PRODUCTIVITY GAINS FROM LABOR OUTSOURCING: THE ROLE OF TRADE SECRETS

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Abstract: Labor outsourcing provides flexibility to producers but also exposes sensitive information to outsiders, which may deter outsourcing if the legal system does not provide adequate protection. I quantify the impact of trade secret protection on labor outsourcing, and consequently, on aggregate productivity. First, using event studies around the staggered adoption of the Uniform Trade Secrets Act, I show that better trade secret protection leads to increased outsourcing of high-skill jobs. Second, to quantify the resulting gains in productivity, I build an equilibrium model of outsourcing and multi-industry dynamics and calibrate it with state-industry level data from the U.S. manufacturing sector. I decompose the cross-state differences in the extent of labor outsourcing into differences in firing cost, industry composition, demand volatility, and trade secret protection. I find that strengthening trade secret protection for all states to match the state with the strictest protection would increase the outsourced employment by 33% and aggregate output by 0.8%. **JEL codes:** E23, E24, L25, O38, **Keywords:** Labor Outsourcing, Productivity, Trade Secrets, Adjustment Costs

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1 Introduction

A healthy economy requires a steady reallocation of workers as producers face fluctuating demand for goods and tasks that are not performed frequently. Labor outsourcing allows producers to make quick adjustments to their workforce, bypassing many hiring and firing costs. However, most jobs, which could 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.[1] In such cases, producers will be reluctant to use outsourced workers, leading to an inefficiently small outsourcing sector, slower reallocation of workers, and reduced aggregate productivity.

In this paper, I quantify the impact that trade secret protection has on aggregate productivity through 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. I find that 45% of the growth in the outsourcing sector from 1977 to 1987 can be explained with the adoption of the UTSA. Next, I develop an equilibrium model of industry dynamics in which firms choose whether to use outsourced workers in each task. I use the calibrated 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 state with the strictest protection, the number of outsourced workers would increase by 33%, and aggregate output would increase by 0.8%.

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, the switch from common to statutory law via the UTSA happened in different years for different states, creating the heterogeneity in protection. Second, the extent of outsourcing varies substantially, both over time and across states. The industries 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. In 2018, these firms had an employment share of 14.3% in California (90th percentile) but only 7.6% in Wisconsin (10th

[1] For example, Wong (2018) has reported on the internal training documents used by Google that prescribed withholding training material from workers not directly employed by Google in fear of 'information security risks.' The report followed an open letter published by Google's outsourced workforce who demanded equal access to information with direct hires.

percentile).

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

To understand the role of trade secret protection in the growth of labor outsourcing, I use the staggered adoption of the UTSA across U.S. states. First, using historical anecdotes and event studies, I argue that the timing of the adoptions was exogenous to outsourcing patterns and was determined by non-economic factors. Second, using a staggered difference-in-differences design following Callaway and Sant'Anna (2020), I show that stronger trade secret protection has a positive and significant impact on the size of the labor outsourcing sector. Third, I supplement the relevance of shared information by showing that there was no significant impact for jobs that are (1) unlikely to involve sensitive information or (2) already subject to auxiliary enforcement through professional associations. Quantitatively, improvements in trade secret law can explain 45% of the outsourcing share growth from 1977 to 1987, translating to roughly 1.76 million new jobs in the outsourcing sector.

To quantify the aggregate productivity gains, I develop 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 their employees or outsourced workers for each task. Unlike employees, the number of outsourced workers can be adjusted freely, and in certain tasks, outsourced workers may be more productive than employees (e.g., due to better training or incentives). However, the productivity of the outsourced workers is limited by how much sensitive information is shared with them. 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 have different technologies, and specifically, different valuations of the productivity advantages of the outsourced workers. In total, the extent of outsourcing can differ across economies due to differences in four components: (1) strength of employment protection; (2) industry compositions; (3) within-industry firm characteristics; and (4) strength of trade secret protection.

I calibrate the model using state-industry-level data from the U.S. manufacturing sector in 2007. I use establishment size distributions and job flows among others to identify the magnitude of firing costs and the parameters of the production technologies (components (1) and (3), respectively). The fundamental identifying assumption for distinguishing (2) and (4) is that the productivity advantage of outsourced workers 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 CES factor intensities as data and estimate the trade secret protection and outsourcing efficiency parameters separately using non-linear least squares. I find the impact of differences in trade secret protection to be considerable: if all states had the same (average) level of trade secret protection, the cross-state dispersion of outsourcing would decline by 22%.

Using the model estimates, I ask how the extent of outsourcing and aggregate productivity would change if all states enforced trade secret protection up to the level of the state with the strictest protection. I find that the ratio of purchased outsourcing to payroll expenses would increase by 4.9 pp (from 12.5% to 17.4%), while the aggregate output would go up by 0.8% ($165B in 2018). A large portion of the output growth would come through the entry of new firms, while the size-productivity correlation across firms 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. The wage levels would increase more than the increase in output, implying an increase in the labor share. There would also be modest gains in business dynamism through increased job reallocation and entry rates in the steady-state. I also find that the output cost of a hypothetical increase in firing costs would be 14% larger compared to an economy where the enforcement level of all states were as low as the state with the most lenient protection. Last, I connect the causal estimates from the difference-in-differences design with the structural estimates to measure the productivity gains from the adoption of the Uniform Trade Secrets Act. I find that the aggregate output would be 0.7% smaller in 2007 if the UTSA was not implemented.

My paper is closely related to others that use estimated distortions in firm decisions to analyze the importance of legal enforcement and trust for aggregate productivity. Bloom, Sadun and Van Reenen (2012) find that the regions that have lower trust measures have firms with more centralized structures, slower worker reallocation, and lower productivity. Akcigit, Alp and Peters (2021), 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 substitute away 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 input choice 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. On the other hand, while their measure of court congestion is constant over time, I can use state-level changes in laws to control for many state-specific covariates through state fixed effects. Furthermore, their model is static, which does not permit analysis of the dynamic flexibility gains from labor outsourcing that is central to this paper's aim.

My paper also contributes to the literature on the cost of employment protection. The interest in patterns of labor flows have expanded after 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%. 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)). 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 and allow outsourced workers to be imperfect substitutes to permanent workers and evaluate distortions that limit their utilization. Second, I show that the cost of employment protection depends crucially on the availability of labor outsourcing.

My paper is also related to the literature that examines the determinants and consequences 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, Kalleberg and Erickcek (2003) and Autor and Houseman (2010) analyze how outsourcing allows employers to screen potential hires. 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.[2] Adding to the literature, I propose and quantify the trade secret protection as a concern in labor outsourcing decisions.

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 calibration strategy and results. Section 6 presents the counterfactual exercises and Section 7 concludes.

2 Background

I start this section by discussing how trade secret law impacts employees and outsourced workers differently. Then, I discuss the historical development of the trade secret law in the U.S., emphasizing the Uniform Trade Secrets Act (UTSA), that I will utilize in the new section.

[2]For papers that analyze the macroeconomic implications of growing labor outsourcing, see Berlingieri (2013) for the structural transformation in the U.S., Giannoni and Mertens (2019) for the trends in labor share, and Bilal and Lhuillier (2020) and Bergeaud et al. (2020) for wage inequality.

2.1 Trade Secret Protection and Labor Outsourcing

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.

There are two main reasons why trade secret law is crucial for labor outsourcing. First, high or low-skilled, all outsourced workers are exposed to some trade secrets. 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. In short, outsourced workers' regular activities inherently create exposure to firm secrets unless the firm explicitly limits their access, which would reasonably reduce their value.

Second, it is harder to prevent outsourced workers from disclosing secrets to third parties compared to employees. Voluntary disclosure of secrets is less likely for employees. Because the employment relationship is generally of longer-term,[3] it allows the design of better incentives for the employee to work in the best interest of the employer. Inevitable disclosure is also less likely for employees. While covenant not to compete (CNC) agreements[4] are ubiquitous among employees that work with sensitive data (Shi, 2020), they are not common in outsourcing agreements, being directly at odds with the business model of most outsourcing firms.[5] Signing a non-disclosure agreement helps, but its enforcement is largely determined by the trade secret law.

The risks outsourcing creates for sensitive information is well known in the industry. Through federal regulations (e.g., the Privacy Act and the Health Insurance Porta-

[3]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. See Amarnare v. Merrill Lynch, Pierce, Fenner & Smith Inc., (611 F. Supp. 344 S.D.N.Y. 1984) and https://www.computerworld.com/article/2589538/it-personnel-microsoft-to-pay-97-million-to-settle-permatemp-case.html.

[4]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.

[5]"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)

bility and Accountability Act), many governmental institutions, banks, health providers, among others, face outright restrictions or regulations of outsourcing activities. Experts and practitioners also advise caution on outsourcing due to potential risks to trade secrets. Pooley (1989), in his practitioner's guide to protecting trade secrets, argues "...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." and "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.".

The data from trade secret litigation also confirms the risks involved in outsourcing. First, limiting access to certain 'labs' does not protect the business from trade secret misappropriation. Almeling, Snyder and Sapoznikow (2009) 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. (2010)). 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)). Third, using the Nexis Uni database, I find that the firms that provide outsourcing services are over-represented in trade secret disputes. These firms constitute 21% of all firms involved in trade secret disputes handled in Federal courts from 2015 to 2020, although their employment share is just 12% (see Appendix B.4 for details.).

2.2 Trade Secret Protection in the U.S.

As opposed to statutory law, common law does not rely on a codified set of rules and instead relies on previous court decisions to reach new ones. Before 1979, trade secrets were protected exclusively under common law. This created two main problems. First, as no two cases are the same, there was uncertainty regarding the law's extent.[6] Second,

[6]"... 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).

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 accused 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 defined 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. Furthermore, 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.[7]

The UTSA had a significant impact on trade secret protection. Almeling, Snyder and Sapoznikow (2009) estimate that trade secret litigation has increased by an order of magnitude since 1980 after showing no trend in the previous thirty years. Furthermore, Png (2017*a*) and Png (2017*b*) show that the UTSA was met by an increase in innovation and patenting activities in adopting states.

In short, firms have reason to avoid labor outsourcing to limit the risks of losing trade secrets. Section 3 tests and confirms this hypothesis using the cross-state legal variation across the U.S. generated by the UTSA. The modeling choices in Section 4 are based on the frictions discussed here.

[7]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.

3 Empirical Analysis

I start this section by documenting two broad facts on domestic[8] labor outsourcing in the U.S., focusing on its growth and its cross-state heterogeneity. Then, I argue that the developments in the U.S. trade secret laws help explain the two facts.

I define labor outsourcing as the purchase of labor-intensive business services that can be done in-house. The industries that provide such services are classified into two 2-digit NAICS sectors.[9] NAICS 54 (The Professional, Scientific, and Technical Services) principally employs high-skill occupations such as management consultants and accountants. NAICS 56 (The Administrative and Support and Waste Management and Remediation Services) principally employs lower-skilled occupations such as machine operators and janitors. The output of both sectors is predominantly used as an intermediate input by other sectors. Furthermore, the firms in these industries are very labor-intensive and dedicate particular workers to their clients to perform customized tasks. Hence, the client firm could also complete the task by directly employing these workers.

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

3.1 Facts on Domestic Labor Outsourcing

Here, I present two sets of facts that demonstrate significant heterogeneity in labor outsourcing over time and across states in the U.S.

