n - r - \Phi(n_-, n) + \beta E V_k(s', n) \end{aligned} \tag{12}$$

where the ratio of outsourcing expenditures over payroll expenses would become

$$\frac{r}{n} = \left[\frac{1 - \alpha(\pi, \delta_k)}{\alpha(\pi, \delta_k)} \Big(1 + \Phi_2'(n_-, n) + \beta E \Phi_1'(n, n')\Big)\right]^{\frac{1}{1-\gamma_k}} \tag{13}$$

where Φ'_j is the first derivative of $\Phi()$ according to its jth element. The expenditure share on outsourced workers would increase if adjusting permanent workers is more costly, i.e., Φ has a larger slope. The importance of adjustment costs is further amplified if the expected future adjustments are larger: σ_k^2 is higher or ρ_k is lower. The outsourced share also goes down as it becomes easier to substitute permanent workers for rented workers, that is, when γ_k is higher. Lastly, firms outsource more when the factor share of outsourcing is larger, i.e., $\alpha(\pi, \delta_k)$ is lower. $\alpha(\pi, \delta_k)$ is low when either the relative marginal product of outsourcing (δ) or the strength of trade secret protection (π) is high.

Although this analysis helps tease out some of the model's central mechanisms, I estimate the full model in the next section. The estimation confirms that the general equilibrium effects have a significant impact on aggregate outsourcing.

4.6 Model Extensions

I solve the model numerically, using grid-search on the value functions and forward iterations to compute firms' stationary distributions. I make a couple of adjustments before estimating the model. These do not affect the primary mechanism but simplify the computation and the estimation of the model.

First, I discretize the idiosyncratic productivity process to 10 grid points using Rouwenhorst (1995)'s method. Second, I add Type 1 Extreme Value (T1EV) shocks to the exit decision, ensuring the equilibrium moments change smoothly with parameter values and simplifies the estimation procedure. Each period, to continue operating, firms need to pay $c^F + \nu_1$, or they exit and pay $\tau \max\{0, n_- - n\} + \nu_2$ where ν_1, ν_2 are identically distributed T1EV shocks with shape parameter η. I assume the ν_1, ν_2 are independent over time, across firms, from productivity shocks, and one another. The difference of two T1EV shocks has a logistic distribution, which allows the analytical characterization of the probability that a firm with state s, n_- chooses to exit. Last, as in Boedo and Mukoyama (2012), each incumbent receives an 'offer' they cannot refuse after production ends with probability κ_j and have to exit. This shock helps generate realistic exit patterns in the model for large establishments.

5 Estimation

In this section, I estimate the model to make quantitative statements. Section 5.1 describes the data, the estimation procedure and the identification strategy. The estimation results are in 5.2. Section 5.3 evaluates the ability of the model to match untargeted moments. Section 5.4 provides the quantitative decomposition of state-level outsourcing heterogeneity while productivity gains from better trade secret protection are discussed in Section 6.

5.1 Data and Estimation Method

I use establishment-level moments for each state-industry pair in the manufacturing sector (NAICS 31-33) from 2007 to estimate the model. I use three primary data sources to compute the moments. The Census of Manufactures (CMF) provides state-industry level revenue shares, revenue payroll ratios, and outsourcing expenditures. The Statistics of U.S. Businesses (SUSB) provides state-industry level moments on establishment size distribution. Lastly, the Business Dynamics Statistics (BDS) provides state-level moments on job flows, which are only available at the manufacturing sector level.

The model has parameters that are global, industry-specific, state-specific, and state-industry specific. I use subscript j to denote that the parameter varies across states and k to denote it varies across industries. The full set of parameters necessary to compute the extended model is the vector[30]:

$$\Omega = \{\beta, \omega, \gamma_k, \sigma_k^2, \kappa_j, \tau_j, c_{jk}^F, c_{jk}^E, \rho_{jk}, \theta_{jk}, \pi_j, \delta_k\} \tag{14}$$

I set β and ω to standard values, and γ_k and σ_k^2 to previous estimates in the literature. I estimate the rest of the parameters ($\kappa_j, \tau_j, c_{jk}^F, c_{jk}^E, \rho_{jk}, \theta_{jk}, \pi_j, \delta_k$) in a two stages. The first stage assumes the information sharing constraint binds and treat $\alpha(\pi_j, \delta_k)$ as a state-industry level parameter α_{jk}. This assumption allows the first stage to be estimated separately for each state. This substantially relieves the computational burden since the stationary distribution of the model has to be solved numerically. The second stage treats α_{jk} as data generated by $\alpha(\pi_j, \delta_k) + \epsilon_\alpha$ where ϵ_α are zero-mean iid shocks and use non-linear least squares to estimate $\{\pi_j\}_{j=1}^J$ and $\{\delta_k\}_{k=1}^K$.

Externally Set Parameters

I set the discount factor $\beta = 0.94$ and the parameter governing the demand substitution between intermediate goods to $\omega = -0.5$. Two sets of parameters are hard to identify with the available data. The first is the elasticity of substitution parameter between permanent and outsourced workers. Identifying it either requires price data with an exogenous price shifter or panel data on establishments that utilize dynamic inputs. Neither data is available, so I take the estimates of Chan (2017) directly, who uses an establishment panel from Denmark to do the latter[31] for four manufacturing industry groups. The second is the variance of the demand process. It is not possible to nonparametrically identify both the persistence and the variance of an AR(1) process from cross-sectional data. I take the industry-level estimates from Bloom et al. (2018), who uses the Annual Survey of Manufacturers to estimate an AR(1) process for the log TFP estimates for each manufacturing industry.[32]

[30] I fix the productivity distribution of entrants (ϕ) and the shape parameter for the T1EV shocks to constant values for now.

[31] Both the relative size of the outsourcing sector, and its skill composition are remarkably similar between Denmark and the U.S.

[32] They estimate value-added production functions and include capital and materials. However, for a Cobb-Douglas production function between materials, capital, labor services (CES of permanent and outsourced workers), and competitive input markets, their variance estimates can be applied to my setting up to a constant multiplier. The multiplier is not identified in my model; hence, its value is irrelevant for the

Method of Moments Estimation and Identification Idea

I estimate $\Omega_E = \{\kappa_j, \tau_j, c^F_{jk}, c^E_{jk}, \rho_{jk}, \theta_{jk}, \alpha_{jk}\}$ via method of moments, minimizing the weighted distance between the model $M(\Omega_E)$ and data M^D moments:

$$\hat{\Omega}_E = \arg\min_{\Omega_E} \Big(M^D - M(\Omega_E)\Big)' W \Big(M^D - M(\Omega_E)\Big) \tag{15}$$

where W is a weighting matrix. The estimator is consistent for any choice of W, but the efficient estimator has $W = V^{-1}$, i.e., the inverse covariance matrix of the data moments. Estimating the covariance matrix requires micro-data. I instead use a diagonal matrix where $W_{nn} = (M^D_n)^{-2}$, which transforms the objective function into one that minimizes total squared percent deviations.

The model admits a general equilibrium where common labor and product markets connect all establishments in a state. The steady-state distribution does not have a closed-form solution either; thus, I provide intuitive arguments on why the selected moments inform the structural parameters. I suppress the state subscript j as all the parameters here are state-specific. The only parameter that maps one-to-one to a moment is the exogenous exit probability κ. The model generates essentially no endogenous exit for the largest firms; thus, κ becomes equal to the exit probability of large establishments (more than 250 employees).

The aggregate entry rate, average establishment size, and the revenue shares of industries jointly inform $\mathbf{c_k}$, the fixed cost of operating, and $\mathbf{c^E_k}$, the entry cost. Both a small c_k and a small c^E_k incentivize entry and are associated with a large industry. Thus, a decrease in either cost would increase the revenue share of an industry. On the other hand, the average establishment size moves in opposite directions when c_k and c^E_k increases. A large average establishment size is associated with a large c_k because establishments would not find it profitable to pay a high operating cost at a small scale and exit instead. On the other hand, a small cost of entry c^E_k would result in a large average establishment size, as the competitive pressure through new entrants would lead small unproductive firms to exit. Thus the two moments provide a single crossing condition for the two parameters. Lastly, the economy's overall scale is not pinned down; therefore, there are only $K - 1$ linearly independent revenue shares. The aggregate entry rate helps pin down the average level of entry costs across industries.

estimation. See Table 10 for the calibrated values of γ_k and σ_k.

While an increase in the returns to scale parameter $\theta_{\mathbf{k}}$ increases both the average establishment size and the revenue share of an industry, the ratio of revenues to payroll expenses allows distinguishing it from c_k and c_k^E. The two costs have no direct influence on this ratio, except through the firms' steady-state distributions. On the other hand, θ_k directly impacts the labor share of revenues by determining the elasticity of revenues to the labor inputs.

It is relatively easier to distinguish the persistence of the idiosyncratic shocks $\rho_{\mathbf{k}}$ and the firing cost τ from the parameters I discussed so far (c_k, c_k^E, and θ_k): while the latter parameters have first-order effects only on the first moments of the firm distribution, ρ_k and τ are crucial for the second moments and the flows.[33] On the other hand, it is notoriously difficult to separately identify adjustment costs and the parameters of the idiosyncratic shock process (Bloom (2009)). I use the share of small establishments (less than 20 employees) and the aggregate job destruction rate. Both a high persistence and a high firing cost reduce the rate of job destruction. If shocks' persistence is high, establishments face the need to change their workforce less frequently while under high firing costs, establishments choose to operate at a sub-optimal scale instead of firing workers. The two parameters also impact the share of small establishments in the same direction. If persistence is high, entrants stay small for a long time until their productivity increases. High firing costs also discourage establishments from increasing the number of workers anticipating the possibility of having to fire them later. On the other hand, for a wide range of reasonable firing costs (0 to 4 years of wages), the impact on the share of small establishments is modest (less than 1%). Thus, a local single crossing condition is satisfied. The intuition for the modest impact of firing costs relies on the firm size distribution's long right tail. Given the high fixed costs of operating and low returns to scale parameters, the return from hiring workers is very high for small productive firms.[34]

Last but not least, the ratio of outsourcing expenses to payroll expenses helps identify α, the factor share of permanent workers. As discussed in Section 4.5, the parameters that have a direct effect on the ratio of outsourcing expenses are γ, σ^2, ρ, τ and α. I externally calibrate γ and σ^2 with structural estimates from the literature. The share of

[33] The only exception to this is the impact on the entry rate, which directly affects the job destruction rate. In model validation, I specifically check whether the estimated model does a good job matching the fraction of job flows through exits.

[34] One moment that would allow a global identification would be the 'job destruction' rate for outsourced workers, i.e., the average decline in outsourcing expenses for firms that decrease their outsourcing. Because outsourcing is not subject to firing costs, its flow helps discipline the fluctuations in the idiosyncratic shock process. Unfortunately, there are no public estimates for this moment.

small establishments again helps distinguish ρ from α, as the impact of α is negligible once the average size of establishments is held constant. Finally, although both a low α and a high τ increase the ratio, the large response of job destruction rate and the small response of the outsourcing ratio to τ allows distinguishing the two.

Nonlinear Least Squares

In the second stage, I minimize the sum of squared residuals between the model implied $\alpha(\pi_j, \delta_k)$ as derived in (10) and α_{jk} as estimated in the first stage (15):

$$\{\hat{\pi}_j, \hat{\delta}_k\} = \arg \min_{\{\pi_j, \delta_k\}} \sum_{j,k} (\hat{\alpha}_{jk} - \alpha(\pi_j, \delta_k))^2 \tag{16}$$

This procedure is similar in spirit to a fixed effects regression; once the factor shares are estimated, the 'state fixed effects' give the π_j and the 'industry fixed effects' give the δ_k. Similar to a two-way fixed-effects regression, it is impossible to separately identify the level of π_j from the level of δ_k. Therefore, in the counterfactuals, I do a normalization a la Hsieh and Klenow (2009) and consider the state with the largest π_j as the baseline for comparisons based on enforcement frictions. Table 4 summarizes the full calibration/estimation strategy, together with sources. The first four rows of parameters are externally calibrated. The ones in the middle are jointly estimated to match the moments in the first stage. The ones in the last two rows are jointly estimated to match the α_{jk} that are estimated in the first stage.

5.2 Estimation Results

I have estimated the model for twenty states so far, where I divide the manufacturing sector into $K = 4$ industry groups: Food Products ($k = 1$), Wood and Paper Products ($k = 2$), Heavy Industry and Extraction ($k = 3$), and Tools, Machinery and Consumer Goods ($k = 4$). Figure 5a presents the estimated factor shares for all industry-state groups.[35]

Figure 5b summarizes how the estimated factor share parameters relate to the observed outsourcing ratios. In a model with no adjustment costs, the outsourcing ratios

[35] I follow the same grouping as in Chan (2017) to have a one-to-one match with his γ_k estimates. The details of how I match the U.S. NAICS 3-digit sectors with the Danish NACE 2-digit sectors are in Appendix B. The first-stage in-sample results are in Table 11, where I provide the results for Michigan for brevity.

