KEEPING INVENTION CONFIDENTIAL

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ABSTRACT

This study investigates the use of a prevalent but rarely studied form of intellectual property protection: trade secrecy. Building on existing survey evidence of firm-level, cross-sectional use of secrecy, we document the effect of stronger legal protections for trade secrets on the project-level use of such secrets. Our setting is the U.S. oil and gas hydraulic fracturing industry, from 2014 to 2018, in states where firms are required to disclose fracturing fluid ingredients to regulators except for substantiated claims of trade secrets. We examine how the enactment of the federal 2016 Defend Trade Secrets Act (DTSA) affects well-level trade secret use across states with varying levels of pre-DTSA protection. We find substantial increases in the use and novelty of trade secrets. Further, we find that wells with trade secret ingredients are on average more productive. However, the DTSA exerts limited additional effect on trade secret–related productivity. Supplementary tests address alternative explanations, show no evidence of IP substitution, and provide additional evidence that we are capturing policy effects. Our results provide rare empirical evidence on actual trade secret use and enhance our understanding of how appropriability shapes use of trade secrets and associated inventive activity.

INTRODUCTION

Intellectual property (IP) protection incentivizes innovation and thus shapes firm performance and economic growth. IP protection takes many forms, yet much of the empirical evidence on innovation focuses narrowly on patented inventions, likely because patenting requires detailed public disclosure that promotes empirical study. Firms report that other forms of IP protection, namely secrecy, are used more frequently and are more effective in protecting innovation (Cohen et al. 2000, Hall 1992, Levin et al. 1987, Linton 2016, Mezzanotti and Simcoe 2023, Sofka et al. 2018). Secrecy is both prevalent and economically important. For instance, the value of trade secrets for U.S. public firms is estimated to be more than $5 trillion and two-thirds of intangible assets (Chen et al. 2021, U.S. Chamber of Commerce 2014), and trade secret theft may cost up to 3% of GDP in industrialized economies (Ciuriak and Ptashkina 2021, Searle 2021). Trade secrets are hard to study systematically because their value and legal protection hinge on non-disclosure. Yet, because of their ubiquity, documenting firms' use of trade secrets is fundamental to understanding innovation.

Existing research provides two main empirical insights into secrecy use and the effects of trade secret-related polices on invention. First, using secrecy to protect inventions is common across firms, industries, locations, and time (Cohen et al. 2000, Arundel 2001, Jensen and Webster 2009, Thomä and Bizer 2013, Sofka et al. 2018). Second, stronger trade secret–related legal protections tend to increase R&D (Ganglmair and Reimers 2024, Png 2017a), and, in some sectors, lead to a decrease in patenting (Contigiani et al. 2018, Png 2017b). If patents were the only IP protection for invention, this would imply a decrease in innovation. However, firms use secrecy (and other means) to protect inventions even more than they use patents (Cohen et al.

2000, Mezzanotti and Simcoe 2023). Yet, we lack direct evidence on how changes in the appropriability regime, including in the legal protections of trade secrets, affect their use.[1]

Accordingly, this paper examines the effects of an increase in legal protection of trade secrecy on how and when firms use trade secrets. We posit that stronger legal protection lowers knowledge leakage risk—the risk of a firm failing to fully appropriate value from its IP. As such, increases in legal protection should lead firms to increase trade secret use. Further, the effect of stronger protections on use should be somewhat mitigated when substitute protections from knowledge leakage (e.g., non-compete enforcement) are present. Stronger protection should also lead to novel trade secret use, i.e., indirect evidence of trade secret–protected inventive activity.

Our context is hydraulic fracturing within the U.S. oil and gas industry. Whereas conventional oil and gas extraction involves drilling wells into reservoirs to access oil/gas, hydraulic fracturing involves forcing high pressure fluids—containing water, proppant, and various chemicals—into a well to fracture the surrounding shale rock and enable oil and gas extraction. Though fracturing is not wholly new (Montgomery and Smith 2010, Hall 2013), the percentage of U.S. wells using fracturing increased from less than 5% in the early 2000s to over 75% by 2019 (EIA 2016, 2018, 2020). Alongside this growth, firms experimented and invented new fracturing techniques and inputs (Curtis 2016, Fetter et al. 2018). Secrecy is a common means to protect IP (Cohen et al. 2000),[2] and likely particularly relevant in fracturing due to both the speed of production and the difficulty of reverse engineering fracturing fluids (Maynard 2013). Novel fracturing fluid recipes can increase well productivity (Fetter et al. 2018) and thus, if protected, can be a source of competitive advantage.

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[1] We define appropriability following the definition used by Teece (1986) and others (Cohen 2010): "A regime of appropriability refers to the environmental factors […] that govern an innovator's ability to capture the profits generated by an innovation."

[2] Surveyed firms named secrecy as the most common and effective IP protection tool in oil and gas (or petroleum) and chemical industries, as well as in many other U.S. industries: food, textiles, paper, rubber and plastics, mineral products, metals, machine tools, electrical equipment, motors and generators, semiconductors, and search and navigation instruments (Cohen *et al.*, 2000).