First, since 1971, the outsourcing sector has more than tripled its employment share in the U.S. economy (from 3% to 11%), far exceeding the growth in services. Figure I depicts the normalized non-farm employment, service employment, and employment in the outsourcing sector. In Appendix C.1, I confirm that the growth in labor outsourcing was not an artifact of (1) the growth in industries that historically had above-average demand for outsourcing, (2) the growth in demand for occupations that historically had been outsourced more than others, (3) or part of a broader trend of shrinking firm boundaries.

[8] I abstract from foreign outsourcing (e.g., call centers abroad) in this section because it constitutes a relatively small fraction (3.5% in 2004) of total labor outsourcing practices (Amiti et al., 2005).

[9] See Appendix B for the few exceptions, the details of the selection of industries, and how I bridge different industry classification systems.

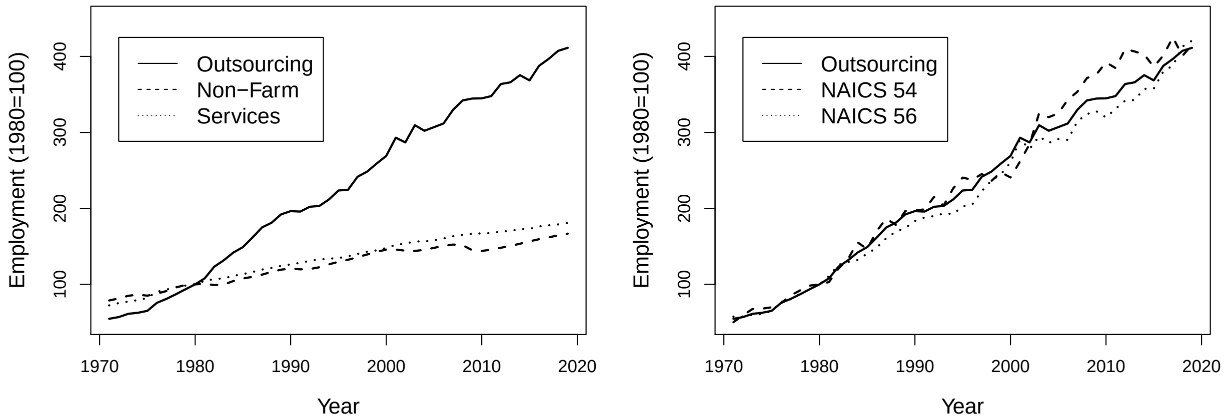


Figure I

Employment Trends in Multiple Industry Groups (1971-2019)

Notes: See Appendix B and Table V for details. 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).

Second, there is considerable heterogeneity across states both in the size of the outsourcing sector and the use of outsourcing. In Appendix C.2, I show that the state at the 90th percentile has an outsourcing employment share of 14.3% while the 10th has 7.6%. Similarly, the ratio of labor outsourcing to payroll expenses ranges from 0.18 to 0.1 for the average manufacturing establishment of the states in the 90th and 10th percentiles. Furthermore, the heterogeneity in outsourcing does not diminish at finer levels of aggregation.

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 the composition of skills, industries, or occupations. Here, I test whether the differences in trade secret protection over time and across states play 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. I use the adoption of the Uniform Trade Secrets Act (UTSA), which was essential both for reducing the uncertainty about the trade secret protection and extending its coverage, particularly for labor outsourcing relationships, as discussed in Section 2.

Second, I need a measure of the extent of outsourcing. Comprehensive data on the users of labor outsourcing does not exist before 2007 (see Appendix B). Thus, I use data on the providers of labor outsourcing,[10] specifically, 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 XII), 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 several difference-in-differences (DiD) comparisons across many 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, TWFE may fail to give (1) consistent test statistics for pre-trends and (2) intuitive measures of treatment effects without strong assumptions (see Appendix D.1 for details). In the following analysis, I primarily yield to the historical setting to argue for the exogeneity of the UTSA adoption, supported by robust statistical tests for pre-trends. I then estimate the impact of trade secret protection using the estimator proposed by Callaway and Sant'Anna (2020), which remains consistent under multiple dimensions of treatment heterogeneity -including dynamic treatment effects- and selection into treatment based on covariates. In Appendix D.2.1, I show that all my results are qualitatively robust to using a naive TWFE estimator.

[10] Whether the demand for or the supply of outsourcing is the more relevant measure depends on which state's law would govern disputes. Although there was no definitive procedure, the governing law was generally of the state where the client operates. As long as outsourcing firms are more likely to serve clients in their states (as opposed to a random assignment), my mechanism predicts a positive relationship between the strength of protection and the size of the outsourcing sector.

Exogeneity of the UTSA Adoption

I start by confirming that the adoption of the UTSA did not coincide with the adoption of other relevant state-level laws. The adoption year of the UTSA has a weak correlation with the adoption of 103 other commercial uniform laws (<0.13) and 3 employment protection laws (<0.04) across states.

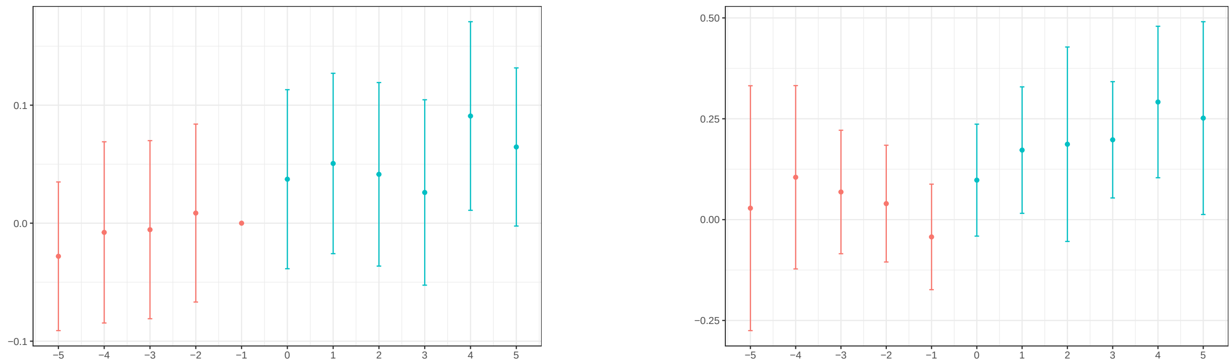
The adoptions' history suggests the timing choices of states were less about economic concerns and more about differences in legal structures and opinions. First, Ribstein and Kobayashi (1996) show the basic economic characteristics like size, population density, and state expenditures were irrelevant 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, Sandeen (2010) documents, many states, who were yet to adopt the UTSA at the moment, postponed their adoption to after 1985 due to the opposition organized by a single attorney who argued certain clauses could be misinterpreted.[11] Last, Png (2017*a*) 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.[12] The convergence also supports the argument for differences in legal opinions: all states adopted a version of the UTSA eventually. The quantitative tests do not suggest the presence of pre-trends either.[13] First, I run the classical event study regression with the leads and lags of the treatment in a TWFE setting

$$y_{it} = \sum_{l \in \{-4,-3,-2,0,1,2,3,4\}} \delta_l A_{itl} + \delta_5 A_{it,l \geq 5} + \delta_{-5} A_{it,l \leq -5} + \beta x_{it} + \alpha_i + \gamma_t + \epsilon_{it} \tag{1}$$

[11] William LaFuze argued (1) the language of the UTSA did not make it clear that it would not preclude breach of contract claims, (2) reasonable royalties should be listed also in the damages section, and (3) remedies against good-faith misappropriators were not explicitly designated to be in "exceptional circumstances". He went on to write letters to several state governors to warn them against adopting the UTSA, which broke the momentum of adoptions going forward.

[12] Similarly, during the United Kingdom's implementation of the Trade Secrets Directive in 2018, the opposition centered around whether the law would be used against journalists and whistle-blowers (IPO (2018)).

[13] Png (2017*a*) 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 II

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 estimates with 95% confidence intervals constructed from standard errors clustered at the state level. I use the outcome regression balancing in the right panel to estimate group-time ATTs for 1987 adopters. The outsourcing shares and employment series are from the IPUMS-CPS database. The controls are GDP, manufacturing GDP, unionization rate, high school and college shares. See Figure I for details on included industries.

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, and x_{it} are additional controls. The coefficient estimates are in Figure IIa. 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 may suffer from the bias suggested by Sun and Abraham (2020): some states in the 'control group' are recent adopters, hence they are still subject to the dynamic effects. Thus, I supplement the analysis by using the estimator by Callaway and Sant'Anna (2020) (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). $ATT(g,t)$ denotes the effect of being treated at time g that is measured in time t, thus allows for heterogeneity across groups and dynamic treatment effects. Furthermore, by conditioning on being treated, it controls for selection into treatment.

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

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

CS identifies $ATT(g,t)$ under the assumptions of parallel trends (conditional on observables) and absorbing treatment. To estimate $ATT(g,t)$ I use the not-yet-treated states as the control group and follow the outcome regression approach (Heckman, Ichimura and Todd, 1997) to match states in the control group to the adopters.

Figure IIb plots the 'event study' estimates from (3), which confirm the qualitative findings of the TWFE estimator: there are no apparent pre-trends, and the full effect is realized only a few years after the adoption. The effect magnitudes, on the other hand, are roughly double of the TWFE estimates. The differences in magnitudes are consistent with the growing impact of the adoption on the outsourcing sector in the following years. The TWFE estimates are biased downwards as part of the control group are recent adopters.

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 using the estimator by CS. The dependent variable is the log employment share of outsourcing sectors. I allow the UTSA adoption decision of states to depend on total GDP, GDP from manufacturing, unionization rate, share of college graduates, and share of high school graduates. To allow for a reasonably sized control group for outcome regressions, I restrict the estimation sample to 1977-1987 in the main text, resulting in a balanced panel with 561 observations. Furthermore, I use all not-yet-treated units in the control group.

The estimated overall treatment effect of the adoption on log employment share is given in column 1 of Table I. The effect of adopting the UTSA is positive and statistically significant at 1% level, consistent with concerns over sensitive information in outsourcing decisions. If the overall treatment effect is taken to be representative across all adoptions, the outsourcing sector would be 45% smaller in 1987 if no states had adopted the UTSA, translating to 1.76M jobs.[14]

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 I, I use the CS estimator for high-skill and low-skill outsourcing sectors separately. In line with my hypothesis, the impact on high skill outsourcing is greater in magnitude and estimated more precisely. 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.[15] 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.

This section quantifies the causal impact of improved trade secret protection on the extent of outsourcing. Measuring the causal impact on productivity is more challenging due to difficulties in measuring productivity itself and isolating the impact through outsourcing. Next, I build a structural model that links trade secret protection, outsourcing, and aggregate productivity to overcome these challenges.

[14]The results are qualitatively robust to changes in the sample period length, using never-treated units in the control group, as well as using a classical DiD/TWFE estimator with various specifications as shown in Appendix D.2. See Figure X in Appendix E for the estimates of group and time averages of $ATT(g, t)$.