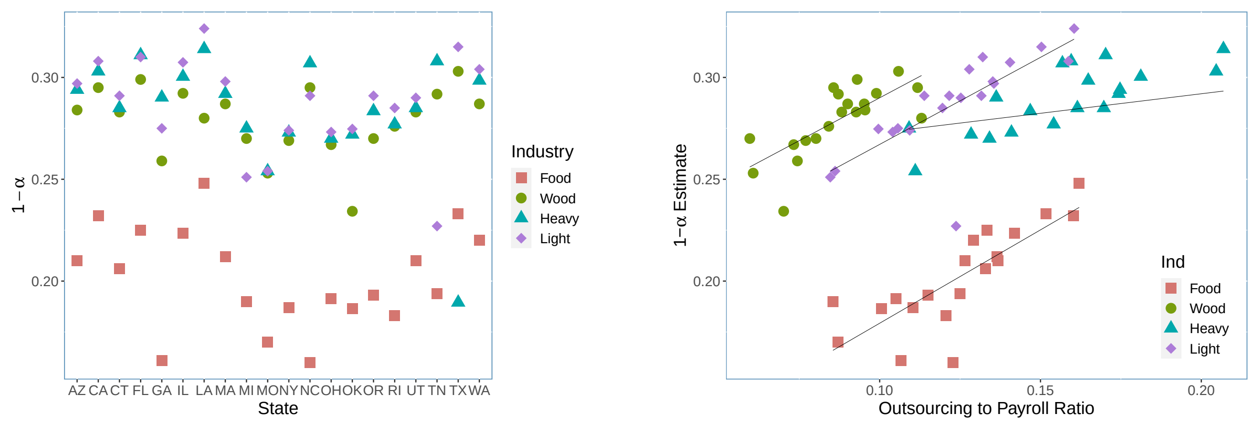
Parameter	Role	Moment	Source
β	Discount Factor	External	0.94
ω	Int. Good Subst.	External	-0.5
γ_k	Permanent/Outsourced Subst.	External	Chan 2017
σ_k^2	Idio. Shock Variance	External	Bloom et al. 2018
κ_j	Exog Exit Prob	Exit Rate Estb Size>250	BDS
τ_j	Firing Cost	Job Destruc. Rate	BDS
c_{jk}	Fixed Cost of Operating	Avg. Estb Size	SUSB
c_{jk}^E	Entry Cost	Ind. Output Shares	CMF
ρ_{jk}	Idio. Shock Persistence	Share of Estb Size<20	SUSB
θ_{jk}	Returns to Scale	Receipts/Payroll	CMF
α_{jk}	Permanent Factor Share	Outsourcing/Payroll	CMF
		Agg. Entry Rate	BDS
π_j	Trade Secret Enforcement	α_{jk}	1st Stage
δ_k	Outsourcing Suitability		

Table 4: The main parameters and the moments used in the estimation. Notes: The details of the data sources and how the moments are calculated can be found in Appendix B

.

would only depend on γ_k and α_{jk} because there would be no flexibility gains from outsourcing. The cross-state patterns are as expected within each industry. However, the estimates suggest the factor share of outsourcing is considerably lower in food manufacturing, even though it outsources as much as the other industry groups. Also, the estimates for heavy manufacturing are broadly similar to wood manufacturing, even though heavy manufacturing has considerably higher outsourcing to payroll ratio

Two channels mainly drive these results. First, permanent and outsourced workers are easier to substitute in food and heavy manufacturing, according to the externally calibrated γ_k values (Table 10). This implies a larger outsourcing ratio for a fixed $\alpha_{jk} > 0.5$ (see (13)). Second, in the data, food and heavy manufacturing establishments have a larger revenue to payroll ratio, even though their average size is not significantly different than the other two groups. Hence, they are estimated to have low θ_{jk} and c_{jk}^E and high c_{jk} (See Figure 15). The low returns to scale together with high fixed costs create a fat-tailed size distribution, and the low c_E ensures the total size of these industries is as large as in the data. In the model, larger firms outsource a bigger fraction of their workforce, fearing mass layoffs in the future. The very large firms in the food and heavy manufacturing hence outsource a large fraction of their workforce, generating the pattern in Figure 5a. Lastly, these two effects are large enough to offset the lower-variance demand shocks for food and heavy manufacturing, given the externally calibrated σ_k values.



(a) Estimated Outsourcing Factor Shares $(1 - \alpha_{jk})$

(b) Ousourcing to Payroll Ratios vs Estimated Outsourcing Factor Shares $(1 - \alpha_{jk})$

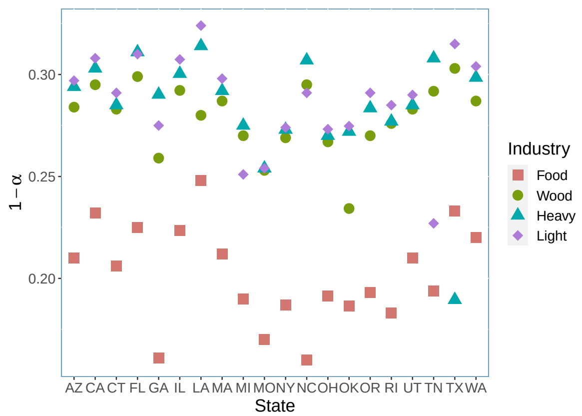
Figure 5: The Estimation Results from the 1st Stage Notes: Each shape refers to a state-industry pair. See Table 11 for details on the first and second stage estimation results and Appendix B for details on the outsourcing to payroll ratios.

Table 12 presents the results from the second stage; hence the main estimation results. I find, without enforcement frictions, the industry that would benefit the most from outsourcing is Heavy Industry and Extraction, and the one that would benefit the least is food manufacturing. Louisiana is the state with the best trade secret protection, and Missouri is the one with the worst. Most importantly, as Figure 6b shows, the results from the structural estimation align with the adoption date of the UTSA, even though I do not use information about the actual trade secret law in the estimation. The states that adopted the UTSA earlier are the ones that have better trade secret protection on average.

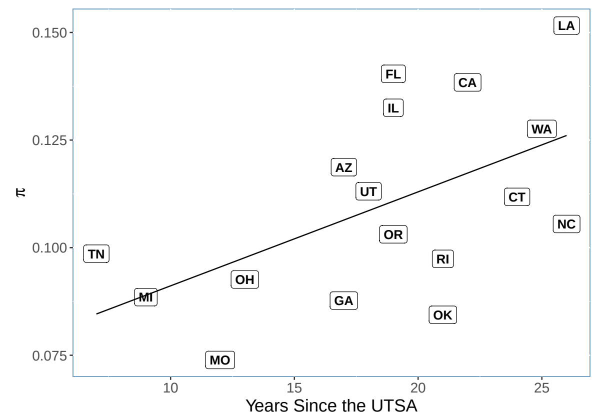
5.3 Model Validation

I validate the model through its ability to match the share of job destruction that happens through establishment exits, establishment shares of industry groups, and the share of employment in small establishments.

Although the estimation targets the rates of exit and job destruction, the share of job destruction through exits can be anywhere between 0 and 1 depending on the exiting establishments' average size. The model does an excellent job of predicting the share (Figure 8a), hence the average size of exiting establishments. The estimation targets the revenue share, the revenue payroll ratio, and the average establishment size for each industry group. If workers' average wages across industries differed significantly, the



(a) Estimated Outsourcing Factor Shares ($1 - \alpha_{jk}$)



(b) Estimated Strength of Protection (π) vs Number of Years Since the Adoption of the UTSA

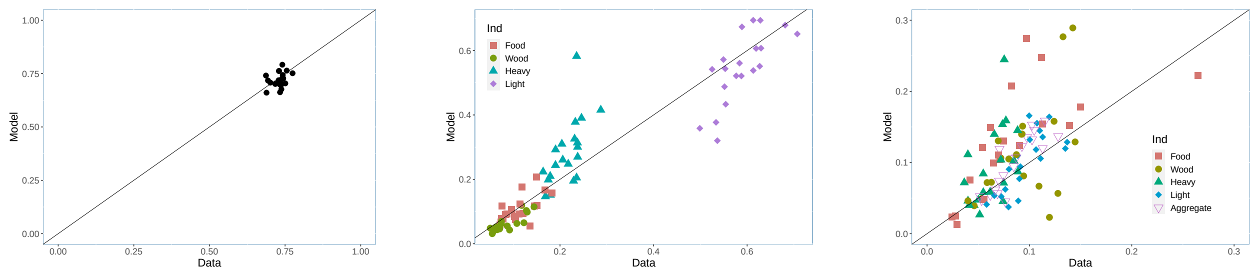
Figure 6: The Estimation Results from the 1st and 2nd Stages Notes: Figure 6b only presents states who adopted the UTSA by 2007.

model would do a bad job predicting the fraction of establishments that belong to each industry. Figure 8b suggests the model still does a good job. The only exceptions are the wages at California's Light and Heavy industries, where the model undervalues the former and overvalues the latter. Lastly, the model targets the share of establishments with less than 20 employees but does not target the size distribution below 20. If the model did a bad job at matching that distribution, it would make a bad prediction of the expected size of establishment conditional on less than 20. Figure 7c suggests the model does an okay job, except for food manufacturing, which is a relatively smaller part of the manufacturing sector. In particular, the model cannot account for the states with small food manufacturing establishments.

The model does a poor job predicting the size distribution's right-tail, generating too few very-large establishments (larger than 250, 500). The model's inability to match both tails is partly due to the assumption of normal shocks to the demand process. A shock distribution that has fatter tails would help the model generate more large establishments.

5.4 Decomposition of the Outsourcing Heterogeneity

In this section, I ask how the cross-state heterogeneity in labor outsourcing would change if all states had the same (1) firing cost, (2) industry composition, (3) within-industry firm characteristics, and (4) trade secret protection. According to the model, these four ob-



(a) Share of Job Destr. by Existing Establishments

(b) Establishment Shares of Industry Groups

(c) Share of Employment in Small Establishments (< 20)

Figure 7: The Untargeted Moments

jects constitute a mutually exclusive and exhaustive list of the differences between states. However, they might interact with one another and amplify/dampen each other's effects. Notably, the industry composition and the within-industry firm characteristics are equilibrium objects, making the decomposition non-trivial.

To equate the labor protection and the trade secret protection across states, I replace the values of τ and π with the average estimates. To 'equate' the industry compositions, I take simple weighted averages of industry-level outsourcing shares for each state, weights being average industry share of employment across states. To find the impact of equating within-industry firm characteristics, I take the average values of the other three (τ, π, and industry shares) for each state and compute the remaining dispersion (See Figure 14). Now I can answer one of the main questions I have started with: what generates the cross-state dispersion in outsourcing use? I use the coefficient of variation (standard deviation divided by the average) as my measure of dispersion. The cross-state dispersion would be

- 19% less with average trade secret protection
- 14% less with average industry composition
- 18% more with average firing cost
- 85% less with average within-industry firm characteristics

The differences in within-industry firm characteristics create the lion's share of the observed dispersion across states. While equating industry shares would reduce the heterogeneity, equating firing costs would amplify it. The counter-intuitive implication is that the states with the higher estimated firing costs outsource less than others due to the other three channels' counteracting force.

Equating the strength of trade secret protection decreases the cross-state dispersion by 19%. This result, however, is built on considerable heterogeneity across states. In particular, there are states with weak trade secret protection that still outsource a significant amount of their workforce. Bringing the strength of trade secret protection up to the average level increases outsourcing shares for these states, pushing for increased dispersion. For example, Tennessee is a state with an above-average outsourcing ratio of 0.2, and improving its trade secret protection up to the average level would bring the ratio up to 0.21.

6 Productivity Gains from Better Trade Secret Protection

In this section, I answer the question I started with: how large are the productivity gains from better trade secret protection? Specifically, I calculate the counterfactual outcomes when every state has the same trade secret protection (π) as the 'best state,' which is Louisiana, according to my estimates.

Table 5 presents the main results. The median state increases its outsourcing to payroll ratio from 0.13 to 0.18. While both the gross and the net output (net of all costs) of the median state grows by 2.1%, the state that benefits the most has a net output growth as large as 3.8%. The growth is mostly through the entry channel: the number of firms increases by 2.1% in the median state. Lastly, wages also reflect productivity growth, increasing by as much as 2.7% for the median state. I compute the aggregate gains as the weighted average of the net output gains in each state, where the weights are equal to each state's manufacturing output in 2007. The aggregate output grows by 1.7%. In the remainder of the section, I quantify individual channels that lead to output gains.

The Role of Employee Movement

Improved trade secret protection decreases the job destruction rate, i.e., increased outsourcing leads to more job stability for permanent manufacturing employees. Yet, the aggregate decline is relatively small, from 10.95% to 10.92%. Although the job destruction

	Base	Best TSP	Gross Output	Net Output	Number of Firms	Wage
Median	0.130	0.179	1.021	1.022	1.021	1.027
Max	0.197	0.264	1.038	1.040	1.037	1.049
Aggregate	0.181	0.225	1.016	1.017	1.016	1.020

Table 5: The counterfactual results after an improvement in trade secret protection Notes: The first and second rows give the result for the median and maximum value across states. The third row gives the aggregate response, which is an output-weighted average of the responses of states. The values for columns 4 to 7 are relative to a baseline value of 1. Base and Max π refer to the outsourcing to payroll ratio in the baseline estimation and the counterfactual where each state's π is equal to the state with the highest π. Gross Output is the aggregate amount of final goods produced, and the net output is gross output net of all entry, operating, and firing costs. The number of firms is aggregated over industries. See Table 14 for state-by-state details.

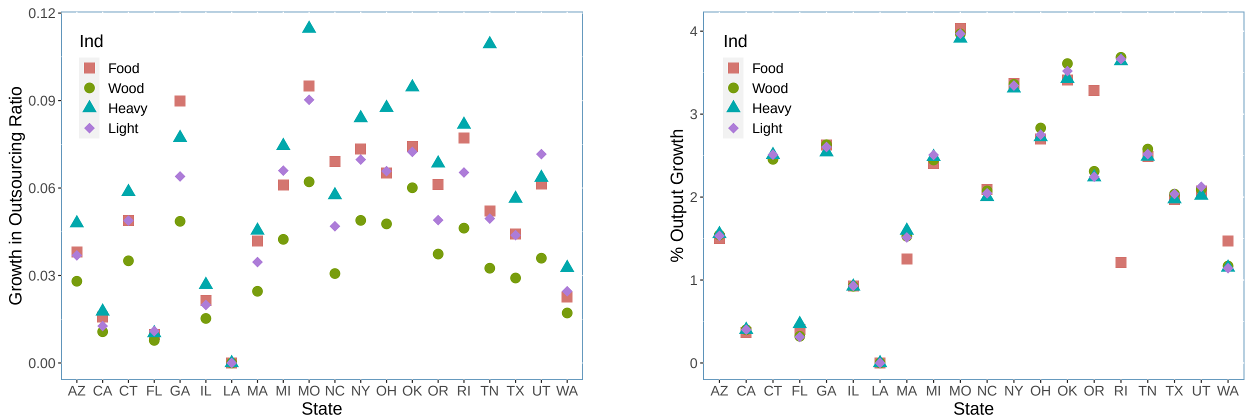
rate remains relatively constant, the total amount of job destruction declines substantially because the fraction of workers under employment goes down. These lead to savings through avoided firing costs: even though the number of firms increases by 1.5%, the aggregate firing cost paid declines by 1.9%. The magnitude of the savings is small on the macroeconomic scale (3 basis points of GDP).

On the other hand, the gains from better allocation of workers are significant. The correlation between size and productivity, a commonly used measure of labor (mis)allocation between firms, wouldn't capture the productivity gains, increasing barely from 0.842 to 0.843. On the other hand, the correlation between the size of the outsourced workforce and productivity increases substantially from 0.893 to 0.902. In other words, the reduction in the firms that have excess and too little permanent workers leads to a better allocation of outsourced workers across firms.

Entry and Exit

The entry/exit channel impacts the aggregate gains both through the number of firms that operate in the steady-state and through the rate of entry/exit as a force that generates steady creative destruction. Although the aggregate rate of entry/exit goes up, it is quantitatively small: the change is 2 basis points relative to a baseline level of 7.91%. On the other hand, the number of firms in the steady-state increases substantially by 1.6%. This increase is reflected by the quantitatively significant growth in aggregate entry costs and operating costs paid by 1.7% and 1.6% (0.2% and 0.6% of GDP).

The increase in the number of firms is accompanied by a 2 p.p. increase in small firms'



(a) The Growth in Outsourcing to Payroll Ratio

(b) The % Growth in Net Output

Figure 8: The State-Industry Level Gains

share (less than 20 employees). This increase is not surprising since the total number of employees employed by the manufacturing firms decreases while the total number of firms increases, i.e., the average firm size must be decreasing. A decrease in the fraction of very large firms accompanies the increase in small firms' fraction. While small firms find it easier to grow in size with the added flexibility provided by outsourcing, they also face more intense competition for workers due to the increased number of firms. For the large firms, flexibility and competition work in the same direction: they find it easier to decrease their size after bad shocks. Hence, firms *hoard labor* to a lesser extent when the outsourcing sector is larger.

The Role of Industries

The industries differ in δ_k; therefore, the importance of trade secret protection is potentially different across industries, which may explain why some states enjoy more significant gains from improved protection than the others.

Figure 8 shows the industry that changes its workforce composition the most is heavy manufacturing, followed by food manufacturing. Both industries heavily rely on secrecy for comparative advantage. The secret formulas and processes are integral parts of food and chemical manufacturing. The negative information on R&D, which cannot be patented, is critical for pharmaceuticals. Similarly, the information on the location of raw materials and manufacturing processes is essential for oil and metals industries.

On the other hand, the industry-level output growth rates are much more similar to one another than the outsourcing growth. This similarity is largely driven by the value of the parameter that controls the demand elasticity of the final good producer ($\omega = -0.5$).[36] Since intermediate goods are gross complements, an increase in one intermediate industry's productivity increases the demand for other intermediate industries. This complementarity aligns the output of different industries together; hence all industries benefit from a productivity gain in one industry.

7 Conclusion

I study the impact of trade secret protection on producers' willingness to use outsourced workers, and consequently, aggregate output. Through an analysis of this channel in the U.S. I make two main points. First, better legal protection for trade secrets can induce managers to use outsourced workers for a larger number of tasks. Second, the consequent expansion in outsourcing use generates a better allocation of workers across firms and a quantitatively significant increase in aggregate output.

To make the first point, I rely on the Uniform Trade Secrets Act and utilize the variation in adoption times across states. My analysis shows that adopters enjoyed a higher pace of subsequent growth in outsourcing employment relative to non-adopters. Also, the effect was more pronounced for tasks that provide greater access to sensitive information. Quantitatively, the improvements in trade secret law explain 13% of the growth in outsourcing employment in the U.S. from 1977 to 1997.

I build and estimate a structural model of industry dynamics to make the second point. The model teases out the part of cross-state heterogeneity in outsourcing that is attributable to variation in trade secret protection and maps it to aggregate productivity measures. Estimating it with data from the U.S. manufacturing sector shows that the gains from better trade secret protection are sizeable. If all states could protect trade secrets as adequately as the 'best state,' the aggregate output would increase by 1.7%.

These findings suggest large gains even for the U.S., a country that is at the forefront of

[36] I choose an elasticity that implies gross complementarity between intermediate goods because I estimate the model using a revenue (instead of value-added) production function. Since I do not model an explicit production network between manufacturing industries, I introduce a reduced-form supply chain through complementarity in final good production.

trade secret protection (See Figure 13). The gains might be even larger for countries where the statutory law is still missing, common law is underdeveloped, or the enforcement of existing laws is lacking. Improving legal protection requires trained judges, lawyers, expert witnesses, and functioning audit and appeals systems that supervise the legal system. None of these come easy or cheap, but neither do tax breaks or R&D subsidies.

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A Proofs

Proof of Lemma 1. I will first show that if a unique $\bar{z}$ exists, it has to satisfy $0 \leq \bar{z} < \zeta^{-1}(z)$. Second, I show the task-level production $y(i)$ is increasing in i. Last, I will show that a unique $\bar{z}$ exists s.t. tasks $i \leq \bar{z}$ only use outsourced and tasks $i > \bar{z}$ only use hired labor in the optimal solution.

First, the manager would not assign any outsourced workers to tasks $i \geq \zeta^{-1}(z)$ because (1) outsourced workers assigned to tasks above $\zeta^{-1}(z)$ do not generate any output while their output would be strictly positive in tasks $i < \zeta^{-1}(z)$ and (2) the marginal contribution of each task's output approaches infinity as the output in that task approaches 0.[37] Hence, the manager would assign a positive measure of permanent workers and no outsourced workers to all tasks $i \geq \zeta^{-1}(z)$.

Second, $y(i)$ should be weakly be increasing in i. Assume towards a contradiction that $y(i_1) > y(i_2)$ for $i_2 > i_1$. Let the total number of permanent and outsourced workers assigned to these tasks be $n(i_1), r(i_1)$ and $n(i_2), r(i_2)$. Then, the marginal product of an outsourced worker in these tasks would be

$$MP_r(i) = \theta Y^{\frac{\theta-\gamma}{\gamma}} y(i)^{\gamma-1}\delta$$

For $y(i_1) > y(i_2)$, the manager could increase Y by reassigning an infinitesimal measure of outsourced workers from task i_1 to i_2. Similarly, the marginal product of a permanent worker in these tasks would be

$$MP_n(i) = \theta Y^{\frac{\theta-\gamma}{\gamma}} y(i_1)^{\gamma-1} g(i)$$

For $y(i_1) \geq y(i_2)$, the manager could increase Y by reassigning an infinitesimal measure of permanent workers from task i_1 to i_2 because $g(i)$ is strictly increasing. Hence $y(i)$ has to be weakly increasing in i.

Last, for tasks $i \leq \zeta^{-1}(z)$, assume towards a contradiction that a permanent worker is assigned to task i_1 and an outsourced worker is assigned to task $i_2 > i_1$ in the optimal so-

[37] Because $\zeta(i)$ is strictly increasing, $\zeta^{-1}(z)$ exists, and is strictly increasing.

lution. Let the total number of permanent and outsourced workers assigned to these tasks be $n(i_1), r(i_1)$ and $n(i_2), r(i_2)$. Then, the manager could increase its output by switching the permanent and the outsourced worker in these tasks because, the strictly increasing $g(i)$ and weakly increasing $y(i)$ imply the last inequality

$$\begin{aligned} MP_n(i_1) + MP_r(i_2) >& MP_n(i_2) + MP_r(i_1) \quad \Leftrightarrow \\ \theta Y^{\frac{\theta-\gamma}{\gamma}} \left(y(i_1)^{\gamma-1} g(i_1) + y(i_2)^{\gamma-1}\delta \right) >& \theta Y^{\frac{\theta-\gamma}{\gamma}} \left(y(i_2)^{\gamma-1} g(i_2) + y(i_1)^{\gamma-1}\delta \right) \quad \Leftrightarrow \\ y(i_1)^{\gamma-1}(g(i_1) - \delta) >& y(i_2)^{\gamma-1}(g(i_2) - \delta) \end{aligned}$$

Hence, if a permanent worker is assigned to task i_1, no outsourced worker would be assigned to a task $i_2 > i_1$ in the optimal solution. This guarantees that a unique $\bar{z}$ exists s.t. tasks $i \leq \bar{z}$ only use outsourced and tasks $i > \bar{z}$ only use hired labor in the optimal solution. □

Proof of Proposition 1. I will first characterize the assignment of workers across tasks for a given $\bar{z}$ and then characterize the optimal choice of $\bar{z}$. The idea is that, hired (rented) workers should be allocated across tasks $i > \bar{z}$ ($i \leq \bar{z}$) in a way to equalize marginal products across those tasks. Second, if the threshold task is interior, i.e. $\exists \bar{z} < z$, then the firm should be indifferent between using hired or rented labor for that task. If not, then the firm should strictly prefer renting to hiring at the threshold task $\exists \bar{z} = z$. First, since the productivity of outsourced workers in tasks does not depend on the identity of the task i, the CES aggregation of the tasks together with the budget constraint for rented workers imply

$$r(i) = \frac{r}{\bar{z}} \tag{17}$$

For permanent workers, the equalization of the marginal product across tasks requires:

$$\gamma g(i)^{\gamma} n(i)^{\gamma-1} = \bar{n}$$

The Assumption 2 gives

$$n(i) = \left(\frac{\gamma}{\bar{n}} g(i)^{\gamma}\right)^{\frac{1}{1-\gamma}} \tag{18}$$

where $\bar{n}$ is a constant. The budget constraint for the permanent workers gives

$$\left(\frac{\gamma}{\bar{n}}\right)^{\frac{1}{1-\gamma}} \int_{\bar{z}}^{1} g(i)^{\frac{\gamma}{1-\gamma}} di = n$$

which pins down the constant term:

$$\bar{n} = \gamma \left(\frac{(1-\gamma)(1-\bar{z}^{\frac{1}{1-\gamma}})}{n}\right)^{1-\gamma} \tag{19}$$

(18) and (19) allow writing $n(i)$ as a function of n and $\bar{z}$:

$$n(i) = \frac{n i^{\frac{\gamma}{1-\gamma}}}{(1-\gamma)(1-\bar{z}^{\frac{1}{1-\gamma}})}$$

Denote with $\tilde{z}$ the threshold task in an unconstrained (by z) allocation of workers across tasks. At task $\tilde{z}$, manager should be indifferent between using permanent or outsourced workers:

$$r\delta = \frac{\tilde{z}^{\frac{2-\gamma}{1-\gamma}} n}{(1-\gamma)(1-\tilde{z}^{\frac{1}{1-\gamma}})}$$

This condition does not give an analytical solution for $\tilde{z}$. The right-hand side is a continuous and strictly increasing function of $\tilde{z}$ that is equal to 0 when $\tilde{z} = 0$ and is unbounded above as $\tilde{z}$ approaches 1. The left hand side is a positive constant. Hence, there exists a unique $\tilde{z}$ that satisfies the condition. If $\tilde{z} > z$, then $\bar{z} = z$. Otherwise, $\bar{z} = \tilde{z}$.

Using the derived formulas for $r(i)$ and $n(i)$, I can write down the total firm output as a function of n, r, and $\bar{z}(n, r)$:

$$\begin{aligned}F(n,r) &= \left(\int_{\bar{z}}^{1}\left(\frac{ni^{\frac{1}{1-\gamma}}}{(1-\gamma)\big(1-\bar{z}^{\frac{1}{1-\gamma}}\big)}\right)^{\gamma}di + \int_{0}^{\bar{z}}\left(\frac{r\delta}{\bar{z}}\right)^{\gamma}di\right)^{\frac{\theta}{\gamma}} \\ &= \Big(\underbrace{\big((1-\gamma)(1-\bar{z}^{\frac{1}{1-\gamma}})\big)^{1-\gamma}}_{\alpha_n(n,r)}n^{\gamma} + \underbrace{\bar{z}^{1-\gamma}\delta^{\gamma}}_{\alpha_r(n,r)}r^{\gamma}\Big)^{\frac{\theta}{\gamma}}\end{aligned}$$

□

Proof of Corollary 1. Once the IC constraint binds, i.e., $\bar{z} = \pi$:

$$Y(n,r) = s\left(\underbrace{\big((1-\gamma)(1-\pi^{\frac{1}{1-\gamma}})\big)^{1-\gamma}}_{\alpha_n}n^{\gamma} + \underbrace{\delta^{\gamma}}_{\alpha_r}r^{\gamma}\right)^{\frac{\theta}{\gamma}}$$

Defining $A = \alpha_n + \alpha_r$ and $\alpha = \alpha_n/A$ allows rewriting this in the classical CES form:

$$Y(n,r) = sA(\pi,\delta)\big(\alpha(\pi,\delta)n^{\gamma} + (1-\alpha(\pi,\delta))r^{\gamma}\big)^{\frac{\theta}{\gamma}}$$

□

B Data Sources

In this section, I describe the data sources and sample construction procedures.

B.1 Measures of Labor Outsourcing

I conduct analyses with data from different time periods and geographical levels, hence the best available data changes according to the question at hand. Throughout the paper, I use employment data that uses NAICS, SIC, and 1990 Census classifications and outsourcing expenditures data from Census of Manufactures (CMF). I carefully designate which industries in NAICS classification provide labor outsourcing services. Then, for other classifications, I choose the industries that correspond the best to the designated NAICS industries.

Definition of Labor Outsourcing

I define labor outsourcing as the purchase of business services that are labor intensive and can potentially be done in-house. First, I restrict attention to business services, because the main decision (hire vs outsource) I analyze in this paper is not relevant for households. I operationalize this criterion by restricting attention to 4-digit NAICS services industries who earn more than 70% of their revenues from serving businesses and government according to the 2017 Services Annual Survey (SAS). Second, I restrict attention to labor intensive services because the decision to outsource capital-intensive services may rely on financial concerns that I abstract from in this paper. I operationalize this criterion by restricting attention to services industries who have less than 5% of their expenditures as depreciation in the 2017 Services Annual Survey (SAS) conducted by the U.S. Census Bureau. Last, I restrict attention to purchase of services where there is a meaningful make or buy decision. I use this criterion intuitively, and rule out the information technology (IT) industry (NAICS 51)[38], finance providing industries (NAICS 52, 53) and central offices of holding companies (NAICS 55).