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

Table I
Regression Estimates

	log Outsourcing Share	High-Skill	Low-Skill	Leg-Acct	Except Comp
	(1)	(2)	(3)	(4)	(5)
UTSA Adoption	0.20***	0.24***	0.06	0.16	0.27***
	(0.05)	(0.07)	(0.13)	(0.11)	(0.07)
Range	'77-'87	'77-'87	'77-'87	'77-'87	'77-'87
Observations	561	561	561	561	561

Notes: The outsourcing shares and employment series are from the IPUMS-CPS database. See Figure I 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). The controls are unionization rate, the share of college and high school graduates, total GDP, and manufacturing GDP. See Appendix B for details on how each variable is constructed. Standard errors are clustered at the state level. *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 *a là* 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 (e.g., firm size distribution and job destruction rates) and structural parameters (e.g., persistence of the productivity shock and labor adjustment costs). Second, it incorporates 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 decreasing returns-to-scale (DRS) intermediate goods sector with K industries, (2) a constant returns-to-scale (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:

$$\max_{\{Y_k\}_{k=1}^{K}} P\left(\sum_{k=1}^{K} Y_k^{\omega}\right)^{\frac{1}{\omega}} - \sum_{k=1}^{K} p_k Y_k \tag{5}$$

where Y_k and p_k denote the quantity and the price of the input purchased from industry k and $1/(1-\omega)$ is the elasticity of substitution across intermediate goods. 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.

I use a task-based production technology. The production of each firm is a CES aggregate of production in individual tasks that are indexed by $i \in [0,1]$:

$$sy = s\left(\int_0^1 y(i)^\gamma di\right)^{\frac{\theta}{\gamma}} \tag{6}$$

where s is the productivity level, $\theta < 1$ 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:

$$y(i) = g(i)n(i) + 1_{\{z \geq \zeta(i)\}}\delta r(i) \tag{7}$$

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.[16]

I assume $g(i)$ is strictly increasing, i.e., (1) the tasks are ordered by how suitable they are to outsourcing, 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 using in-house workers ($g(i)$) strictly increases with the required amount of information for the task to be outsourced.[17] 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 also harder to interpret and complicates the notation. Nevertheless, this assumption is conservative for evaluating the impact of strengthening trade secret laws: the tasks that would provide the highest marginal gain once outsourced are assumed to be the ones that are already outsourced.

[16] I abstract from capital as an additional input in the production process. Veracierto (2001) has previously shown that modeling capital explicitly has little impact on the quantitative inference on steady-state labor flows in industry dynamics models.

[17] Using project level data from a large financial services firm, Bidwell (2012) documents that outsourced projects require significantly less firm-specific knowledge than internal projects. Mayer, Somaya and Williamson (2012) reach the same conclusion using patent level data on legal outsourcing.

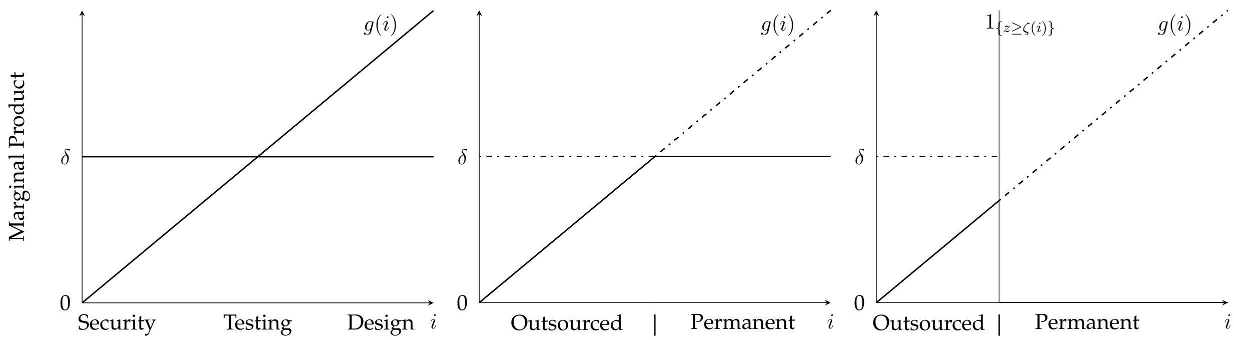


Figure III

The Task Allocation Problem of a Software Design Firm

Notes: The dashed line pieces denote the upper-envelope of the two lines, which reflect the optimal firm choices when the marginal costs are constant and equal.

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 III 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 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 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 III. However, when the information-sharing constraint is binding, as in the right-hand side panel, effective marginal product becomes zero for the outsourced workers in 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 triggers theft 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 to each task $(n(i), r(i))$, and how much information to share with the outsourced (z) to solve:

$$
\begin{aligned}
F(n,r) &= \max_{\{n(i),r(i)\}_{i=0}^{1},z} \left(\int_0^1 y(i)^{\gamma} di \right)^{\frac{\theta}{\gamma}} \\
\text{(Task production)} \quad & y(i) = g(i)n(i) + 1_{\{z \geq \zeta(i)\}} \delta r(i) \\
\text{(Resource Constraints)} \quad & \int_0^1 r(i)di = r, \quad \int_0^1 n(i)di = n \\
\text{(Information-Sharing)} \quad & z \leq \pi
\end{aligned}
\tag{8}
$$

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 $\bar{z}$ s.t. $0 \leq \bar{z} \leq \zeta^{-1}(z)$, 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 $\{n(i), r(i)\}_{i=0}^{1}$ 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 not 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, for solving (8) it is not 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:

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

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

where $\bar{z}$ is an implicit 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 corollary is not relevant for solving the model but allows estimating the model for each state of the U.S. separately.[18]

Corollary 1. *If the information sharing constraint binds in a neighborhood of π, the solution to (8) can be written as*

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

in that neighborhood, where $\alpha(\pi,\delta)$ is strictly decreasing in π.

To sum up, under certain assumptions, the solution to the task allocation problem boils down to a CES function, where the factor intensities are determined both by the marginal product of outsourced workers (δ) and the strength of trade secret protection (π). Stronger protection leads to a larger factor intensity of permanent workers $\alpha(\pi,\delta)$ because a smaller share of tasks use permanent workers. 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 - Dynamic Elements

The firms are ex-ante identical, but they are subject to idiosyncratic productivity shocks s that follow independent AR(1) processes $s' = \rho s + \epsilon$ where $\epsilon \sim N(0,\sigma^2)$. 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.[19] The incumbent firms have to pay a fixed cost of operating c every period or exit

[18] After estimation, I confirm that Corollary 1 applies for the vast majority of the firms under the estimated parameters. I discuss its benefits and caveats in detail in Section 5.

[19] I do not model a separate hiring cost, since its implications are indistinguishable from those of firing costs in this model. The estimated τ therefore reflect both hiring and firing frictions.

and pay a one-time cost of firing all workers (τn_{-}). The entrants have to pay a cost of entry c^E before drawing a productivity shock from the distribution $\phi(.)$. Both the fixed cost of operating and the entry cost are paid in the units of final goods.

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 an intermediate firm with V:

$$\begin{aligned} V(s, n_{-}) = max\{\max_{n,r}\ p_k sF(n, r) - n - r - \tau \max\{0, n_{-} - n\} - \\ Pc + \beta EV(s', n), -\tau n_{-}\} \end{aligned} \tag{11}$$

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.[20] 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. Lastly, potential entrants compare the cost of entry to the expected future discounted profits to decide whether to enter or not.

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

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

1. $V_k(s, n_-)$ solves (11) $\forall k \in K$ (Intermediate Problem)

2. $EV_k(s, 0) = Pc_k^E \quad \forall k \in K$ (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 cross-state heterogeneity 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.

The model allows industries to differ in several dimensions, including the 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 heterogeneity to trade secret laws. First, 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. Second, it takes into account that firms that belong to the same industry may be fundamentally different across states and face different operating costs or fluctuations in productivity. 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 the information sharing concerns. Thus, the model establishes a link between observed cross-state differences in outsourcing to the differences in trade secret laws.

I conceptualize 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, there are two additional barriers against this free flow of ideas coming into fruition. First, when the legal protection is lacking, companies invest in costly physical barriers to prevent theft.[21] Second, in business partnerships, the sides become more hesitant to share information, which is the main idea of this paper.[22] I assume these 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 positive correlation between trade secret protection and GDP per capita across countries is consistent with this idea.

4.5 Extensions for the Calibrated Model

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 calibrating 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 and set $\phi(.)$ such that the entrants start with the 5th largest productivity level. Second, I add Type 1 Extreme Value (T1EV) shocks to the exit decision, ensuring the equilibrium moments change smoothly with parameter values which simplifies the estimation procedure. Each period, to continue operating, firms need to pay $c^F + \nu_1$, or they exit and pay $\tau n_- + \nu_2$ 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, incumbents receive an 'offer they cannot refuse' after production ends with probability κ_j

[21] 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.

[22] 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

and have to exit. This shock helps generate realistic exit patterns in the model for large establishments.

5 Calibration

In this section, I calibrate 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 calibrate the model. I use three primary data sources to compute the moments. The Census of Manufactures (CMF) provides state-industry level revenue shares, revenue to 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 for the whole manufacturing sector for each state.

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:

$$\Omega = \{\beta, \omega, \gamma_k, \sigma_k^2, \kappa_j, \tau_j, c_{jk}^F, c_{jk}^E, \rho_{jk}, \theta_{jk}, \pi_j, \delta_k\} \tag{12}$$

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 (κ_j, $\tau_j, c_{jk}^F, c_{jk}^E, \rho_{jk}, \theta_{jk}, \pi_j, \delta_k$) in two stages. The first stage assumes the information sharing constraint binds and treats $\alpha(\pi_j, \delta_k)$ in (10) as a state-industry level parameter α_{jk}. This assumption allows the first stage to be estimated separately for each state and substantially relieves the computational burden since the stationary distribution of the firms 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 uses 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 wage data with an exogenous wage shifter or an establishment-level panel with information on 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[23] for four manufacturing industry groups. The second is the variance of the productivity 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 use the Annual Survey of Manufacturers to estimate an AR(1) process for the log TFP estimates for each manufacturing industry.[24]

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:

$$\hat{\Omega}_E = \arg \min_{\Omega_E} \left(M^D - M(\Omega_E)\right)' W \left(M^D - M(\Omega_E)\right) \tag{13}$$

where W is a weighting matrix with $W_{nn} = (M^D_n)^{-2}$, which transforms the objective function into one that minimizes total squared percent deviations.

[23]Both the relative size of the outsourcing sector, and the share of high-skilled outsourcing are similar between Denmark and the U.S..

[24]Unlike this paper, Bloom et al. (2018) includes 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 scales the aggregate output hence is not relevant for the estimation. See Table XI for the calibrated values of γ_k and σ_k.

The model admits an equilibrium where common labor and product markets connect all establishments in a state and the steady-state distribution of firms does not have a closed-form solution; thus, I can only provide intuitive arguments on how 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 c_k, the fixed cost of operating, and c_k^E, the entry cost. Both a small c_k and a small c_k^E 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_k^E 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_k^E 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.

While an increase in the returns to scale parameter θ_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 ρ_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.[25] On the other hand, it is notoriously

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

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 having to fire workers later. 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) around the estimated parameters, 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.[26]

Last but not least, the ratio of outsourcing expenses to payroll expenses helps identify α, the factor intensity of permanent workers. 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 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 $\hat{\alpha}_{jk}$ estimates from the first stage (13):

$$\{\hat{\pi}_j, \hat{\delta}_k\} = \arg \min_{\{\pi_j, \delta_k\}} \sum_{j,k} (\hat{\alpha}_{jk} - \alpha(\pi_j, \delta_k))^2 \tag{14}$$

[26]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.