This definition roughly translates to two 2-digit industries: NAICS 54 (The Professional, Scientific, and Technical Services) and NAICS 56 (The Administrative and Support and Waste Management and Remediation Services) with the following exceptions. I exclude 4-digit subsectors 5419 (Other Professional, Scientific, and Technical Services, roughly employs 8% of the total employment in NAICS54, consists mainly of veterinary and photographic services) and 5615 (Travel Arrangement and Reservation Services, roughly employs 3% of the total employment in NAICS56) because 46% and 68% of their revenues come from households respectively. I also exclude the 3-digit subsector 562 (Waste Management and Remediation Services, roughly employs 5% of the total employment in NAICS56) because depreciation roughly corresponds to 10% of its expenses.

Table 6 presents the list of 4-digit NAICS industries that fall into my definition of labor outsourcing sectors, ordered according to the share of employment with a Bachelor's degree. The total employment in these industries is around 17 million workers, where the

[38]The portion of the IT sector that provides personalized services to each client firm will still be in my sample as NAICS 5415 Computer Systems Design and Related Services.

Industry	NAICS	Emp. (1000s)	Rev. ($B)	HH Share	Deprec.	College
Scientific R&D	5417	710	166	0.05	0.04	0.79
Comput. Sys. Design and Rel.	5415	2,154	304	0.00	0.03	0.73
Manag., Sci., and Tech. Consult.	5416	1,501	210	0.06	0.02	0.72
Advertising and Related	5418	493	72	0.07	0.04	0.70
Legal	5411	1,142	203	0.29	0.01	0.69
Architect., Eng., and Rel.	5413	1,493	253	0.03	0.02	0.67
Specialized Design	5414	142	15	0.30	0.02	0.64
Account., Tax, Book., Payroll	5412	1,009	136	0.15	0.02	0.61
Office Admin.	5611	517				0.38
Facilities Support	5612	160				0.38
Other Support	5619	331				0.38
Employment	5613	3,669				0.31
Business Support	5614	890				0.26
Investigation and Security	5616	951				0.19
Serv. to Buildings	5617	2,158				0.09
Admin. and Support	561		632	0.15	0.03	

Table 6: Labor Outsourcing Sector in NAICS Classification Notes: Employment figures are from the 2018 Current Employment Statistics. Total revenues and the ratio of depreciation expenditures to total expenditures is from are from the 2017 Services Annual Survey (SAS). The share of revenues from households are from the 2019 Q3 Quarterly Services Survey (QSS). The fraction of employment with Bachelor's degree (or more) is from 2019 IPUMS CPS. The SAS and QSS do not have full breakdowns by 4-digit sectors of NAICS 561, the last row provides the aggregate values.

employment shares of NAICS 54 and 56 are almost equal with 8.5 million workers each.

Overview of Data Availability on Labor Outsourcing

I use data on both the demand for outsourcing and the supply of outsourcing. Unfortunately, historical data on demand for outsourcing has may problems. The U.S. Census first started collecting establishment-level data on outsourcing use in 1977 with Annual Survey of Manufactures (ASM) and Census of Manufactures (CMF), but restricted attention to purchase of capital-intensive services: repair and communication services.[39] Furthermore, the treatment of transactions with the establishments' Central Administrative Offices (CAO) or other auxiliary establishments of the same firm has changed in 1997. Within SIC classification, these auxiliary establishments were classified according to the primary activity of the establishment they are serving. On the other hand, NAICS classifies these establishments according to their own activity, thus these transactions show up as purchased services for the main establishment after 1997. See the discussions in Siegel and Griliches (1992), Berlingieri (2013), and Fort et al. (2016) for more details. The U.S.

[39] Siegel and Griliches (1992) documents that even for the manufacturing sector, these services constituted only 28% of total service purchases once compared with Input-Output (I-O) tables for 1977.

Census only started to collect relevant information on purchase of labor outsourcing services 1992 through ASM and CMF, while the measurement of expenditures on temporary workers only started in 2007.

The historical data on the supply of labor outsourcing (employment and value-added) is available through multiple sources, each with their own issues. The Bureau of Economic Analysis (BEA) publishes historical employment and output figures for sone state-industry pairs based on 1987 SIC classification (SA25, SA25N, SAEMP25), but does not provide a clear separation of labor outsourcing sector from other sectors. In particular, it uses two-digit SIC industry 73 Business Services which combines labor outsourcing with many other capital intensive services such as equipment rental. County Business Patterns (CBP) collects very detailed industry level employment and number of establishment figures at the county level from the universe of employer establishments. However, (1) industry classifications change several times from its start with no clear bridge, and (2) it uses extensive censoring and imputation on employment values.[40] The decennial Census provides a large sample size together with a consistent industry definition provided by IPUMS USA, but the data frequency does not allow observing the impact of changes in laws. For historical data analysis, I rely on the March Current Population Survey (CPS) together with the historically consistent industry definition (1990 Census industry classification) provided by the IPUMS CPS. The CPS has a smaller sample size than the other data sources and suffers from small sample size in some state-industry bins, which does not necessarily create bias in diff-and-diff estimates.

Code	Subsector	Emp (1000s)	College	Skill Classification
20	Landscape and horticultural	1,731	0.10	Low-Skill
721	Advertising	672	0.70	High-Skill
722	Services to dwellings and other buildings	1,944	0.09	Low-Skill
731	Personnel supply	1,464	0.31	-
732	Computer and data processing	3,541	0.72	High-Skill
740	Detective and protective	1,051	0.19	Low-Skill
841	Legal	1,903	0.69	High-Skill
882	Engineering, architectural, and surveying	1,855	0.67	High-Skill
890	Accounting, auditing, and bookkeeping	1,397	0.61	High-Skill
891	Research, development, and testing	791	0.79	High-Skill
892	Management and public relations	2,103	0.72	High-Skill

Table 7: Labor Outsourcing Sector in Census 1990 Classification Notes: Employment figures are from the 2018 American Community Survey through IPUMS USA. The fraction of employment with Bachelor's degree (or more) is from 2019 IPUMS CPS and the skill classification is based on how the industry compares to the U.S. average of 0.34.

[40]See Eckert et al. (2020) for an ongoing project on making CBP available for historical comparisons.

Data Sources for the Panel Data Analysis

The Current Population Survey: I use the CPS mainly for state-industry level employment figures for labor outsourcing industries and education controls. I use the Annual Social and Economic Supplement (ASEC) samples of CPS through IPUMS CPS. The IPUMS database provides an industry classification system 'ind990' that is based on the classification system used in 1990 Census and provides comparability over time. See Table 7 for the list of included industries. I also construct state-level manufacturing employment measures using Census 1990 industries with codes between 100 to 392 and total employment measures using employment status variable being at work (empstat=10). Lastly, IPUMS censors state-industry level employment estimates when the data quality is too low, hence the final sample becomes an unbalanced panel ranging from 1970 to 2019. I construct the state and industry level educational attainment measures from the ASEC samples, restricting attention to individuals of age 25 to 65. I use the 'educ' variable and classify values 71 to 100 as high school and above, and 110 and above as 4-year college and above. When necessary, I classify the industries that have educational attainment levels significantly above the U.S. average as high-skill labor outsourcing industries and those with significantly below as low-skill labor outsourcing industries.

The Trade Secret Protection Index: "The index is constructed as a simple average of scores for three items of substantive law (i to iii), one item of civil procedure (iv), and two items of remedies (v to vi): (i) Whether a trade secret must be in continuous business use; (ii) Whether the owner must take reasonable efforts to protect the secret; (iii) Whether mere acquisition of the secret constitutes misappropriation; (iv) The limitation on the time for the owner to take legal action for misappropriation; (v) Whether an injunction is limited to eliminating the advantage from misappropriation; and (vi) The multiple of actual damages available in punitive damages. The index is the sum of the scores for each of the six items divided by six, so it is scaled between 0 and 1. For each item, a higher score represents stronger legal protection of trade secrets based on milestones including both common law (decisions in cases that set legal precedent) and the UTSA taking effect." (Png, 2017a). Png (2017b) extends this measure further until 2010.

The Control Variables: I use data from the BEA to construct state level employment, population and gross domestic product (GDP) measures to serve as controls. The population measures are from the Table SA30, the employment measures are from SA25, and the inflation-adjusted GDP measures from SAGDP2S. The BEA/BLS Account covers 1987-

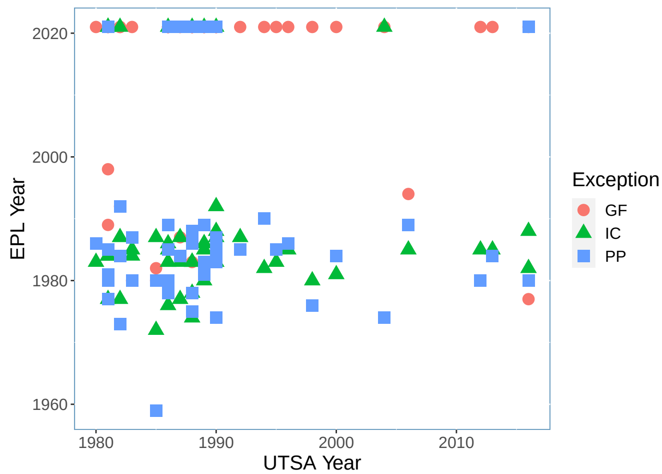

Figure 9: Employment Protection Laws and the UTSA The Figure has the adoption year for the Uniform Trade Secrets Act on the x-axis and for the exceptions to the at-will employment (Good Faith, Implied Contract, and Public Policy) on the y-axis. For the states that did not adopt the UTSA, the adoption year has been set to 2016 for the adoption of the DTSA. For the states that did not adopt the exceptions, the adoption year has been set to 2021.

2018 period while the BEA publishes another table for 1963-1997 period with the same industry definitions. I merge the two and compare the series in the period they coincide. The differences are very small compared to the trends I document. The decomposition results in Section3.1 are broadly similar when I only use 1963-1997 or the 1987-2018 periods. I use the state-level union membership density estimates from Hirsch et al. (2001) who uses the CPS Outgoing Rotation Group earning files. I use the data on the state-level Wrongful Discharge Laws (WDL) from Autor (2003) who provides public access to the data sample through his website. Figure 9 plots how the adoption dates of the WDL across states compare against the adoption of the UTSA.

I use the adoption data presented in Ribstein and Kobayashi (1996) and Autor (2003) which document the state-level adoption for 103 uniform laws and the exceptions to the at-will employment respectively to argue the UTSA adoption dates do not coincide with other laws. See also Figure 9.

Data Sources for the Cross-Sectional Analysis

The Census of Manufactures: The CMF collects information from the universe of manufacturing establishments as part of the Economic Census. The public data from CMF provides state and industry level data on revenues and detailed expenses, including expenses related to purchase of labor outsourcing services. I construct the labor outsourcing expenses by combining expenses on 'Temporary staff and leased employee expenses' (PCHTEMP), 'Data processing and other purchased computer services' (PCHADPR)[41], 'Purchased professional and technical services' (PCHPRTE), and 'Advertising and promotional services' (PCHADVT). I use the 'Annual Payroll' (PAYANN) as total expenses on employees on payroll, 'Total value of shipments' (RCPTOT) as total revenues, and 'Value Added' (VALADD) as value added. I use the 2007 CMF for the structural model estimation and the 2017 CMF for documenting cross-state heterogeneity in the use of labor outsourcing.

The public tables for 2007 Economic Census have state-industry level estimates for payroll, revenues, and value added but outsourcing expenses are only tabulated separately at the state and industry level. The identification only requires the state and industry level aggregates for identification. However, the two-stage estimation method I use requires state-industry level estimates for outsourcing, even though the extra information is not used to identify the parameters. I construct synthetic state-industry estimates that are consistent with the state and industry level estimates and use these in the first-stage estimation[42]

The Statistics of U.S. Businesses: The SUSB uses data from the universe of employer establishments and publishes statistics on establishment size distributions. I use it to construct and estimate the fraction of establishments with fewer than 20 employees and the average establishment size in each state-industry pair. To estimate the average establishment size, I compute a weighted average of average establishment sizes in each bin by weighting the bins by the listed number of establishments.

The Business Dynamics Statistics: The BDS is created from the Longitudinal Business Database and provides information on the universe of the U.S. establishments. Unfortunately, the state-level data the BDS provides is only available at the level of major industry sector. Hence, I use the BDS information to discipline state-level parameters only. In particular, I construct establishment-level job destruction and exit rates for the manufac-

[41]This expense does not include 'Expensed computer hardware and other equipment' and 'Expensed purchases of software', hence only documents the purchase of IT services. See Appendix B for how I define labor outsourcing.

[42]The 2017 tables do report estimates for outsourcing expenses at the state-industry level. I use the same synthetic construction for 2017 as if only the state and industry level estimates are observed. The correlation between the actual and the synthetic estimates is 0.6. Considering the frequent censoring applied at the state-industry level, the synthetic data should closely follow the actual data.

turing sector in each state. I also use the exit rate of establishments with more than 250 employees to discipline the exogenous exit rate parameter.

Data Conversions

The Elasticity of Substitution: I use the estimates from Chan (2017) as elasticity of substitution parameters (between permanent and outsourced workers) in the structural model. Chan (2017) groups 3-digit manufacturing industries in the second revision of The Statistical Classification of Economic Activities in the European Community (NACE) industry classification into four broad manufacturing industry groups: Food Products, Wood and Paper Products, Heavy Industry and Extraction, and Tools, Machinery and Consumer Goods. I match the NACE 2-digit sectors to 2007 NAICS 3-digit sectors using the official correspondence table from the Eurostat.[43] I leave NAICS industries out of my analysis if they do not strongly match to one of the 2-digit NACE industries. Table 8 lists both the NACE and NAICS industries included in this classification.

Food	Wood	Heavy	Machinery	Food	Wood	Heavy	Machinery	Left Out
10	2	6	25	311	321	324	332	313
11	16	9	26	312	322	325	333	314
12	17	19	27			326	334	315
		20	28			327	335	316
		21	29			331	336	323
		22	30				337	339
		23	31					
		24	32					

Table 8: Manufacturing Industry Groups (Chan, 2017) for 2-digit NACE and 3-digit NAICS Classifications

The TFP Process: I use the estimates from Bloom et al. (2018) to discipline the industry-level estimates of the variance of the productivity process. It is impossible to reach at the variance estimates at the group level without the micro-data, so I equate variance of the group equal to the weighted average of the variances. Since the average level of the TFP/demand shock is not identified in my model, I only need the relative variances of

[43] See https://ec.europa.eu/eurostat/ramon/miscellaneous/index.cfm?TargetUrl=DSP_NACE_2_US_NAICS_2007.

different industries. In addition, since I model the TFP/demand as a log-normal process, errors in the parametrization of the variance process are partially corrected through the estimation of the persistence parameters. Bloom et al. (2018) provides the estimates with the 4-digit 1987 SIC classification. Using the conversion table by Eckert et al. (2020), I first construct weights to compute variance estimates at the NAICS level and take a weighted average to get group level variance estimates.

Data Sources for the Cross-Country Analysis

The EU KLEMS Accounts: The EU KLEMS Growth and Productivity Accounts aims to provide data on industry level employment, output, and productivity estimates. The accounts include several updates that extend the coverage of countries, include more detailed industries, and make changes and corrections to the previous releases. I use the March 2008 release (Timmer et al. (2007)) which has a smaller coverage of countries relative to more recent releases, but goes back as early as 1970. In particular, I use the 'Number of Persons Engaged' (EMP) variable and use industry code 74 (Other business activities) as labor outsourcing. Although this industry code is not as precise as the definitions I have used with the Census and NAICS classifications, the implied labor outsourcing share is remarkable similar to the one I have derived for the U.S. through the 1990 Census classification.

The OECD Structural Analysis Database: The STAN collects and estimates data on industry level input and output from the countries' own national accounts, using a harmonized industry definition in the process. I use the industry codes M-N (Professional, scientific and technical activities; administrative and support service activities) as labor outsourcing, which roughly corresponds to NAICS 54 and 56 but also includes equipment rental and leasing activities.

The OECD Employment Protection Index: The OECD have information on several types of employment protection, "...compiled using the Secretariat's own reading of statutory laws, collective bargaining agreements and case law as well as contributions from officials from OECD member countries and advice from country experts." The index has four versions that improves the method and increases the scope of the previous one. I restrict attention to the first version because it provides the longest panel of data. I use the strictness of employment protection (individual and collective dismissals) as a measure of firing cost consistent with the cross-state analysis I do in the main text. The index ranges from 0 to 5 from the weakest to strongest protection and is available yearly from 1985 to 2019.

The OECD Trade Secret Protection Index: I use two cross-country measures of trade-secret protection. The first one is an index constructed by Lippoldt and Schultz (2014) for the OECD, which combines information on whether 26 criteria were satisfied in the trade secret law of 37 between 1985 and 2010. It ranges from 0 to 5 from the weakest to strongest protection. The index is only available for years ending in 0 and 5.

The Global IP Trade Secret Protection Index: The second index I use is constructed by the Global Innovation Policy Center of the U.S. Chamber of Commerce. It ranges from 0 to 3 from the weakest to strongest protection. Its country coverage is much larger than the OECD index with 50 countries but it only goes back as far as 2012.

C Cross-Country Evidence

In this section, I analyze the cross-country patterns of labor outsourcing and trade secret laws and discuss four more facts on (1) the growth of outsourcing, (2) the cross-country heterogeneity in outsourcing, (3) the cross-country heterogeneity in trade secret protection and (4) how these patterns relate to the trade secret laws. I restrict attention to the analysis of the supply of labor outsourcing through employment data, because there is no available data for the demand side that allows cross-country comparisons. Hence, the scope of my analysis is determined by the availability of industry level employment data that allows cross-country comparisons.

Fact 3: The employment share of the labor outsourcing sector has grown globally since the 1970s.

The large growth in the employment share of the labor outsourcing sector was not specific to the U.S. I use the EU KLEMS Accounts (2008 Rev.) to construct measures of employment in labor outsourcing sectors for 14 countries in 1970 and 2005. Figure 10 presents how the employment share of the labor outsourcing sector has changed from 1970 to 2005. The sector has grown dramatically across all the countries in my sample and the growth

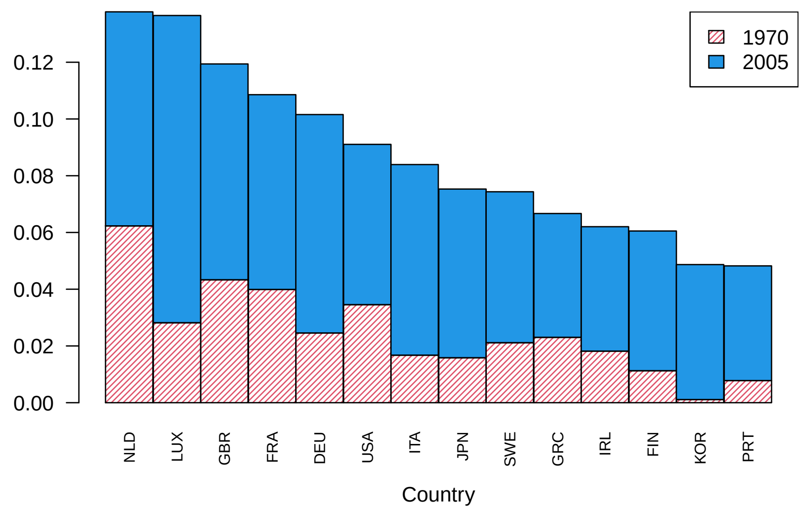

Figure 10: The Employment Share of the Labor Outsourcing Sector in 1970 and 2005 The total height of the bar denotes the size of the employment share of the labor outsourcing sector in 2005 while the shaded height denotes the share in 1970. The employment data is from the 2008 Revision of the EU KLEMS Accounts. I define the labor outsourcing sector as the industry code 74 (Other business activities). See Appendix B for details.

in the U.S. is not an anomaly.

Fact 4: There is a large cross-country heterogeneity in the intensity of labor outsourcing.

The employment share of the labor outsourcing sector differs significantly across countries, similar to the heterogeneity present across the states of the U.S. I use the Organisation for Economic Co-operation and Development (OECD) STAN Accounts to construct measures of employment in labor outsourcing sectors for 34 countries in 2017. Figure 11 presents how the employment share of the labor outsourcing sector differs across countries. The employment share for the country in the 90th percentile (France, 15%) is twice of the country in the 10th percentile (Croatia, 7%) .

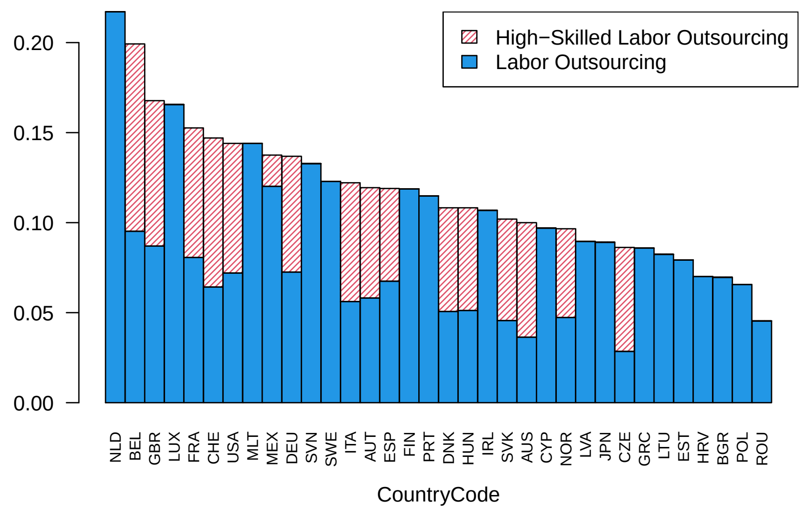

Figure 11: The Employment Share of the Labor Outsourcing Sector in 2017 The total height of the bar denotes the size of the employment share of the labor outsourcing sector. I depict the share of the high-skill labor outsourcing sector with the shaded height of the bar for countries where the data is separately available. The employment data is from the 2017 OECD STAN Accounts. I define the labor outsourcing sector as the industry codes M-N (Professional, scientific and technical activities; administrative and support service activities). See Appendix B for details.

Fact 5: There is large variation in trade secret protection globally.

There have been many developments in the protection of trade secrets globally since 1970. The World Trade Organisation proposed the TRIPS Agreement (Agreement on Trade-Related Aspects of Intellectual Property Rights) in 1994. The Article 39 of the TRIPS Agreement is specifically dedicated to trade secrets and describes broadly what is protected under the definition. The member countries promise to enforce the protection of trade secrets, yet there is substantial heterogeneity in both the form and the enforcement of the laws across countries.

China has been at the center of trade secret violation discussions for some time (Bradsher (2020)). China provides protection for trade secrets under the Anti-Unfair Competition Law (AUCL) which was enacted as early as 1993, and amended in 2017 and 2019. Yet, foreign firms operating in China frequently complain about the lack of enforcement. The U.S. International Trade Commission conducted a survey of firms (USITC et al. (2011)) that are in IP-intensive sectors and are "particularly susceptible to IPR (intellectual property rights) violations in China." According to their report, "Firms that provided quantitative responses estimated that improved IPR protection and enforcement in China could result in as much as a 10–20 percent increase in sales, royalties, and license fees earned in China, and a 2–5 percent increase in employment in their U.S. operations. These employment gains could translate into approximately 922,588 new U.S. jobs among IP-intensive firms." More importantly, even though firms were suffering from trade secret theft, "Only 0.6 percent of those firms that reported material losses due to trade secret misappropriation during 2007–09 stated that they had pursued any trade secret misappropriation proceedings in China."

Sherwood (1990) reports the results of a survey on 1800 Brazilian firms in 1989. In the survey, although half of the firms have had 'trade secret losses', in 86% of those cases, there was no attempt for a legal procedure. The firms reported as the main reasons they did not take legal action were "...lack of sufficient proof, a gap in the law on which to base a legal action, or the expectation that litigation would be too expensive or that enforcement would be poor even if the case were won.".

The European Union has enacted the Directive on the Protection of Trade Secrets (EUTSD) in 2016 after a lengthy process of drafting and consultations "to harmonise the existing diverging national laws [within the EU] on the protection against the misappropriation of trade secrets, so that companies can exploit and share their trade secrets with privileged business partners across the Internal Market, turning their innovative ideas into growth and jobs". Before 2016, even the provision that guided the trade secret protection changed across countries. A large majority used their criminal code or an unfair competition law and the only country that had a specific trade secret law was Sweden. Furthermore, the countries differed in which types of damages were granted and on what conditions injunctive reliefs were issued.[44] According to an industry survey on 537 firms in 13 countries ran by Baker and Mckenzie for the EU,"40% of EU companies would refrain from sharing trade secrets with other parties because of fear of losing the confidentiality of the information through misuse or release without their authorisation" and among 110 firms who had at least one case of misappropriation "only 57 (40.7% of responses) sought remedies in EU courts".

[44]See Figure 4, Table A9, and Table A2.2 in https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=SWD:2013:0471:FIN:EN:PDF

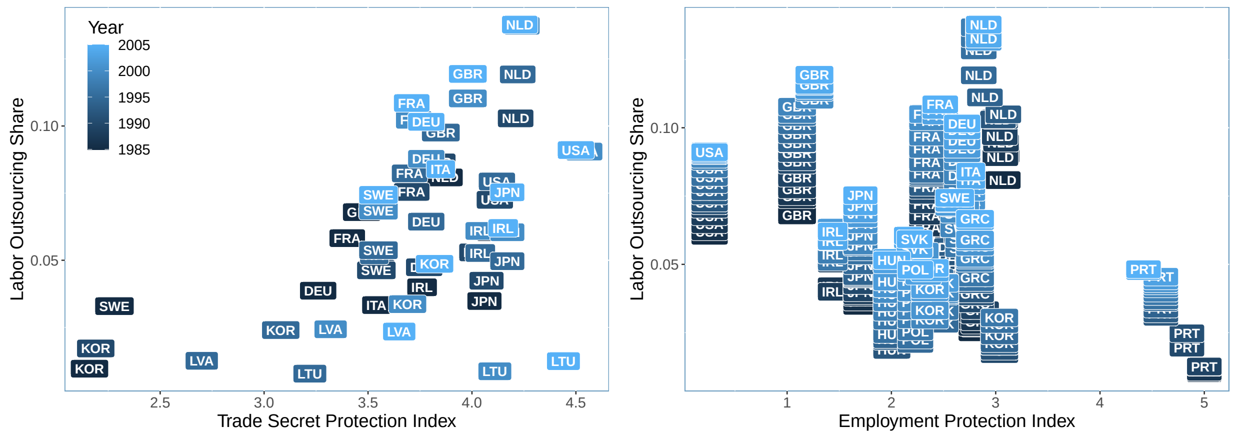

Figure 12: The Employment Share of the Labor Outsourcing Sector The x-axis is the OECD Trade Secret Protection Index in the left panel and the OECD Employment Protection Index in the right-panel. Each box refers to one country-year observation where the boxes with darker colors refer to earlier years. The employment data is from the 2008 Revision of the EU KLEMS Accounts. I define the labor outsourcing sector as the industry code 74 (Other business activities). Both indices range from 0 to 5 with 5 being the strongest protection. See Appendix B for details.

Fact 6: The strength of trade secret protection and the size of the labor outsourcing sector are positively correlated across countries.