Table II
The Main Parameters and the Moments Used in the Calibration

Par	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>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 Intensity	Outsourcing/Payroll	CMF
		Agg. Entry Rate	BDS
π_j	Trade Secret Enforcement	$\hat{\alpha}_{jk}$	1st Stage
δ_k	Outsourcing Suitability		

Notes: The details of the data sources and how the moments are calculated can be found in Appendix B.

This procedure is similar in spirit to a fixed effects regression; once the factor intensities 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 là* Hsieh and Klenow (2009) and consider the state with the largest π_j as unconstrained and use it as the baseline for comparisons based on enforcement frictions. Table II summarizes the full calibration/estimation strategy, together with data 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} estimates from the first stage.

5.2 Estimation Results

I have estimated the model for 28 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 IVa presents the estimated factor intensities for all industry-state groups.[27]

[27]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 Ap-

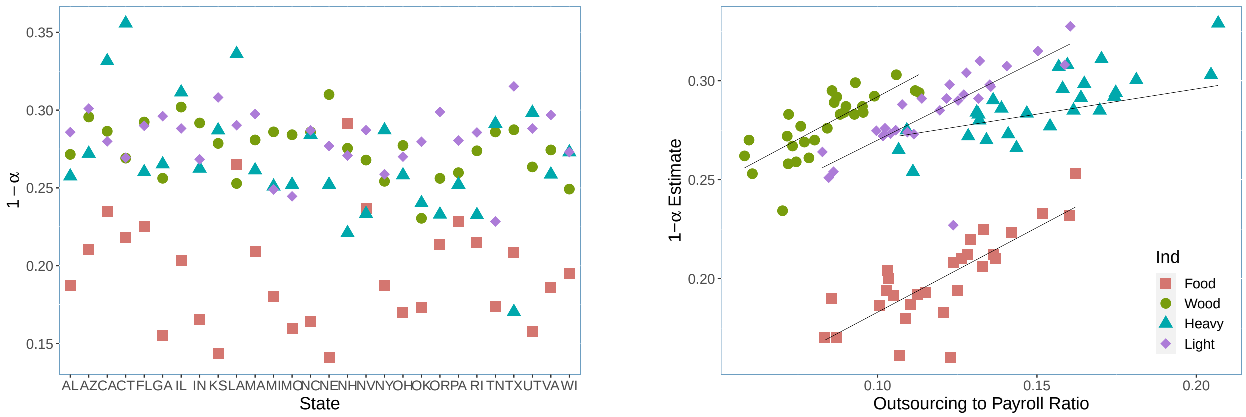
Figure IVb summarizes how the estimated factor intensity parameters relate to the observed outsourcing ratios. In a model with no adjustment costs, the outsourcing ratios would only depend on γ_k and α_{jk} because there would be no flexibility gains from outsourcing. The cross-state patterns are as expected within each industry. However, the estimates suggest the factor intensity 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 a 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 XI). This implies a larger outsourcing ratio for a fixed $\alpha_{jk} > 0.5$. 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^E_{jk} and high c_{jk} (See Figures XIII and XIV in Appendix E.). 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 IVa. Lastly, these two effects are large enough to offset the lower-variance productivity shocks for food and heavy manufacturing, given the externally calibrated σ_k values.

Table XII 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 manufacturing, and the one that would benefit the least is food manufacturing. The average productivity of an outsourced worker (δ_k) is estimated to be twice as large in the former than the latter (0.35 vs 0.17). Louisiana is the state with the strongest secret protection, and Oklahoma is the one with the weakest. Most importantly, as Figure Va shows, the estimates for the strength of trade secret protection align with the adoption date of the UTSA: the states that adopted the UTSA earlier are the ones that have better trade secret protection on average.[28] Figure Vb further shows that states with

pendix B. The parameter estimates and the model fit from the first-stage are given in Figures XIII and XIV respectively in Appendix E.

[28]Although the eventual adoption of UTSA should make de jure protection similar, adopting earlier would provide the time to improve de facto protection through more experienced lawyers and judges.



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

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

Figure IV

The Estimation Results from the 1st Stage

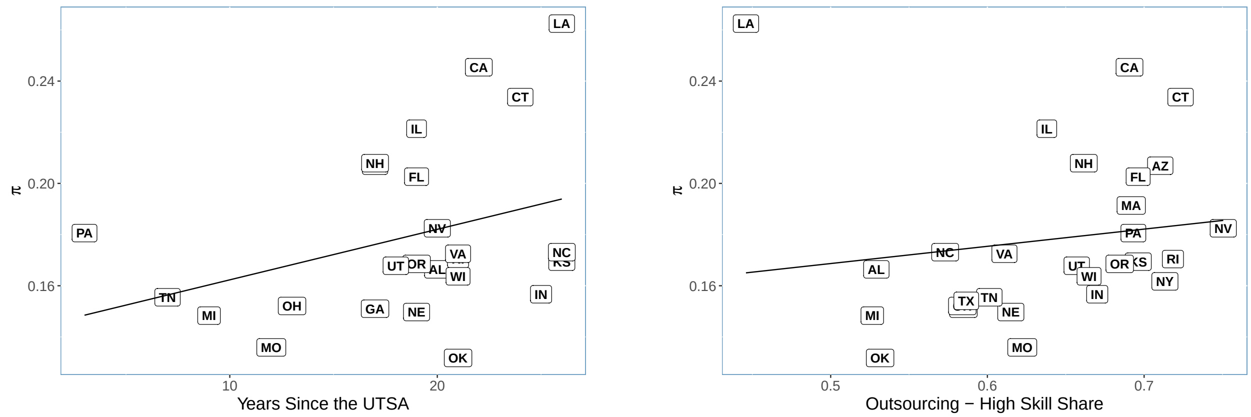
Notes: Each shape refers to a state-industry pair. See Figure XIII in Appendix E for details on the first and second stage estimation results and Appendix B for details on the computation of outsourcing to payroll ratios.

better protection spend a larger fraction of their labor outsourcing budget on high-skilled tasks. The two figures provide an important first step for validating the model: the estimation results are consistent with (1) the actual legal environment of the states and (2) laws being more important for information-sensitive tasks, even though neither pattern was targeted in the estimation.

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 VIa), 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 model would do a bad job predicting the fraction of establishments that belong to each industry. Figure VIb suggests the model still does a good job. The main exceptions are



(a) Estimated Strength of Protection (π) vs Number of Years Since the Adoption of the UTSA (Correlation 0.34)

(b) Estimated Strength of Protection (π) vs the Share of Outsourcing in High-Skilled Tasks (Correlation 0.15, 0.56 without LA)

Figure V

The Estimation Results from the 2nd Stage

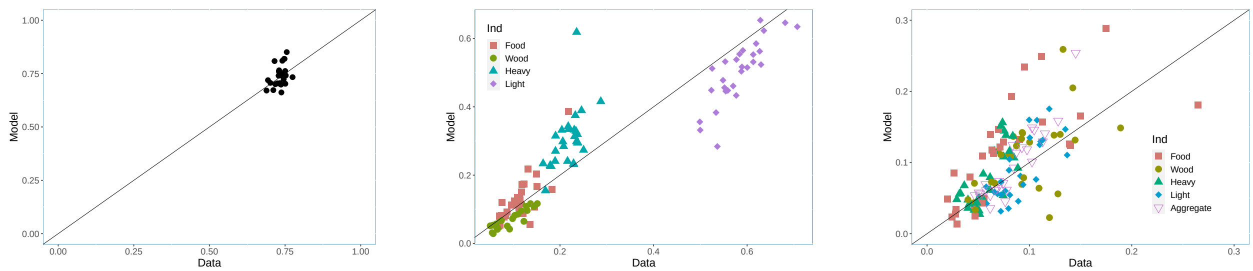
Notes: Figures only present states who adopted the UTSA by 2007.

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 being smaller than 20. Figure VIc suggests the model does an okay job, except that 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 productivity 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 objects 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 ef-



(a) Share of Job Destr. by Existing Establishments

(b) Establishment Shares of Industry Groups

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

Figure VI
The Untargeted Moments

fects. 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 the 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. 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

- 22% less with average trade secret protection,
- 9% less with average industry composition,
- 6% more with average firing cost,
- 83% 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 on average due to the other three channels' counteracting force.

Equating the strength of trade secret protection decreases the cross-state dispersion by 22%. 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, Texas is a state with an above-average outsourcing ratio of 0.17, and improving its trade secret protection up to the average level would bring the ratio up to 0.19. See Figure XI and Table XIII in Appendix E for the detailed state-level results.

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? First, I evaluate a counterfactual improvement in trade secret protection which brings all states of the U.S. to par with the state with the best trade secret protection. Second, combining the causal estimates from Section 3.2 with the calibrated model, I quantify the productivity gains achieved through implementing the UTSA.

6.1 A Comprehensive Improvement in Trade Secret Protection

In this exercise, I calculate the steady-state counterfactual outcomes when every state has the same trade secret protection (π) as the 'best state', which is Louisiana, according to my estimates.

Table III presents the main results. The median state increases its outsourcing to payroll ratio from 0.11 to 0.17. While both the gross and the net output (net of all costs) of the median state grows by 0.9%, the state that benefits the most has a net output growth as large as 1.9%. The growth is mostly through the entry channel: the number of firms increases by 0.8% in the median state. Lastly, wages also reflect productivity growth, increasing by as much as 1.5% 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 gross output grows by 0.7%. For comparison, the gross output increases by 1.4% when the firing costs of all states are set to the minimum firing cost among all states ($\sim$2 months of wages). In other words, improving the trade secret protection could generate half of the output gains from a nationwide reduction in firing costs. In the remainder of the section, I quantify individual channels that lead to output gains.

Table III

The Counterfactual Results After an Improvement in Trade Secret Protection

	Base	Best TSP	Gross Out	Net Out	# of Firms	Wage
Median	0.11	0.17	1.009	1.009	1.008	1.015
Max	0.17	0.25	1.019	1.020	1.019	1.030
Aggregate	0.13	0.17	1.007	1.008	1.006	1.014

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 Best TSP refer to the outsourcing to payroll ratio in the baseline calibration 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 XIV for state-by-state details.

The Role of Labor Adjustment Costs

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 11.09% to 11.07%. Although the job destruction 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 0.6%, the aggregate firing cost paid declines by 2.8% (4 basis points of GDP).

The gains from reduced frictions are visible in the outcome measures. The correlation between size and productivity, a commonly used measure of labor (mis)allocation between firms, would also have a modest increase for both in-house employees and outsourced workers from 0.819 to 0.823 and from 0.820 to 0.824 respectively (1 at the frictionless equilibrium). In other words, the reduction in the firms that have excess and too little employed workers leads to a better allocation of outsourced workers across firms as well.

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 2.3 basis points relative to a baseline level of 6.91%. On the other hand, the number of firms in the steady-state increases substantially by 0.6%. This increase is reflected by the economically significant growth in aggregate entry costs and operating costs paid by 0.6% (0.1% and 0.3% of GDP).

The increase in the number of firms is accompanied by a 0.2 p.p. increase in small firms' 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 large firms (more than 100 employees) by a 0.4 p.p. 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 are more likely to decrease their size after bad shocks. Hence, firms hoard labor to a lesser extent when the outsourcing sector is larger.