In this section, I ask whether there is any evidence of a link between the protection of trade secrets and labor outsourcing decisions across countries. Since there are large unobserved differences across countries beyond the intellectual property law, I treat the evidence here more descriptive rather than causal. I use a panel data on the employment shares of labor outsourcing sector through 2008 EU KLEMS and the trade secret protection index constructed by Lippoldt and Schultz (2014). The final sample has quintennial observations for 12 countries between 1985 and 2005. The left panel of Figure 12 presents the patterns of trade secret protection and the extent of labor outsourcing. There is overall a positive correlation, with countries improving in both dimensions (e.g. Korea) and others that do not really increase the extent of outsourcing even though the law has improved (e.g. Lithuania). I do a similar analysis using the OECD employment protection index as shown in the right panel of Figure 12, and no real pattern emerges having in mind the little time-series variation present in employment protection laws.

Table 9: Cross-Country Panel Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
TSP	0.52**	0.68***	0.22***	0.24**	0.16***	0.18***
	(0.21)	(0.10)	(0.08)	(0.09)	(0.06)	(0.06)
log(ManufShare)				0.38		0.35
				(0.34)		(0.34)
EPL					−0.22	−0.21
					(0.13)	(0.13)
Country and Year Fixed Effects	Year	Country	Both	Both	Both	Both
Range	1985-2005	1985-2005	1985-2005	1985-2005	1985-2005	1985-2005
Nobs	49	49	49	49	49	49

Notes: The dependent variable is the log outsourcing sector share of employment. TSP refers to the OECD Trade Secret Protection index and the EPL refers to the OECD Strictness of Employment Protection index. Standard errors are clustered at the state level. The employment shares of the outsourcing sector and the manufacturing sector are computed from the 2008 EU KLEMS Accounts. See Appendix B for details on sample construction and included industries.

To dig deeper, I run simple panel regression, controlling for country and year fixed effects. The country fixed effects allow controlling for important country-specific variables that are important for outsourcing but does not change much over time, such as the degree of corruption and trust. The time fixed effects allow controlling for global trends in outsourcing, for example due to increasing use of information technology. I also use the share of manufacturing employment in each country to control for country-specific structural change. Table 9 presents the results of the panel regressions. The trade secret protection index has a statistically significant correlation with the outsourcing shares, after controlling for country and year specific variables.

Even though the trade secret protection and the extent of outsourcing tend to evolve together across countries, my analysis here does not rely on an exogenous variation in trade secret laws. Hence, it is important not to derive causal implications from this analysis.

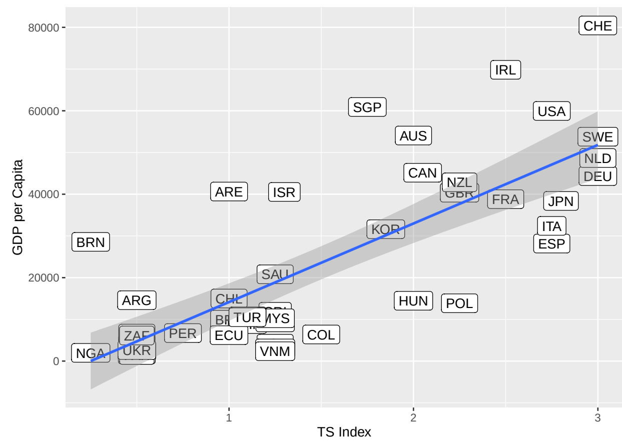

Figure 13: Trade Secret Protection and GDP per capita The x-axis is the Global IP Trade Secret Protection Index and y-axis is the GDP per capita. Each box refers to one country observation. The GDP per capita data is from the 2008 Revision of the EU KLEMS Accounts. Global IP Trade Secret Protection Index ranges from 0 to 3 with 3 being the strongest protection. The line is the ordinary least squares estimate together with a 95% confidence interval. See Appendix B for details.

D Estimation Details

The estimation of the structural model requires solving for the distribution of firms across the number of permanent workers and idiosyncratic shocks. Since I do the estimation for multiple industries and multiple states of the U.S., even solving for the equilibrium can quickly become infeasible. I do several tricks to decrease the computational burden. I describe these tricks in three levels: the design of the model environment, the assumptions that allow approximating the equilibrium, and the estimation algorithm.

The Design of the Model Environment

I design the model environment in a way that allows estimating each state separately. This requires each state to have separate product and labor markets. Since neither the aggregate size of the workforce nor aggregate output is identified for states in the model, these restrictions do not play a role in the estimation. In other words, one can do the estimation ignoring cross-state interactions, then appropriately weight the states according to their size to compute nation-level aggregates. However, these restrictions do play a role in the counterfactual exercises. In particular, I assume the policies do not change the extent of cross-border activities: when one state improves its trade secret law, increased productivity does not attract workers or businesses from other states. Although this assumption is restrictive, it is necessary to keep the problem feasible. Another alternative would be to allow cross-state interactions, but decrease the cross-industry and cross-state heterogeneity across firms substantially. I anticipate the bias in policy evaluations that would arise from assigning the heterogeneity from other factors to trade secret protection would be larger than the bias from ignoring cross-state interactions. I leave the formal assessment for future projects.

Approximating Assumptions

The main identification assumption, i.e. the benefits to outsourcing varies across industries but not over time, implies a parameter that is constant across states. This parameter does not preclude separately computing the equilibria for each state, but requires the estimation to be done simultaneously for all states. Estimating all states simultaneously would necessitate the estimation of 1050 parameters altogether, which is computationally infeasible. To avoid this issue, I do the estimation under Assumption 3, where the parameters for the trade secret protection (π_j) and the outsourcing efficiency δ reduce to a factor share in a CES production function. Then, I treat the estimated factor shares ($\hat{\alpha}_{jk}$) as the sum of the model implied factor shares ($\alpha(\pi_j, \delta_k)$) and a symmetric zero-mean error term. This allows separately estimating each state, collecting the factor shares, and estimating the trade secret protection parameters (π_j) in the second stage.

At the estimated parameters, the assumption does not impact the vast majority of firms and does not have a large impact on the model implications.[45] I do not impose Assumption 3 when I compute the counterfactuals, i.e., firms are not forced to use more outsourced workers when the trade secret protection improves.

Estimation Algorithm

Computing the stationary equilibrium requires two computationally intensive steps: (1) computing the value function of firms for each industry, and (2) computing the equilibrium rate of entry in each industry that ensures market clearing under the implied steady

[45] This does not preclude the possibility that it significantly impacts the estimated parameters, i.e., imposing the assumption at the 'correct' parameters would impact a significant portion of the firms. A complete verification requires simulating data from the model under different parameter sets and assessing the ability of the model to estimate those parameters accurately when the assumption is imposed.

state distribution of firms. I use Value Function Iteration (VFI) for the first step and a forward iteration with an exact transition function for the second step. It is possible to compute the equilibrium under a second with 200 grids points for permanent workers and 10 grid points for the idiosyncratic shock process with the classical algorithm by Hopenhayn and Rogerson (1993).[46] My model has two added levels of complexity on top of the classical version. First, due to the non-convex adjustment cost for permanent workers together with the task-based production function, the choice of outsourced workers requires the use of a non-linear solver for each choice of the number of permanent workers. Second, my model requires computing K (number of industries) prices, stationary distributions, and entry rates and the computation time does not scale linearly in K. I estimate the model efficiently without adding an extra layer of approximation. The classical algorithm (for one industry) prescribes

1. Use the free entry condition to determine the price of output
2. Find the mass of entrants that clears the labor market in the stationary distribution

When there are K industries that source from the same labor market, I need additional conditions to pin down the relative sizes of each industry. The final good industry provides K intermediate good demand conditions on top of the labor market clearing condition that help pin down the final good price and the K entry masses for each industry. Normally, for each guess of the parameters, solving the equilibrium requires simultaneously finding K prices that satisfy K free entry conditions, where each guess for the price requires running the VFI again to find the implied value of entry. I use two tricks to ensure that I only need to run the VFI once for each industry for each guess of the parameters.

First, instead of finding the equilibrium intermediate good price for a given entry cost parameter, I treat the price as the parameter and the entry cost as the equilibrium object in the estimation. Hence, I only need to evaluate the VFI once for the given price, and the associated value of entry gives the 'equilibrium' entry cost. This uses the fact that the demand shares for the intermediate goods, intermediate good prices, and the level of productivity/demand shocks across industries are not separately identified. Hence, I can assume any K product prices, compute the associated entry cost, and set the demand shares to equate the relative size of each industry to data.

[46] I utilize the monotonicity and the concavity of the policy function in the stock of permanent workers, and the Howard's improvement algorithm. All three generate significant gains in computation speed.

Second, although I model the entry cost and the fixed cost in the units of the final good, I measure them in units of the market wage which I normalize to unity. Hence, each firm's value function only requires knowing the intermediate good price of its own industry and not the prices of the other intermediate goods. This allows computing the intermediate good prices separately. This trick uses the fact that the full equilibrium does not need to be computed for the estimation. When I compute the counterfactuals, I revert to measuring these costs in units of the final good price, hence computing the full equilibrium.

To sum up, for each set of (remaining) parameters, I use $K-1$ relative industry sizes from the data, $K-1$ conditions that ensure that the industry sizes are consistent with the equilibrium, K free entry conditions, one labor market condition and one aggregate entry rate to pin down K entry costs, K masses for entrants, K intermediate good price.[47] The gains in speed come from using the parameters to ensure equilibrium conditions while using the equilibrium objects to match moments. So my algorithm is to do the following steps for each set of 'parameters', where the parameters have the equilibrium price level but do not have the entry costs.

1. Use the revenue shares of industries from the data to pin down the price ratios[48], hence p_k (since the price level is a parameter)
2. Use the free entry condition to pin down the associated entry costs c_k^E
3. Choose the mass of entrants for each industry m_k to ensure the equilibrium distribution of firms in each industry is consistent with the revenue shares of industries from the data and the labor market clearing conditions

These tricks significantly speed up the computation of the equilibrium moments for each set of parameters without relying on any approximation. However, they also distort how the moments respond to changes in parameters. In particular, it reduces the efficiency of gradient based solvers, because once the parameters change, the normalization also changes. Since my model already has non-convexities due to adjustment costs and exit decisions, I prefer the gains in the speed of evaluating moments over the lost gains in efficiently searching the parameter space.

[47]The use of the entry rate to pin down the price level happens over the whole estimation, rather than for each set of parameters.

[48]This step practically puts infinite weight on the revenue share moments, forcing the estimation to match revenue shares exactly. I can always run my estimation algorithm to get a very good starting point, and let the usual procedure run without imposing this condition before finalizing the estimation.

E Trade Secret Protection

In this section, I analyze some of the legal concepts and issues that relate to trade secret protection in more detail. Section E.1 discusses the problems with trade secret protection under common law, Section E.2 discusses why non-disclosure agreements are not sufficient to ensure trade secret protection, and Section E.3 discusses how the courts determine which state's law should govern a trade secret dispute.

E.1 Trade Secret Protection under Common Law

Before 1979, protection of trade secrets was established exclusively through common law. In addition, trade secret protection varied substantially across U.S. states. This created further uncertainty: to understand the legal practice, one had to analyze a separate set of cases for each state.

This problem was further amplified when the Supreme Court has ruled that state courts cannot use decisions made by federal courts as common law in Erie Railroad Co. v. Tompkins 304 U.S. 64 (1938). This landmark decision led to each state relying on the decisions made by their own courts, removing the only unifying body from the picture. Edward S. Rogers, who was chairman of the board of executives of Sterling Drug Co. and a member of Lawyers' Advisory Committee of U.S. Trademark Association would later say "Soon there was built up by decisions of the Federal Court a great body of Federal Law dealing with trademarks and unfair competition. It was a great convenience to the bar because lawyers knew or could easily learn what the decisions were and there were enough of them to give a comprehensive picture. Then came Erie ... which required Federal Courts to apply the law of the State in which they sit, and there was chaos. There were 48 different sovereignties, the decisions of whose courts were the only law. The body of Federal decision which was 50 years evolving was not binding either on the State or the Federal Courts. Nobody knew what the law was. It was frequently found that there were no applicable State decisions or that the decisions in the States comprising the same circuit were not uniform." (Rogers, 1964). Justice Joseph Story explained what creates this uncertainty as early as 1837: "One great advantage, therefore, of a code, an advantage which in a practical view can scarcely be over-estimated, is that it supersedes the necessity, in ordinary cases at least, of very elaborate researches into other books; and indeed, it often supersedes in all cases, but those of rare and extraordinary occurrence, the necessity of consulting an immense mass of learned collections and digests of 243 antecedent decisions." (Sandeen, 2010)

To resolve these issues, the American Law Institute has published several 'Restatements of Torts' before 1979, which summarized the theme of the previous decisions. However, the statements had no legal binding and were necessarily vague where uncertainty was the highest.

E.2 Non-Disclosure Agreements

A natural solution to prevent trade secrets from reaching the competitors would be to sign a non-disclosure agreements (NDA)[49], which are common practice today in outsourcing. However, the majority of cases do not involve a spy with malicious intent who steals obvious secrets hoping not to get caught. Instead, the issue either arises from a disagreement between the parties on what is secret and what would constitute a misappropriation, or an otherwise legitimate actor who sees a loophole in the agreement and tries to make quick profits.[50] In these scenarios, the NDA is far from being sufficient to ensure protection. First, to be enforceable, an NDA should explicitly designate what pieces of information are secret, which is very hard in practice (Elzankaly (2018)). The agreements that try to make an exhaustive list tend to fail, hence, the majority define secrets as broad and vague as possible to leave room for potential litigation. Pooley (1989) prescribes "Overnarrow definitions of your trade secrets may restrict available protection." and

> As a practical matter, many experienced consultants will require you to define and describe your trade secrets in some detail. After all, consultants make their living by hopping from one firm to another in the same industry. They may justifiably insist on a strict limitation of their obligations not to use what you consider to be your trade secrets.
>
> A word to consultants: do not sign a general nondisclosure clause if you can

[49]See Footnote 47 in Martinis et al. (2013) for example of a standard NDA.