The Cost of Employment Protection

Stricter employment protection laws should be less distorting when substituting from in-house employment to outsourcing is easier. To test this hypothesis, I conduct two additional counterfactual exercises: a uniform increase in the firing costs by three months of wages when all states have the lowest and the highest trade secret protection levels.

In both scenarios, the increase in firing costs leads to a growth in the outsourcing share, but the growth is 116% larger in the high protection economy (0.95 vs. 0.44). As a result, the drop in the job creation/destruction rate is 10% larger (0.46 vs. 0.42) and the decline in output is 14% larger in the low protection economy (1.05% vs. 0.9%). In other words, the (mis)allocative impact of stricter employment protection is substantially higher when outsourcing is less available.

6.2 Productivity Gains from the UTSA

In this exercise, I connect the causal estimates from Section 3.2 with the structural model to quantify the productivity gains from adopting the UTSA. Replicating the adoption in the model is not straightforward because (1) most states adopt before data on outsourcing users become available, and (2) the corresponding change in the trade secret protection parameter π is unobserved. I first calibrate my model to the aggregate U.S. economy in 2007, the earliest year where data on outsourcing expenditures is available. Using the estimated δ values in Section 5, I calibrate the values of π^b and π^{cf} to generate the baseline aggregate outsourcing ratio in 2007, and the counterfactual ratio in the absence of the UTSA, estimated with the staggered DID design in Section 3.2, respectively. Then, I compare the model output with $\pi = \pi^b$ and $\pi = \pi^{cf}$.

The calibration exercise gives $\hat{\pi}_b = 0.178$ and $\hat{\pi}^{cf} = 0.145$.[29] According to the model estimates, the outsourcing to payroll ratio would be 19% smaller in 2007 if the UTSA wasn't enacted. Both the net and gross output would be 0.7% smaller. The entry channel would play a large role again: the number of firms increases by 0.72% in the median state. These estimates confirm that the increase in outsourcing through the UTSA also leads to large aggregate productivity gains.

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 infor-

[29] See Table XV in Appendix E for the parameter estimates and the model fit for the aggregate calibration.

mation. Quantitatively, the improvements in trade secret law explain 45% of the growth in outsourcing employment in the U.S. from 1977 to 1987. I build an equilibrium 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. Calibrating 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 0.8%.

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

There are certain limitations of the paper that might be improved upon through future research. First, the empirical analysis is limited by the lack of historical data on the demand for outsourcing. The study of the growth of outsourcing would significantly benefit from making more historical data available. Second, as the paper aims to measure the impact of trade secret protection on outsourcing, I model the protection as a hard constraint on which tasks can be outsourced. Explicitly modeling trade secret theft could provide additional insights. Third, I rely on data from the manufacturing sector to calibrate the structural model. The findings may not represent the whole economy if the productivity gains in the service sector differ substantially.

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A Proofs

Proof of Lemma 1. I 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 show that a unique $\bar{z}$ exists s.t. tasks $i \leq \bar{z}$ only use outsourced and tasks $i > \bar{z}$ only use permanent workers in the optimal solution.

Because $\zeta(i)$ is strictly increasing, $\zeta^{-1}(z)$ exists, and is strictly increasing. First, no outsourced workers are assigned 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. Second, $y(i)$ is weakly 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 solution. 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 permanent workers in the optimal solution. □

Proof of Proposition 1. I 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, permanent (outsourced) 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 permanent or outsourced workers for that task. If not, then the firm should strictly prefer outsourcing 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 outsourced workers imply $r(i) = \frac{r}{\bar{z}}$. For permanent workers, the equalization of the marginal product across tasks requires $\gamma g(i)^{\gamma} n(i)^{\gamma-1} = \bar{n}$. Using $g(i) = i$ gives

$$n(i) = \left(\frac{\gamma}{\bar{n}} g(i)^{\gamma}\right)^{\frac{1}{1-\gamma}} \tag{15}$$

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:

$$\bar{n} = \gamma \left(\frac{(1-\gamma)(1-\bar{z}^{\frac{1}{1-\gamma}})}{n}\right)^{1-\gamma} \tag{16}$$

(15) and (16) 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 $\bar{z}(n, r)$:

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

□

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

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

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

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

Since $\big((1-\gamma)(1-\pi^{\frac{1}{1-\gamma}})\big)^{1-\gamma}$ strictly decreases and $\pi^{1-\gamma}\delta^{\gamma}$ strictly increases in π, α_n strictly decreases with π. □

B Online Appendix: Data Sources

B.1 Measures of Labor Outsourcing

I first define which industries in the NAICS classification provide labor outsourcing services. Then, I choose the industries that correspond the best to the designated NAICS industries for other classifications.

Definition of Labor Outsourcing

I define labor outsourcing as the purchase of business services that are labor-intensive and traditionally done in-house. The Census Bureau classifies these services under two-digit industries NAICS 54 and NAICS 56. First, I focus on business services by restricting attention to 4-digit NAICS services industries that earn less than 30% of their revenues from serving households according to the 2017 Services Annual Survey (SAS). Second, I focus on labor-intensive services by restricting attention to 4-digit industries with less than 5% of their expenditures as depreciation in the 2017 SAS. These criteria lead to 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.[30]

Table IV 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

[30] The descriptions used by the Census Bureau support my classification. For NAICS 54, it reads: "These establishments make available the knowledge and skills of their employees, often on an assignment basis, where an individual or team is responsible for the delivery of services to the client." For NAICS 561, the description reads: "Many of the activities performed in this subsector are ongoing routine support functions that all businesses and organizations must do and that they have traditionally done for themselves. Recent trends, however, are to contract or purchase such services from businesses that specialize in such activities and can, therefore, provide the services more efficiently."

Industry	NAICS	Emp.	Rev.	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 IV

Labor Outsourcing Sector in NAICS Classification Notes: Employment (1000s) figures are from the 2018 Current Employment Statistics. Total revenues ($B) 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.

B.2 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 V 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). 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.

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 V

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.

The Control Variables: I use data from the BEA to construct state level employment, population and gross domestic product (GDP) measures. 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 1987-2018 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, Macpherson and Vroman (2001) who uses the CPS Outgoing Rotation Group earning files. 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 VII.

The Trade Secret Protection Index: I use the index constructed by (Png, 2017*a*) and extended by Png (2017*b*) in the robustness tests performed in Appendix D.2.

B.3 Data Sources for the Cross-Sectional Analyses

The Census of Manufactures: 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

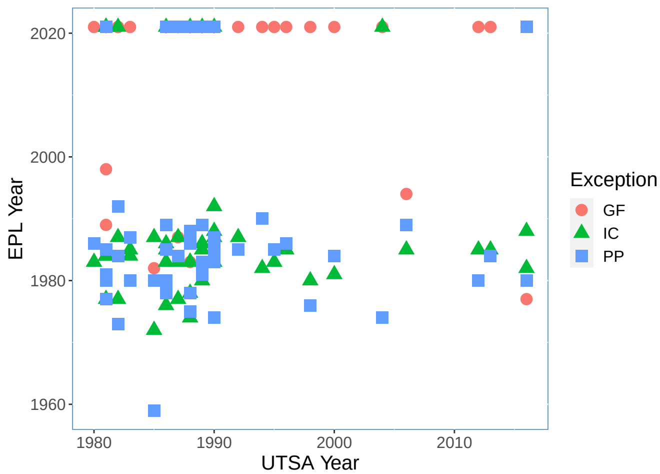


Figure VII

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.

on 'Temporary staff and leased employee expenses' (PCHTEMP), 'Data processing and other purchased computer services' (PCHADPR)[31], '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 moments from the 2007 CMF for the structural model estimation (to avoid the impact of the Defend Trade Secrets Act of 2016) 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. My identification strategy only requires the state and industry level aggregates. However, the two-stage method that simplifies the estimation requires all the state-industry level estimates. I use restricted-access microdata from the 2007 CMF to construct the state-industry level outsourcing numbers.

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 con-

[31]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.

struct 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 manufacturing 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 in Denmark. I match the NACE 2-digit sectors to 2007 NAICS 3-digit sectors using the official correspondence table from the Eurostat.[32] I leave NAICS industries out of my analysis if they do not clearly match to one of the 2-digit NACE industries. Table VI lists both the NACE and NAICS industries included in this classification.

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

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 VI

Industry groups according to (Chan, 2017) for 2-digit NACE and 3-digit NAICS classifications

The TFP Process: Bloom et al. (2018) provides estimates of the variance of the TFP process 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.

B.4 Data Sources for the Trade Secret Disputes Analysis

Nexis Uni: Nexis Uni provides a database of cases in the U.S. courts. I restrict attention to disputes handled in federal courts under the trade secret law and for which 'trade secrets' is a keyword. I extract the defendant and plaintiff names from the legal name of each dispute.

Orbis: Orbis provides detailed information on global private companies including which industry each company operates in. I use a fuzzy matching algorithm similar to Boehm (Forthcoming) to match the sides in Nexis Uni to the companies in the Orbis database. First I capitalize all letters in both datasets and remove common words and expressions (e.g. inc, co). Second, using the Jaro-Winkler string distance metric, which measures how much needs to be edited to make two strings identical, I identify matches that have scores above 0.92 out of 1. Third, I restrict attention to sides for which there is a unique two-digit NAICS code match. Given the potential for inaccuracies in industry classification at finer digits, I classify all firms that are in two-digit sectors 54 and 56 as outsourcing providers in this exercise.

C Online Appendix: Facts on the U.S. Domestic Labor Outsourcing

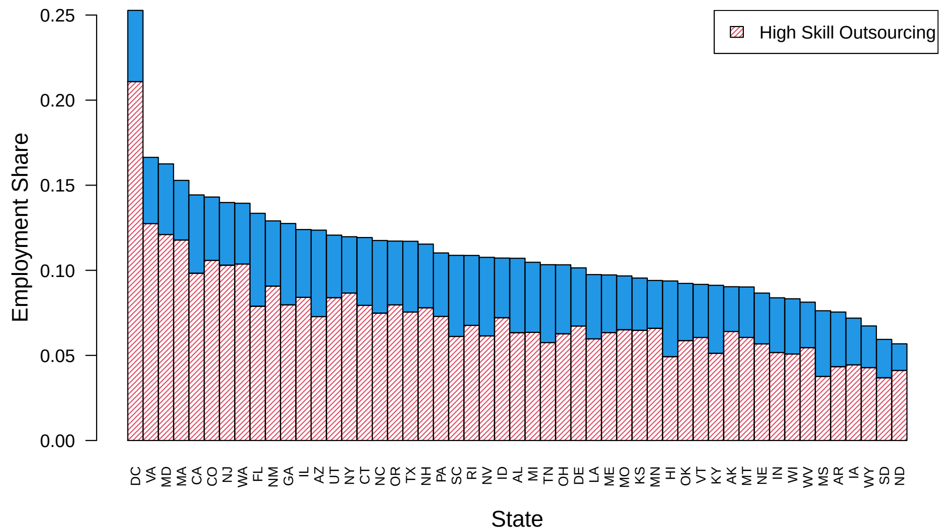
C.1 The outsourcing sector's employment share has tripled since the 70s.

The outsourcing sector's employment share increased from 3% in 1971 to 11% in 2019. The growth in outsourcing was 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.