[50]According to the analysis of trade secret cases in federal courts in 2008 by Almeling et al. (2010), of cases where plaintiff eventually lost, 61% were because the plaintiff could not validate the information was a trade secret, 30% were because plaintiff could not prove information was misappropriated and 30% were because plaintiff could not prove it took reasonable measures to protect the secret. The percentages do not necessarily add up to 100% due to multiple issue being present in some cases.

avoid it. Remember more than one person can possess the same trade secret, discovered independently. If you have to sign, insist on a precise definition and clarify your other consulting relationships.

Second, an NDA is only enforceable on information that is not readily available elsewhere. For example, if the secret is previously presented in a public fair, or if it is not clear what portion of the secret is already known in the industry, the NDA may not be enforced. Third, enforcement of the NDA requires taking proper precautions to protect the information, where the definition of proper is purposefully vague. While verbally discussing a document which is explicitly classified to be secret, additional information the firm gives may not be protected (Pooley (2020)). Fourth, the NDA can assign damages to violations, but cannot prevent further use or the disclosure of the secret once it is revealed. Fifth, although the NDA may designate a monetary transfer in case of a violation, it is rarely enforced and the court tends to update the number according to its own estimate of the actual damages. Last, but not least, small and inexperienced companies may not be able to draft a functional NDA. The trade secret law still provides protection if there is an implied confidentiality in the agreement when the NDA is missing or invalid (Smith v. Dravo Corp., 203 F.2d 369 (7th Cir. 1953)). Since the NDA fail to ensure a common understanding in most cases, the details of the trade secret law becomes important in how well the secrets are protected.

E.3 Governing Law in Trade Secret Disputes

If the governing law is important for trade secret disputes, can the sides benefit from the non-uniformity of laws across the U.S. by designating their favorite choice-of-law? The answer is largely no.

In transactions where both sides operate in the same state, the laws of that state govern the trade secret disputes.[51] In multi-state transactions, the U.S. law permits the sides to put a choice-of-law clause in their contract, designating which state-law should govern the disputes over it. There is no definitive rule that determines the enforceability of these clauses, but two legal principles favor the state the client is based.

First, either the disputed action or one of the sides should have an organic connection

[51] The discussion in this section is largely based on Covey and Morris (1983).

to the state that will handle the case. Designating a 'choice of law' in a contract (e.g. a non-disclosure agreement) is neither necessary nor sufficient to ensure the designated state court will handle the dispute. Either side can file a lawsuit in a state court that is different from the one designated on the contract and the state court designated on the contract can reject handling the dispute if it feels there is no organic connection between the state and the dispute. The organic connection requirement also prevents the sides to use simple loopholes in the legal system: a firm that operates in Florida cannot request the laws of Delaware to be applied in disputes just because it is officially established there. On the contrary, the courts tend to reject attempts to pick a 'favorite state law' in disputes. Schaller (2009) summarizes the procedure for trade secret disputes:

> The choice of law can be complex in trade secret cases. There is no federal choice-of-law code that dictates the application of governing law in state law diversity cases. Instead, in diversity jurisdiction cases, absent an enforceable contractual choice of law clause, a district court must apply the choice of law rules of the state in which it sits... For trade secret purposes, the applicable law might be that of the place where the secrets were stolen, the place where the secrets were disclosed or used, the place where the economic effects of misappropriation were felt, or possibly the place where products incorporating the secrets were ultimately sold. The test employed usually focuses upon which jurisdiction has the greatest "interest" or "governmental interest" in the litigation, upon which jurisdiction has the most significant relationship to the dispute, or some combination of these rules. Other jurisdictions follow the lex loci delecti rule, meaning they apply the law of the place where the misappropriation actually took place. At times, however, courts seem to follow no specific standard at all...This costly, confusing and uncertain inquiry can be bypassed in some jurisdictions if an enforceable choice-of-law clause exists in a nondisclosure or similar contract between the parties. The chosen law will be honored if the contract bears some reasonable relationship to the designated jurisdiction and does not offend any public policy of the state in which the court is sitting. Thus, designating the law of plaintiff's state of incorporation will not carry the day if plaintiff and defendant have their relationship centered elsewhere...See e.g. Curtis 1000, Inc. v Suess, 24 F.3d 941, 943-44 (7th Cir. 1994) (holding that the designated law of Delaware lacked sufficient connection to trade secret and non-compete dispute between plaintiff headquartered in Georgia and defendant working in Illinois.

Second, when the outsourcing firm signs multiple contracts with multiple clients with the same choice of law clause, the courts may interpret these non-disclosure agreements as one of adhesion. In other words, the choice-of-law clause could be perceived as one dictated by the outsourcing firm to the client, resulting from inequality of bargaining power. In the case where the choice of law favors the outsourcing firm over the client, the court may not enforce the choice-of-law clause.

There is another fundamental force that steers the choice of law towards the client's state: if a dispute ends up in a court, the client will have to be physically present in the courtroom. Hence, the clients have an intrinsic motive to designate the home state as the governing law.

This is also supported in Almeling et al. (2010) and Almeling et al. (2011) for trade secret disputes. Although their data do not include the location of the sides or the dispute, they find the applied law differed substantially in cases, indicating that there was no convergence to the law of a particular state.

F Generalized Differences-in-Differences Methods

In a setting with two time periods and two groups (treatment and control), the differences-in-differences (DiD) estimator gives a consistent estimate of the average treatment effect for the treated (att) under the parallel trends assumption. Furthermore, one can test the parallel trends assumption using pre-treatment trends under additional assumptions.

The staggered adoption setting allows aggregating the information from DiD comparisons across multiple pairs of units over many periods. One simple counterpart of the DiD estimator with multiple periods and staggered adoption is the Two-Way Fixed Effects (TWFE) estimator and it is widely used in empirical studies. This estimator corresponds to a regression with both time and unit fixed effects where the main regressor is a dummy D_{it} that equals 1 if unit i is under the effect of the treatment at time t. The TWFE does not adopt the nice properties of the DiD estimator due to two reasons. First, Goodman-Bacon (2018) and de Chaisemartin and D'Haultfœuille (2020) have recently shown TWFE estimate does not have a clear economic interpretation when the treatment effect is heterogeneous across units. The estimate can even be outside the convex hull of the pairwise DiD estimates of individual adoptions. Second, Abraham and Sun (2018) pointed out that the TWFE estimator estimates the treatment effect by comparing units whose treatment has changed to those whose treatment remained constant. Thus, the control group includes units who have recently received treatment. In the presence of dynamic treatment effects, this introduces a bias in the estimates as well as tainting the tests for pre-treatment trends.[52]

My setting is likely subject to both dimensions of heterogeneity. First, the effect of the UTSA can be smaller or larger for the states who adopted it later. It can be smaller if there are treatment spillovers to the control states, e.g. through the inter-state provision of these services. It can also be larger if the UTSA becomes more effective as states that already adopted it accumulate decisions based on it to be used as a reference for future decisions. Second, the adoption potentially has dynamic effects, i.e., its effect on outsourcing may depend on how much time has passed since adoption. It is reasonable to think the effect may take a few years to fully realize since (1) it takes time for the clients to understand the law changes and demand more outsourcing and (2) it takes time for the outsourcing sector to grow to meet the growing demand.

G Outsourcing and Trade Secrets

In this section, I provide some direct evidence on how the concerns over protecting trade secrets indeed impact the outsourcing decisions of the firms. First, I discuss the government regulations that limit the form and extent of outsourcing due to concerns over loss of trade secrets.[53] Second, I provide anecdotes from experts and practitioners that emphasize the importance of trade secrets in outsourcing relationships.

[52] See Roth (2018) for further issues with statistical tests for pre-trends, even in the classical DiD settings.

[53] I do not model regulation explicitly, but the information sharing constraint can easily be interpreted as such.

G.1 Government Regulations

Financial Institutions

The Federal Financial Institutions Examination Council[54] publishes the Outsourcing Technology Services Booklet that regulates whether and how financial institutions can outsource a variety of IT functions "... to help ensure financial institutions operate in a safe and sound manner.".

Health Providers

Health Insurance Portability and Accountability Act (HIPAA) regulates the use of outsourcing by health institutions through the Omnibus Rule which requires the 'business associates' of health providers to also comply with the HIPAA Rules (Breach Notification Rule, HIPAA Security Rule, HIPAA Privacy Rule, etc.) and holds the health provider responsible for any loss of private information that happens through the business associate.

Governmental Agencies

The Privacy Act of 1974 regulates the extent to which governmental agencies can share information that pertains to an individual: "No agency shall disclose any record which is contained in a system of records by any means of communication to any person, or to another agency, except pursuant to a written request by, or with the prior written consent of, the individual to whom the record pertains [subject to 12 exceptions]" 5U.S.C. § 552a(b). The first of these 12 exceptions, namely "need to know within agency", makes it easier to communicate this information within the agency relative to third-party agencies such as outsourcing firms.[55] There are also supplemental clauses through other regulations, such as the Protection of Privacy and Freedom of Information chapter of Federal Acquisition Regulation. Specific governmental agencies also have additional regulations

[54] The FFIEC consists of five banking regulators—the Federal Reserve Board of Governors (FRB), the Federal Deposit Insurance Corporation (FDIC), the National Credit Union Administration (NCUA), the Office of the Comptroller of the Currency (OCC), and the Consumer Financial Protection Bureau (CFPB).

[55] In certain instances, the courts allow treating the employees of contractors as the employees of the agency, e.g. Mount v. USPS, 79 F.3d 531, 532-34 (6th Cir. 1996), in some others they do not, e.g. Minshew v. Donley, 911 F. Supp. 2d 1043, 1072 (D. Nev. 2012).

restricting the use of contractors. For example, Department of Defense Privacy Program of 2007, C1.3.1.4. requires that for any contracted job, an internal system of contractor performance review to be established and special training to be given on the privacy programs.

G.2 Self-regulation

I restrict attention to either self-reports of firms and managers, first-hand documentation of these practices by observers, or recommendations from experts. Some of the evidence here explicitly mention outsourcing decision, while some imply it through emphasizing the importance of the length of a relationship to build trust.

"Because consultants have many of the privileges of a regular employee, though for a shorter period of time, they must be subject to nondiclosure obligations as well. Indeed, it is essential to secure such agreements from consultants: the nature of their work suggests they will work later for a competitor, or may compete with you directly. In fact, the consultant may be serving other masters at the same time as working for you. The consultant presents all the problems of the 'peripatetic employee' magnified several times. Therefore, you must be extremely cautious and clear in establishing and managing your relationship. " Pooley (1989)

"Limit the consultant's access to that portion of your facilities, records, and staff that is necessary to complete the work. Closely supervise what is done. At termination of the relationship, get additional reassurances of what the consultant will do to protect the integrity of your data, including the results of this project." Pooley (1989)

"Outsourcing the IT function is likely to involve the supplier processing the organisation's data in some form. The organisation remains responsible for compliant handling of its data even if this is under the control of a supplier. Risks may arise over the confidentiality of the organisation's data and intellectual property. For instance, there may be misuse of confidential data relating to the organisation, its employees and customers; and inadequate security measures implemented by the supplier." Kendrick (2009)

"To protect against dependency and spillover risks, a company can rely on detailed legal contracts with vendors. But such documents are time-consuming and expensive to negotiate, and enforcement is uncertain and costly, thus discouraging outsourcing."

Adler (2003)

"Referred to by Adler (2003) as spillover risk , outsourcing firms are exposed to the possibility that confidential or critical information might leak to competitors or be used by the outsourcing firm to eventually take over the client firm's business." Schniederjans et al. (2015)

"Much essential company information, including strategic plans, is stored in computers. Under no circumstances should such information fall into the hands of competitors. The security risks involved in outsourcing are therefore frequently cited as a reason for not contracting out one's information services delivery; these companies prefer to keep their internal IT departments (Willcocks and Fitzgerald 1994; Klepper and Jones 1998; Miller and Anderson, 2004). The IT procurement manager of Case III explains:

Our primary processes of producing coatings, fibres, chemicals and pharmaceuticals are supported by IT, which consequently has very much added value. Contracting out activities so close to our primary processes is not desirable. The risk of production secrets falling into the hands of our competitor by way of external suppliers is far too great." Beulen and Ribbers (2010)

"It is not unusual, however, for confidentiality orders to require that all experts or consultants, whether testifying or not, be disclosed before they receive access to confidential documents produced by the other side. Such provisions reflect legitimate concerns that the disclosure of trade secret information to a consultant who has other clients in the industry or who may participate in the industry in other capacities, creates the risk of competitive injury." Quinto and Singer (2012)

"The principal issue at the start of the Du Pont-Masland litigation was whether Masland was using Du Pont's trade secrets in manufacturing artificial leather, or whether he was using methods that were common knowledge among chemists in that line of business. The district court initially denied a preliminary injunction because Masland insisted that he was not using Du Pont trade secrets. During the litigation, Masland proposed to get expert testimony to establish that the processes that Du Pont claimed as trade secrets were in fact common knowledge among chemists. Fearing that litigation would reveal their secrets to their competitors, Du Pont wanted to prevent Masland from drawing his experts from the ranks of their competitors, preferring that he serve as his own expert or that he use experts drawn from the Government or academia." Fisk (2000)

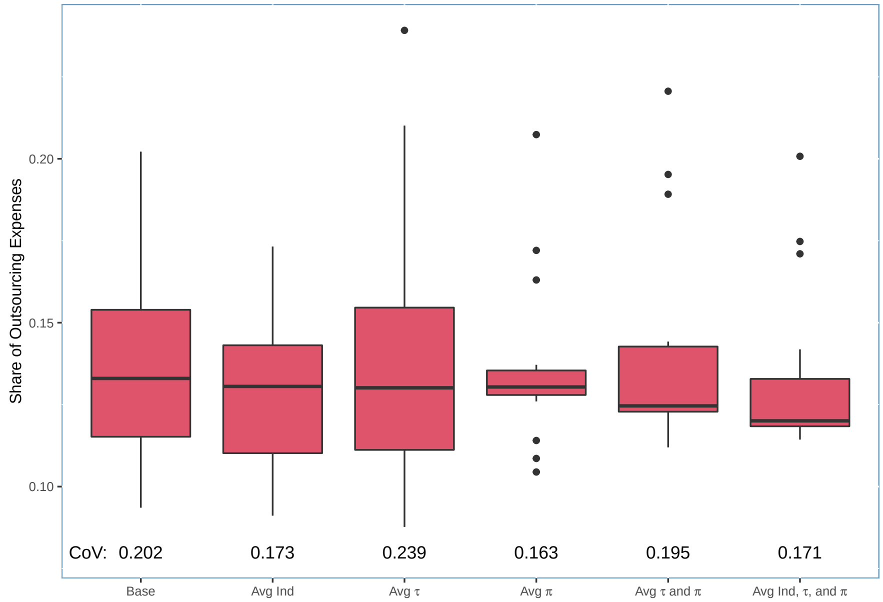

Figure 14: The distribution and the coefficient of variation for outsourcing to payroll ratios under baseline and the counterfactual scenarios Notes: Base refers to the baseline, Avg Ind refers to the counterfactual with the average composition of industries, Avg τ (π) refers to counterfactual with the average level of τ (π). The last two refers to counterfactuals where multiple objects are equal to their average values across states. See Table 13 for state-by-state details.

H Additional Figures and Tables

Industry Group	σ_k	γ_k
Food	0.555	0.417
Wood	0.407	0.653
Heavy	0.516	0.568
Light	0.427	0.62

Table 10: Externally Calibrated Industry-level Parameters Notes: The σ_k values are computed from Bloom et al. (2018) by taking weighted averages of 'Uncert_tfp' estimates for 4-digit SIC sectors. The γ_k values are from Table 9 in Chan (2017).

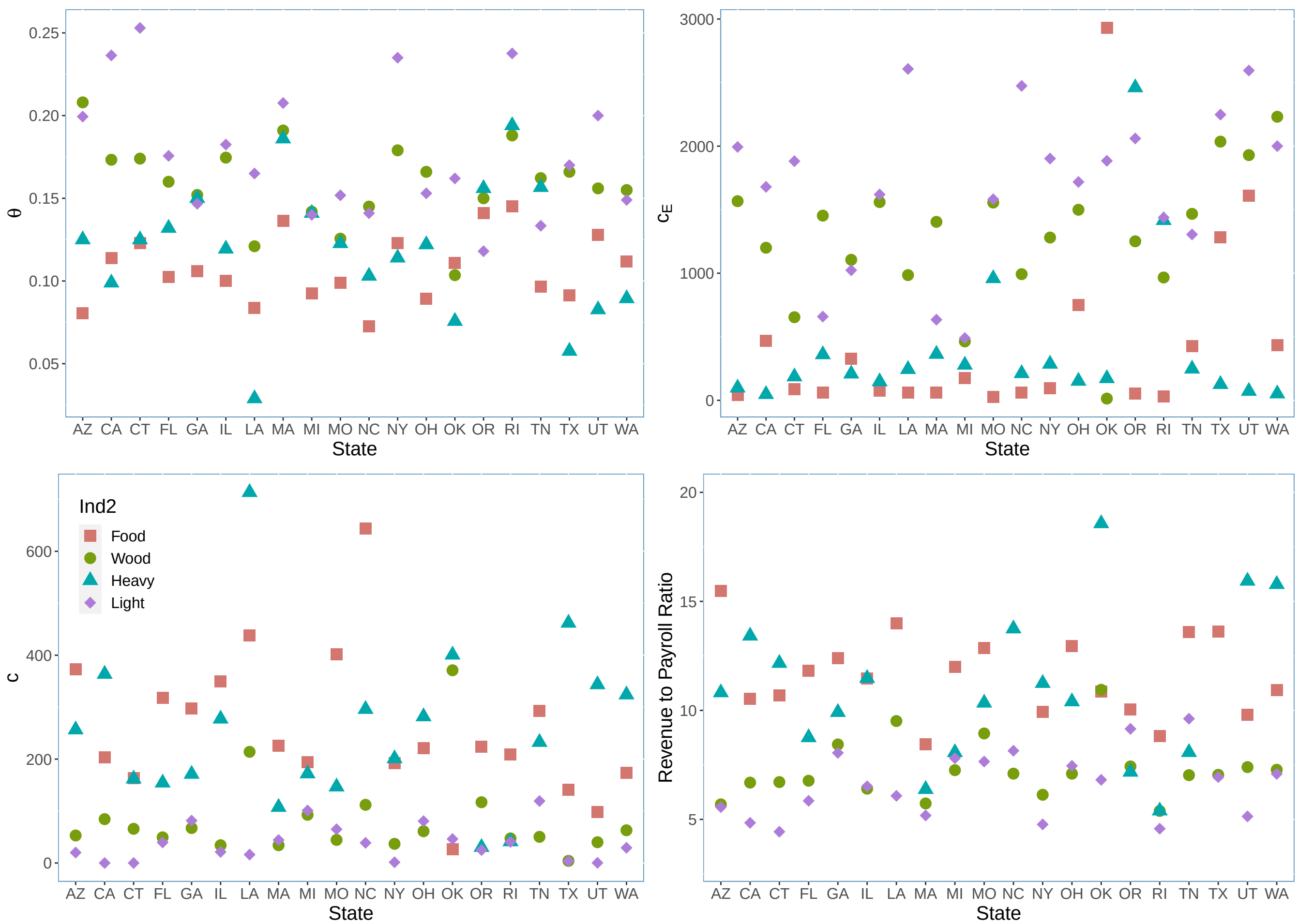

Figure 15: First Stage Estimates and Revenue Payroll Ratios Notes: The first three panels plot the first stage estimation results for returns to scale parameters $(\theta_j k)$, entry costs c^E_{jk}, and fixed operating costs c_{jk} respectively. The bottom right panel has the revenue payroll ratios from the CMF for each state-industry pair. See Appendix B for details on the data sources.

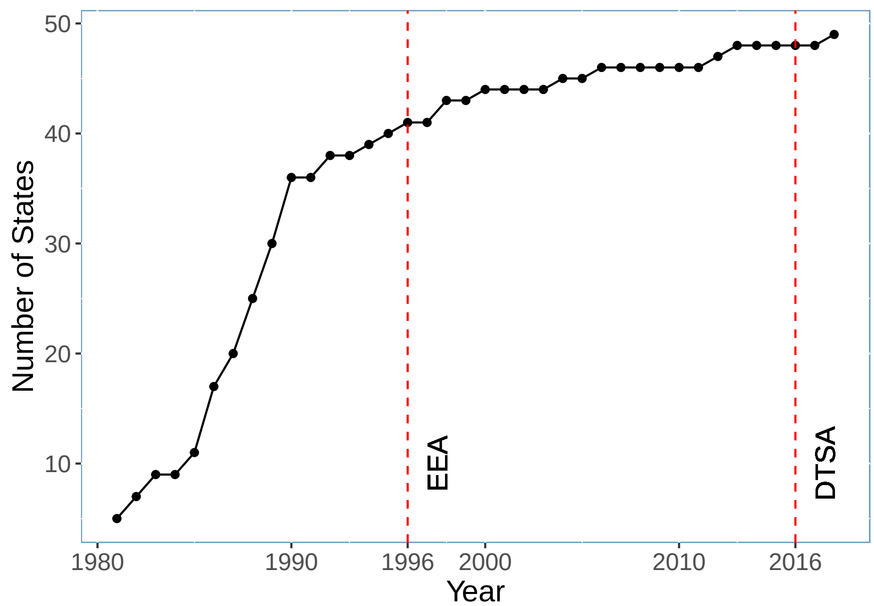

Figure 16: Number of States that Adopted the UTSA (1980-2016) Notes: EEA refers to the Economic Espionage Act of 1996 and DTSA refers to the Defend Trade Secrets Act of 2016. The figures combines adoption years in Png (2017b) with public announcements.

Parameter		Moment	Model	Data
τ	0.2	% Job Dest. Rate	9.24	8.74
c_1^E	176	% Exit Rate	6.15	6.29
c_2^E	463	Revenue Share 1	0.314	0.323
c_3^E	280	Revenue Share 2	0.0424	0.0461
c_4^E	490	Revenue Share 3	0.264	0.287
c_1^F	194	Avg Estb. Size 1	35.5	35
c_2^F	93	Avg Estb. Size 2	44.7	44
c_3^F	172	Avg Estb. Size 3	54	53.5
c_4^F	101	Avg Estb. Size 4	62.6	60.5
θ_1	0.092	Revenue/Payroll 1	12	12
θ_2	0.14	Revenue/Payroll 2	7.62	7.26
θ_3	0.14	Revenue/Payroll 3	8.14	8.07
θ_4	0.14	Revenue/Payroll 4	8.22	7.81
ρ_1	0.95	Size $<$ 20 Share 1	0.762	0.715
ρ_2	0.97	Size $<$ 20 Share 2	0.505	0.591
ρ_3	0.95	Size $<$ 20 Share 3	0.46	0.454
ρ_4	0.98	Size $<$ 20 Share 4	0.538	0.608
α_1	0.81	Outsourcing/Payroll 1	0.0868	0.0855
α_2	0.73	Outsourcing/Payroll 2	0.0604	0.0596
α_3	0.72	Outsourcing/Payroll 3	0.115	0.109
α_4	0.75	Outsourcing/Payroll 4	0.0836	0.0847

Table 11: First-stage Estimation Results (Michigan)

State	π	α_{Food}	α_{Wood}	α_{Heavy}	α_{Light}
AZ	0.12	0.21	0.28	0.29	0.30
CA	0.14	0.23	0.30	0.30	0.31
CT	0.11	0.21	0.28	0.28	0.29
FL	0.14	0.22	0.30	0.31	0.31
GA	0.09	0.16	0.26	0.29	0.28
IL	0.13	0.22	0.29	0.30	0.31
LA	0.15	0.25	0.28	0.31	0.32
MA	0.12	0.21	0.29	0.29	0.30
MI	0.09	0.19	0.27	0.28	0.25
MO	0.07	0.17	0.25	0.25	0.25
NY	0.09	0.19	0.27	0.27	0.27
NC	0.11	0.16	0.30	0.31	0.29
OH	0.09	0.19	0.27	0.27	0.27
OK	0.08	0.19	0.23	0.27	0.27
OR	0.10	0.19	0.27	0.28	0.29
RI	0.10	0.18	0.28	0.28	0.28
TN	0.10	0.19	0.29	0.31	0.23
TX	0.10	0.23	0.30	0.19	0.31
UT	0.11	0.21	0.28	0.28	0.29
WA	0.13	0.22	0.29	0.30	0.30

Table 12: State-Level Estimates for Trade Secret Protection The first-stage estimation results for α_{jk} and the associated second-stage estimation results for π_j

State	Base	Avg τ	Avg π	Avg Ind	Avg τ and π	Avg Ind, τ and π
AZ	0.14	0.13	0.13	0.14	0.12	0.12
CA	0.17	0.16	0.13	0.16	0.12	0.12
CT	0.13	0.12	0.13	0.13	0.12	0.12
FL	0.14	0.15	0.10	0.13	0.12	0.12
GA	0.11	0.12	0.13	0.11	0.14	0.14
IL	0.15	0.15	0.13	0.14	0.12	0.12
LA	0.18	0.19	0.13	0.15	0.14	0.12
MA	0.14	0.13	0.13	0.14	0.12	0.12
MI	0.11	0.12	0.13	0.10	0.14	0.13
MO	0.09	0.09	0.14	0.09	0.13	0.12
NY	0.12	0.11	0.14	0.11	0.12	0.12
NC	0.13	0.13	0.13	0.12	0.14	0.13
OH	0.12	0.11	0.14	0.11	0.12	0.12
OK	0.10	0.10	0.13	0.10	0.12	0.12
OR	0.11	0.11	0.11	0.11	0.11	0.11
RI	0.12	0.11	0.14	0.12	0.12	0.12
UT	0.16	0.17	0.17	0.17	0.19	0.20
TN	0.20	0.21	0.21	0.15	0.22	0.17
TX	0.14	0.13	0.13	0.13	0.12	0.12
WA	0.13	0.13	0.11	0.13	0.11	0.11
CoV	0.20	0.24	0.16	0.17	0.20	0.17

Table 13: The baseline and the counterfactual outsourcing to payroll ratios for states of the U.S.The last row reports the coefficient of variation.

State	Base	Best TSP	Gross Output	Net Output	Number of Firms	Wage
AZ	0.14	0.18	1.014	1.015	1.014	1.018
CA	0.17	0.18	1.003	1.004	1.003	1.008
CT	0.13	0.18	1.024	1.025	1.025	1.023
FL	0.14	0.15	1.003	1.004	1.003	1.005
GA	0.11	0.18	1.025	1.026	1.023	1.038
IL	0.15	0.18	1.009	1.009	1.009	1.011
LA	0.18	0.18	1.000	1.000	1.000	1.000
MA	0.14	0.18	1.014	1.015	1.014	1.018
MI	0.11	0.17	1.024	1.025	1.022	1.034
MO	0.09	0.19	1.038	1.040	1.037	1.049
NY	0.12	0.19	1.031	1.033	1.032	1.038
NC	0.13	0.18	1.020	1.020	1.019	1.028
OH	0.12	0.19	1.026	1.027	1.025	1.036
OK	0.10	0.18	1.033	1.035	1.033	1.042
OR	0.11	0.16	1.022	1.023	1.022	1.026
RI	0.12	0.19	1.035	1.037	1.036	1.035
UT	0.16	0.22	1.020	1.021	1.018	1.034
TN	0.20	0.26	1.024	1.025	1.024	1.037
TX	0.14	0.18	1.019	1.020	1.019	1.023
WA	0.13	0.15	1.011	1.012	1.011	1.012
Median	0.130	0.179	1.021	1.022	1.021	1.027
Max	0.197	0.264	1.038	1.040	1.037	1.049

Table 14: The counterfactual results after an improvement in trade secret protection The values for columns 4 to 7 are relative to a baseline value of 1.