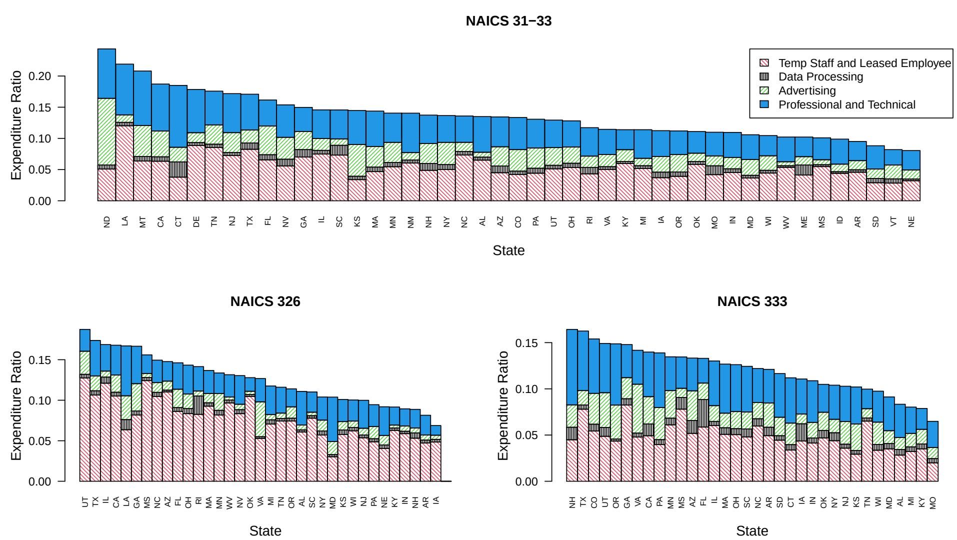
I further check whether the growth in services outsourcing is part of a broader trend of shrinking firm boundaries. On the contrary, the ratio of all intermediate inputs to value-added has decreased from 0.83 to 0.76 during the same period. Although each industry uses more intermediate inputs on average, the structural shift from manufacturing to services more than canceled the growth. My analysis complements the one by Berlingieri (2013) who 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.

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

I define a state's 'supply' of outsourcing as how much outsourcing services it provides, and its 'demand' as how much outsourcing services is used there. The two measures need not equal as outsourcing services provided by a firm in one state can be used by a firm in



(a) Employment Share of Outsourcing Sectors
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 Appendix B and Table V for details on how I pick and classify sectors into low and high skill outsourcing.



(b) Ratio of Outsourcing Expenses to Annual Payroll in Manufacturing Sectors
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). For each, only the states with data on each of the four outsourcing expenses are included. The data is from the 2017 Census of Manufactures.

Figure VIII

The Cross-state Supply of and Demand for Labor Outsourcing (2017)
Notes: The details on data sources and the state abbreviations are available in Appendix B.

another state. 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 VIIIa 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 VIIIb, which provides expense estimates for employer establishments. For each state, I plot the ratio of labor outsourcing expenses to the state's 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. For example, 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.[33] Fourth, states with higher outsourcing ratios are also the ones that have a larger share of their outsourcing in high-skill tasks, with a correlation of 0.32.

D Online Appendix: Additional Material for the Effect of Trade Secret Laws

D.1 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

[33] The degree of heterogeneity seems to persist 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).

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, Sun and Abraham (2020) 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.[34]

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.

D.2 Robustness Checks

In this section, I provide results from various robustness checks for the regression analysis in Section 3.2.

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

D.2.1 Two-way Fixed Effect Estimates

In this section, I show that the empirical results in Section 3.2 are qualitatively robust to using a variety of model specifications with a naive two-way fixed effects (TWFE) estimator. I extend the time period to 1970-1997 since TWFE allows an unbalanced panel, and the size of the control group does not diminish over time because any unit that is not treated at a certain year is a member of the control group.[35] I use two measures of trade secret protection here, namely, adoption of the Uniform Trade Secrets Act (UTSA) and the trade secret protection index (TSP index henceforth) constructed by Png (2017*a*) and extended by Png (2017*b*). 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).

Trade secret protection may have differed both pre- and post-adoption across states. I use the TSP index as the regressor in the main specification to take treatment intensity into account, 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. I also estimate TWFE models with the adoption dummy or the TSP index as the main regressor with no instruments. The results are qualitatively and quantitatively similar across the TWFE models, and qualitatively in line with the results from the CS estimator. In the main specification, I estimate a TWFE-IV model of the form:

$$y_{it} = \beta tsp_{it} + \tilde{\beta} x_{it} + \alpha_i + \gamma_t + \epsilon_{it} \tag{17}$$

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 taxes. I instrument the TSP index with the adoption dummy for the UTSA and use White standard errors clustered at the state level.

Table VII presents the regression results. Trade secret protection has a positive and

[35] It is possible to extend the data as far as 2019. However, in 1997, the industry classifications switch from SIC to NAICS, which makes comparisons of industry groups unreliable, especially for the outsourcing sector. Second, the Economic Espionage Act (EEA) is enacted in Fall 1996, changing the legal structure for outsourcing that crosses state borders. Since almost all of the UTSA adoption happens before 1997 (Figure XII), I choose to limit the regression period.

Table VII
Two-way Fixed Effects Estimation

	Adoption	Index	IV	Adoption	Index	IV
	(1)	(2)	(3)	(4)	(5)	(6)
TS Protection	0.05*	0.12*	0.12*	0.06**	0.13**	0.14**
	(0.03)	(0.06)	(0.06)	(0.03)	(0.06)	(0.06)
Demographics				Yes	Yes	Yes
Ind Composition				Yes	Yes	Yes
Union				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 I 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, total GDP, and manufacturing GDP. 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

statistically significant effect at 5% level. Moreover, the quantitative estimates are similar across specifications without controls or instrumentation, albeit considerably smaller than the overall ATT estimate found using the CS estimator[36]. The difference in magnitudes may indicate large dynamic treatment effects, as suggested by the event study estimates in Figure II. Using the estimated model in the preferered specification in column (6), I find the outsourcing sector would be 11% smaller in 1997 had all the controls changed as they did, but the TSP indices remained the same as the 1977 levels, translating to 0.75M jobs. The DID specification in column (4), which is the most similar to the CS estimation in Section 3.2, implies that the outsourcing sector would be 9% smaller in 1997, translating to 0.6M jobs.

I also repeat the placebo tests using the main TWFE specification (Column (6) in Table VII). Table VIII shows that all the qualitative results are identical to those from the CS estimator which were presented in Table I.

[36]The adoption of the UTSA leads to an increase in the TSP index by 0.4 on average. Hence the coefficients in Columns (2), (3), (5), and (6) should be multiplied by 0.4 before comparing with coefficients in columns (1) and (4) or the CS estimates.

Table VIII
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	’70-’97	’70-’97	’70-’97	’70-’97	’ 70-’97
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 I 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 VII for details on the controls. *p<0.1; **p<0.05; ***p<0.01

D.2.2 Sample Period

A longer sample period allows using more adoptions to estimate the effect of UTSA. On the other hand, the size of the control group in the CS estimator shrinks dramatically for late adopters because all states adopt the law eventually. This is a problem because the outcome regressions in the matching procedure become less precise as degrees of freedom decreases. In the main text, I reach a compromise between the two concerns by limiting the sample period to 1977-1987, which leaves 29 states in the control group for those states that adopted the UTSA in 1987. 1987 provides a natural end-point because the industry classification system changes afterwards, making comparisons over time more difficult. In this section, I check how this decision impacts the main results.

Figure IX provides the ATT estimates for samples with varying end dates. The value for 1987 equals the estimate in column 1 of Table. The estimates are statistically significant and positive irrespective of the sample length, yet the magnitude becomes smaller for longer periods. This pattern could indicate the adoptions being less effective or matching procedure becoming less precise in later years. In particular the size of the control group drops to 12 for states that adopt at 1990.

The results of the placebo regressions are also qualitatively robust to small changes in the sample periods. Table IX provides the estimates for multiple sample periods, other than the ’77-’87 sample used in Table I. The results are broadly robust, with the exception of the significance of the coefficient for legal and accounting services in smaller samples,

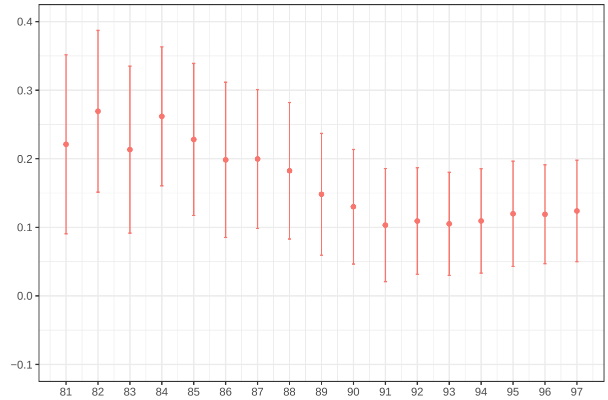


Figure IX

Overall Treatment Effect Estimates from Different Samples Notes: The X-axis refers to the end date of the associated sample. All samples start from 1977. Y-axis provides the overall treatment effect estimates defined in (4) together with 95% confidence intervals. I use the outcome regression balancing procedure to estimate group-time ATTs with not-yet-treated units in the control group. The outsourcing shares and employment series are from the IPUMS-CPS database. The controls are GDP, manufacturing GDP, unionization rate, high school and college shares. See Figure I for details on included industries.

the magnitude of which is still smaller than the coefficient in column 2.

D.2.3 Control Group

CS estimator avoids the bias generated by dynamic treatment effects by restricting attention to units that are not-yet-treated in the control group. If there are any anticipation effects generated by a future adoption, however, having states in the control group that will soon adopt can create a bias. In that case, using never-treated units in the control group would be a better strategy. In my sample, there are no never-treated units in the true sense. However, some of the states adopt the law later than the others. Hence, I treat the states that adopted the UTSA after 1989 as the never-treated group for the sample 1977-1987.[37] Table X shows that the main results are robust to the choice of the control group.

E Online Appendix: Additional Figures and Tables

[37]Considering the randomness involved in many of the adoptions described in Section 3.2, it is unlikely that anticipation effects will be strong more than three years in advance.

Table IX

Regression Estimates for Different Sample Periods

	log Outsourcing Share	High-Skill	Low-Skill	Leg-Acct	Except Comp
	(1)	(2)	(3)	(4)	(5)
’77-’85	0.23***	0.31***	-0.07	0.24***	0.33 ***
	(0.06)	(0.08)	(0.13)	(0.09)	(0.08)
’77-’86	0.20***	0.25***	0.04	0.19*	0.28***
	(0.05)	(0.08)	(0.14)	(0.11)	(0.08)
’77-’87	0.20***	0.24***	0.06	0.16	0.27***
	(0.05)	(0.07)	(0.13)	(0.11)	(0.07)
’77-88	0.18***	0.21***	0.09	0.14	0.23***
	(0.05)	(0.07)	(0.13)	(0.10)	(0.07)
’77-’89	0.15***	0.15***	0.11	0.10	0.17**
	(0.05)	(0.07)	(0.13)	(0.10)	(0.07)

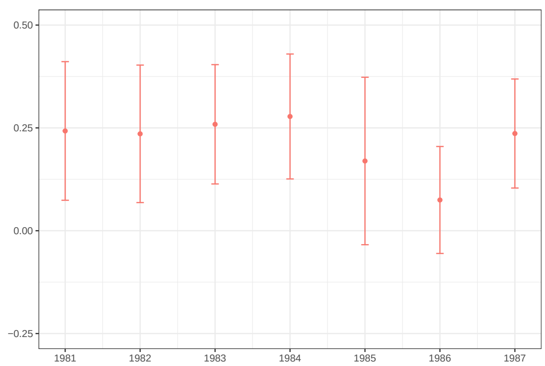
Notes: The outsourcing shares and employment series are from the IPUMS-CPS database. See Figure I for details on included industries and their assignment into skill bins. The fourth column is the total employment in 3-digit 1990 U.S. Census sectors 841 (Legal services) and 890 (Accounting, auditing, 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 VII for details on the controls. *p<0.1; **p<0.05; ***p<0.01

Table X

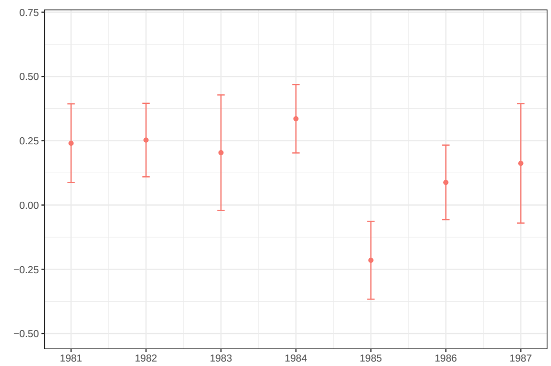
Regression Estimates with Never-treated States as Controls

	log Outsourcing Share	High-Skill	Low-Skill	Leg-Acct	Except Comp
	(1)	(2)	(3)	(4)	(5)
UTSA Adoption	0.22***	0.31***	-0.03	0.13	0.33***
	(0.06)	(0.08)	(0.15)	(0.13)	(0.09)
Range	’77-’87	’77-’87	’77-’87	’77-’87	’77-’87
Observations	561	561	561	561	561

Notes: The outsourcing shares and employment series are from the IPUMS-CPS database. See Figure I 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 VII for details on the controls. *p<0.1; **p<0.05; ***p<0.01



(a) Treatment Effects for Each Calendar Year



(b) Treatment Effects for Each Adoption Group

Figure X

Estimated Group and Time Averages of the ATT(g,t) Notes: These estimates are time and group averages of ATT(g,t) as defined in (2) together with 95% confidence intervals. I use the outcome regression balancing procedure to estimate group-time ATTs with not-yet-treated units in the control group. The outsourcing shares and employment series are from the IPUMS-CPS database. The controls are GDP, manufacturing GDP, unionization rate, high school and college shares. See Figure I for details on included industries.

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 XI

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) which provides substitution elasticities that are aggregated over tasks.

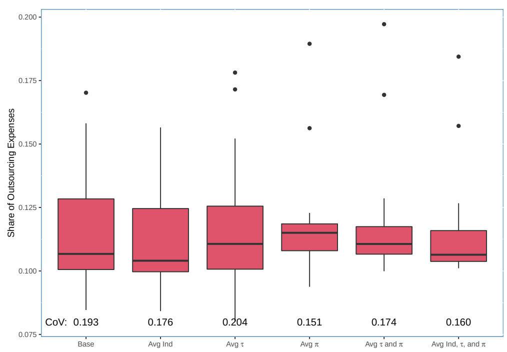


Figure XI
The Distribution and the Coefficient of Variation for Outsourcing to Payroll Ratios Under Baseline and the Counterfactual Scenarios Notes: Base refers to the baseline, Avg Ind refers to the counterfactual with the average composition of industries, Avg τ (π) refers to counterfactual with the average level of τ (π). The last two refers to counterfactuals where multiple objects are equal to their average values across states. See Table XIII for state-by-state details.

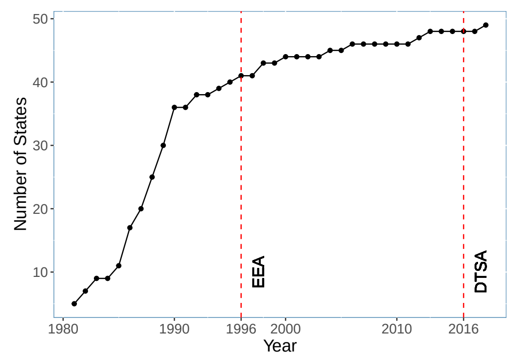
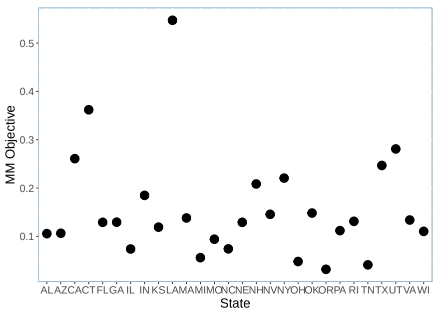
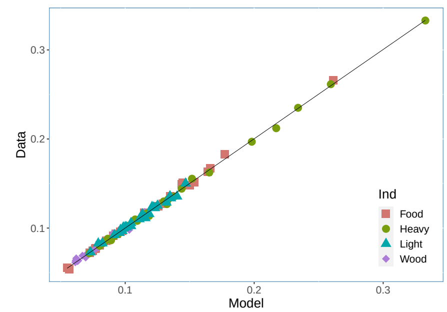


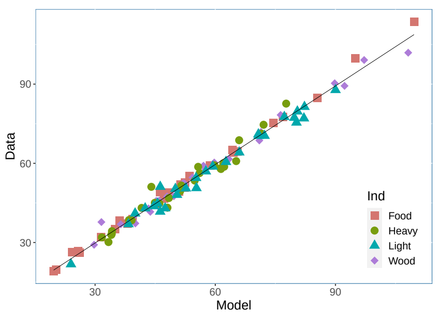
Figure XII
The Number of States that Adopted the UTSA (1980-2016) Notes: EEA refers to the Economic Espionage Act of 1996 and DTSA refers to the Defend Trade Secrets Act of 2016. The figures combines adoption years in Png (2017*b*) with public announcements.



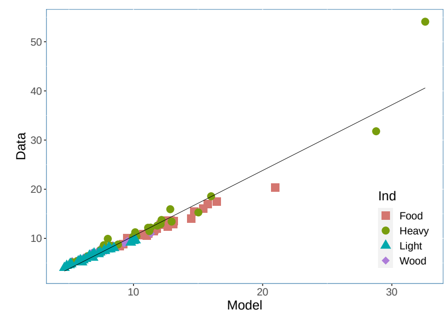
(a) Sum of Squared Percentage Deviations for the 21 Moments



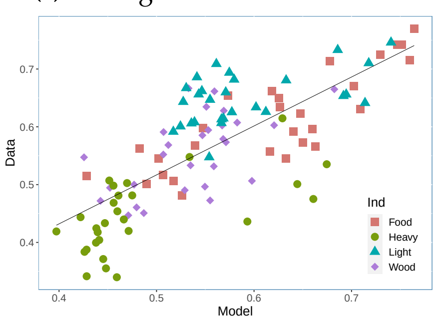
(b) Outsourcing to Payroll Ratios



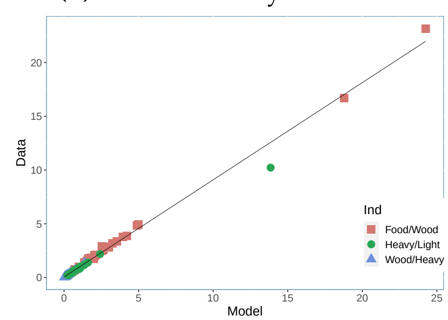
(c) Average Establishment Sizes



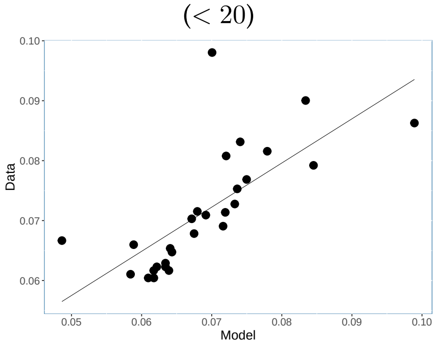
(d) Revenue to Payroll Ratios



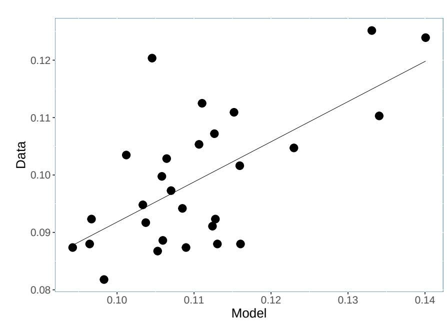
(e) Share of Small Establishments (< 20)



(f) Industry Output Ratios



(g) Entry Rates

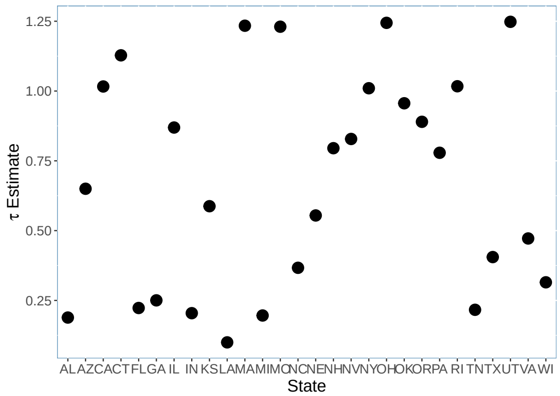


(h) Job Destruction Rates

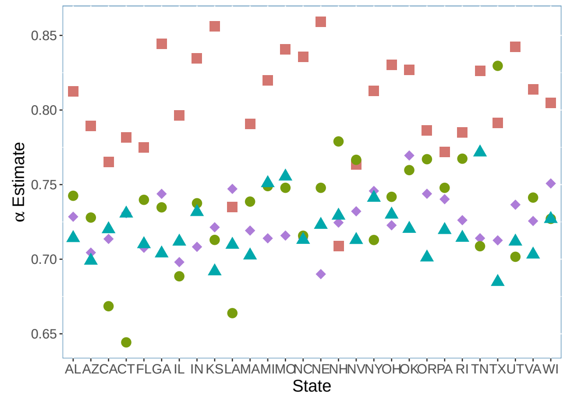
Figure XIII

The Model Fit (Targeted Moments)

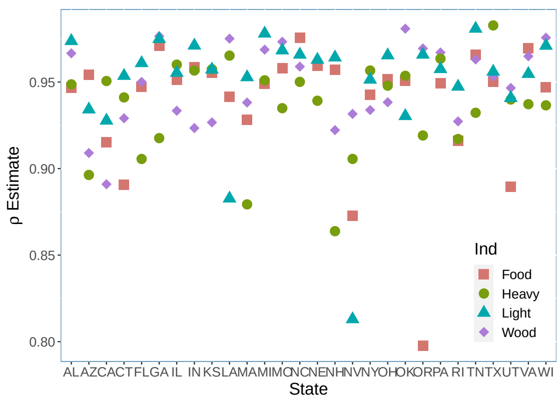
Notes: Each shape refers to a state in Panels XIIIa, XIIIg, and XIIIh, and to a state-industry pair in the rest. Panel XIIIa presents the $\hat{\Omega}_E$ values given in (13), which are bounded below by 0. See Table II for the data sources for the targeted moments.



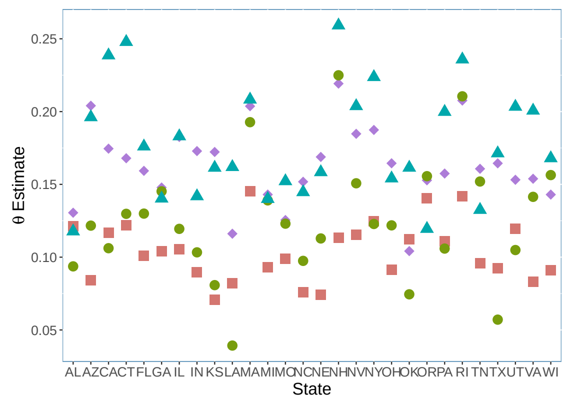
(a) Firing Costs



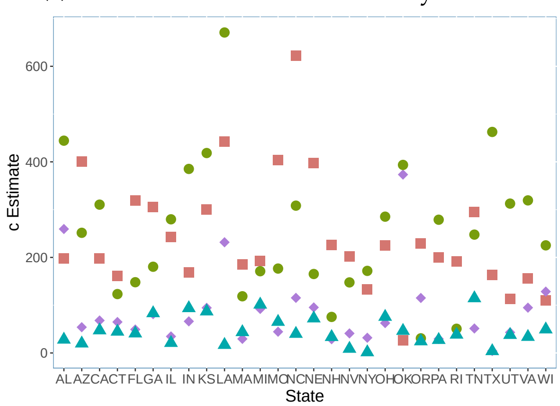
(b) Employee Factor Shares



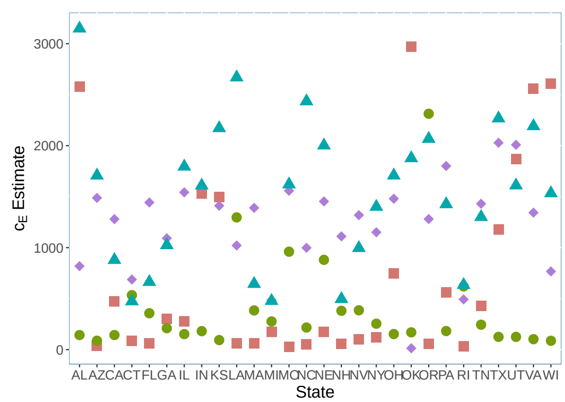
(c) Persistence of the Productivity Shocks



(d) Returns to Scale



(e) Fixed Costs of Operating



(f) Entry Costs

Figure XIV
The First-Stage Parameter Estimates
Notes: Each shape refers to a state in Panels XIVa and to a state-industry pair in the rest. See Table II for a summary of the model parameters.

State	π	α_{Food}	α_{Wood}	α_{Heavy}	α_{Light}
AL	0.17	0.19	0.27	0.26	0.29
AZ	0.21	0.21	0.30	0.27	0.30
CA	0.25	0.23	0.29	0.33	0.28
CT	0.23	0.22	0.27	0.36	0.27
FL	0.20	0.22	0.29	0.26	0.29
GA	0.15	0.16	0.26	0.27	0.30
IL	0.22	0.20	0.30	0.31	0.29
IN	0.16	0.17	0.29	0.26	0.27
KS	0.17	0.14	0.28	0.29	0.31
LA	0.26	0.27	0.25	0.34	0.29
MA	0.19	0.21	0.28	0.26	0.30
MI	0.15	0.18	0.29	0.25	0.25
MO	0.14	0.16	0.28	0.25	0.24
NE	0.15	0.14	0.31	0.25	0.28
NV	0.18	0.24	0.27	0.23	0.29
NH	0.21	0.29	0.28	0.22	0.27
NY	0.16	0.19	0.25	0.29	0.26
NC	0.17	0.16	0.29	0.28	0.29
OH	0.15	0.17	0.28	0.26	0.27
OK	0.13	0.17	0.23	0.24	0.28
OR	0.17	0.21	0.26	0.23	0.30
PA	0.18	0.23	0.26	0.25	0.28
RI	0.17	0.21	0.27	0.23	0.29
TN	0.16	0.17	0.29	0.29	0.23
TX	0.15	0.21	0.29	0.17	0.32
UT	0.17	0.16	0.26	0.30	0.29
VA	0.17	0.19	0.27	0.26	0.30
WI	0.16	0.20	0.25	0.27	0.27

Table XII

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 Ind	Avg τ	Avg π	Avg τ, π	Avg Ind, τ, π
AL	0.10	0.10	0.11	0.11	0.12	0.12
AZ	0.12	0.12	0.12	0.11	0.11	0.11
CA	0.16	0.15	0.15	0.12	0.11	0.10
CT	0.15	0.15	0.14	0.12	0.10	0.10
FL	0.10	0.10	0.12	0.09	0.10	0.10
GA	0.10	0.10	0.11	0.12	0.13	0.13
IL	0.14	0.13	0.14	0.12	0.11	0.10
IN	0.10	0.09	0.11	0.11	0.12	0.12
KS	0.10	0.10	0.10	0.11	0.11	0.10
LA	0.15	0.13	0.17	0.10	0.12	0.11
MA	0.13	0.12	0.11	0.12	0.10	0.10
MI	0.10	0.10	0.11	0.12	0.13	0.12
MO	0.10	0.09	0.09	0.12	0.11	0.11
NE	0.09	0.09	0.09	0.11	0.11	0.11
NV	0.12	0.11	0.11	0.12	0.11	0.11
NH	0.13	0.13	0.13	0.12	0.11	0.11
NY	0.10	0.10	0.10	0.11	0.11	0.10
NC	0.12	0.11	0.12	0.12	0.12	0.12
OH	0.10	0.10	0.09	0.12	0.11	0.11
OK	0.08	0.08	0.08	0.11	0.11	0.11
OR	0.10	0.10	0.10	0.10	0.10	0.10
PA	0.12	0.11	0.11	0.12	0.11	0.11
RI	0.11	0.10	0.10	0.11	0.10	0.10
TN	0.14	0.16	0.15	0.16	0.17	0.18
TX	0.17	0.13	0.18	0.19	0.20	0.16
UT	0.11	0.11	0.10	0.12	0.11	0.10
VA	0.10	0.10	0.11	0.11	0.11	0.11
WI	0.10	0.10	0.11	0.11	0.12	0.12
CoV	0.19	0.18	0.20	0.15	0.17	0.16

Table XIII

The Baseline and the Counterfactual Outsourcing to Payroll Ratios for States of the U.S.The last row reports the coefficient of variation computed across states.

State	Base	Best TSP	Gross Out	Net Out	# of Firms	Wage
AL	0.10	0.15	1.005	1.006	1.004	1.015
AZ	0.12	0.16	1.006	1.007	1.006	1.009
CA	0.16	0.17	1.003	1.003	1.003	1.002
CT	0.15	0.17	1.003	1.004	1.003	1.005
FL	0.10	0.13	1.008	1.008	1.008	1.007
GA	0.10	0.16	1.009	1.010	1.007	1.019
IL	0.14	0.17	1.003	1.004	1.003	1.006
IN	0.10	0.16	1.009	1.010	1.007	1.018
KS	0.10	0.15	1.009	1.009	1.008	1.014
LA	0.15	0.15	1.000	1.000	1.000	1.000
MA	0.13	0.18	1.012	1.014	1.013	1.014
MI	0.10	0.17	1.011	1.012	1.009	1.021
MO	0.10	0.18	1.016	1.017	1.015	1.026
NE	0.09	0.14	1.006	1.007	1.005	1.014
NV	0.12	0.17	1.006	1.008	1.005	1.014
NH	0.13	0.17	1.009	1.009	1.009	1.009
NY	0.10	0.17	1.010	1.012	1.010	1.019
NC	0.12	0.17	1.003	1.003	1.001	1.016
OH	0.10	0.18	1.013	1.014	1.012	1.023
OK	0.08	0.17	1.019	1.020	1.019	1.027
OR	0.10	0.15	1.009	1.010	1.009	1.015
PA	0.12	0.17	1.008	1.009	1.008	1.014
RI	0.11	0.17	1.011	1.013	1.011	1.017
TN	0.14	0.21	1.004	1.005	1.001	1.022
TX	0.17	0.25	1.011	1.012	1.009	1.030
UT	0.11	0.18	1.013	1.014	1.013	1.019
VA	0.10	0.15	1.008	1.008	1.007	1.014
WI	0.10	0.15	1.012	1.012	1.011	1.015
Median	0.11	0.17	1.009	1.009	1.008	1.015
Max	0.17	0.25	1.019	1.020	1.019	1.030

Table XIV

The State-Level Counterfactual Results After an Improvement in Trade Secret Protection The values for columns 4 to 7 are relative to a baseline value of 1.

Moment	Data	Model	Parameter	Value
Job Destruction Rate	11.77	10.10	Firing Cost	0.81
Entry Rate	6.75	7.40	Fixed Operating Cost (c) - Food	246
Average Establishment Size - Food	56.75	53.42	Fixed Operating Cost - Wood	30
Average Establishment Size - Wood	43.96	43.98	Fixed Operating Cost - Heavy	309
Average Establishment Size - Heavy	49.14	50.48	Fixed Operating Cost - Light	29
Average Establishment Size - Light	44.83	44.28	Employee Factor Share (α) - Food	0.80
Outsourcing to Payroll Ratio - Food	0.12	0.12	Employee Factor Share - Wood	0.72
Outsourcing to Payroll Ratio - Wood	0.08	0.08	Employee Factor Share - Heavy	0.72
Outsourcing to Payroll Ratio - Heavy	0.15	0.15	Employee Factor Share - Light	0.71
Outsourcing to Payroll Ratio - Light	0.12	0.12	Shock Persistence (ρ) - Food	0.96
Share of Small Establishments - Food	0.52	0.62	Shock Persistence - Wood	0.94
Share of Small Establishments - Wood	0.59	0.55	Shock Persistence - Heavy	0.96
Share of Small Establishments - Heavy	0.52	0.45	Shock Persistence - Light	0.95
Share of Small Establishments - Light	0.59	0.65	Returns to Scale (θ) - Food	0.098
Revenue to Payroll Ratio - Food	12.89	12.42	Returns to Scale - Wood	0.151
Revenue to Payroll Ratio - Wood	7.53	7.26	Returns to Scale - Heavy	0.089
Revenue to Payroll Ratio - Heavy	14.13	13.97	Returns to Scale - Light	0.171
Revenue to Payroll Ratio - Light	6.97	6.53	Entry Cost (c^E) - Food	581
Output Ratio Food/Wood	2.47	2.58	Entry Cost - Wood	1827
Output Ratio Wood/Heavy	0.15	0.15	Entry Cost - Heavy	186
Output Ratio Heavy/Light	1.02	0.91	Entry Cost - Light	1494
GMM Objective Function Value		0.13		

Table XV

The Model Fit (Targeted Moments) and the Parameter Estimates for the Aggregate Economy

Notes: See Table II for the data sources for the targeted moments and Table II for a summary of the model parameters.

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