Two key features of this industry enable us to study trade secret use systematically. First, since the early 2010s, regulators have mandated the disclosure of all non–trade secret fracturing fluid ingredients in nearly all U.S. states with meaningful fracturing activity (McFeeley 2012, Fetter 2018).[3] Second, in a subset of the disclosure mandating states, regulators require firms who claim certain ingredients are trade secrets to justify their claims (McFeeley 2012).[4] These two features—disclosure of ingredients combined with substantiated and therefore bona fide trade secrets—allow us to observe trade secret use at a granular level and thereby to create (1) a well-level dataset of fracturing ingredients, including indicators for trade secret ingredients and (2) measures of novel trade secrets (i.e., indirect measures of trade secret-protected invention).[5]

To measure an increase in legal protection of trade secrets, we use the federal Defend Trade Secrets Act (DTSA), enacted in May 2016. The DTSA increased trade secret protection by adding a federal jurisdiction for trade secret cases stronger than existing state-level protections. We examine heterogeneous effects of the DTSA, distinguishing states with lower pre-DTSA protection (referred to hereafter as High Treatment States) from states with higher pre-DTSA protection (Low Treatment States) (Png 2017a, 2017b). We estimate the effects of DTSA on: (1) the use of trade secrets, measured as any use and proportion of trade secret ingredients used to fracture the well; and (2) the use of new trade secrets. We also examine the association between trade secret use and well productivity, and how that changes post-DTSA.

[3] The states with disclosure requirements and notable fracturing activity as of 2014 (the beginning of our study period) were: Alabama, Arkansas, California, Colorado, Indiana, Louisiana, Michigan, Mississippi, Montana, New Mexico, North Dakota, Ohio, Oklahoma, Pennsylvania, Texas, Utah, West Virginia, and Wyoming. Our sample consists of Arkansas, Colorado, Louisiana, Oklahoma, Pennsylvania, Texas and Wyoming, as they also have requirements for claiming trade secrecy.

[4] Note that justification involves attesting that the ingredient is a trade secret and that it is commercially valuable in being held secret, among other features (more details in context section). Arkansas, Colorado, Pennsylvania, and Wyoming require both formal submission and chemical family disclosure of the secret to regulators, while Louisiana, Oklahoma, and Texas require chemical family disclosure.

[5] Specifically, for each well we have a list of all ingredients, their category of purpose, and the specific ingredient name (if said ingredient is not "secret"). For example, well ID 05-077-10201-0000 has 34 listed ingredients: 32 of them are fully disclosed (ingredient name listed as e.g., acetophenone, water) and two of them are secret. Notably, we know that both secret ingredients are in the "friction reducer" category. We do not and cannot know the content of the trade secret. We use the category of secret ingredients to build several of our measures of new trade secret use.

We find that trade secret use increases substantially. Use of trade secrets at the well level increases by 22 percentage points (pp) post-DTSA in High Treatment States. Consistent with knowledge leakage risk driving use, we find that the effects are stronger under three conditions: in states with less stringent, indirect secrecy protection policies (lower non-compete enforcement); in situations with lower levels of interfirm trust between service firms and their fracturing customers (producer firms); and when location-related leakage to rival firms is more likely. Further, firms substantially increased their use of new trade secrets. For instance, the use of new-to-the-firm secret ingredients increased by 1pp (over 0.1% in High Treatment States). Wells with trade secret ingredients are also more productive, consistent with trade secrets providing a source of competitive advantage, though DTSA-induced increases in protections do not appear to unequivocally increase productivity. Supplementary analyses show little evidence of IP substitution (no evidence of decreased use of new disclosed ingredients or substitution between secrecy and patenting) or of increased attempts to cloak toxicity via trade secrets.

We provide the first direct evidence that firms respond to increased trade secret legal protection with increased use of such secrets. The study also provides some indirect evidence of increased trade secret–protected invention: firms increase their use of new trade secrets. Research shows that stronger trade secrecy protection leads firms to decrease patenting in some sectors (Contigiani et al. 2018, Contigiani and Testoni 2023, Png 2017a). However, trade secret protection was also found to increase R&D spending (Png 2017b). Our research suggests a missing piece in these findings: stronger trade secret protection may lead to increased trade secret–protected invention. Thus, the overall impact of trade secret protection on innovation is likely more positive, and more nuanced, than the patent-focused literature would suggest.

More broadly, we provide systematic study of a common and important but rarely analyzed form of IP. Given the widespread codification and cross-sector availability of patent data, scholars have understandably focused almost exclusively on measuring innovation using patents. Yet much innovation is not patented (Arora et al. 2016, Cohen et al. 2000, Fontana et al. 2013), and patents serve several non-innovation aims (Hall and Ziedonis 2001, Kang and Lee 2022, Noel and Schankerman 2013, Ziedonis 2004). In short, we have a limited picture of when and how firms invent and innovate. Our in-depth empirical study of the use of trade secrets therefore adds to growing non–patent-based empirical research relating appropriability to innovation, a literature that has generally explored copyright and trademarks (Block et al. 2015, Li et al. 2018, Nagaraj 2018, Castaldi 2020, Biasi and Moser 2021).

The paper proceeds as follows. The first section below provides background on trade secrets and IP protection, and the relationship between increased protection and use. The section thereafter introduces our context, the U.S. Hydraulic Fracturing sector. Then we provide some motivation for our empirical analyses. We then outline our data, empirical approach, and results. Last, we discuss the findings, limitations, and their implications for management and policy.

TRADE SECRETS AS IP PROTECTION: BACKGROUND

A trade secret is a commercially valuable item of information that derives value from being secret, and that firms must actively and effortfully conceal (Friedman et al. 1991).[6] As they are both difficult to imitate and valuable (Hall 1992), trade secrets can be a source of competitive advantage (Lemley 2008, Penrose 1959, Risch 2007, Sharapov and MacAulay 2022).

[6] The primary definition of trade secrets in the U.S. during the period of our study is based on the Uniform Trade Secrets Act ("UTSA") (1985): information, including a formula, pattern, compilation, program, device, method, technique, or process, that (a) derives independent economic value, actual or potential, from not being generally known to and not being readily ascertainable by proper means by other persons who can obtain economic value from its disclosure or use, and (b) is the subject of efforts that are reasonable under the circumstances to maintain its secrecy.

Across industries, locations, and time, firms often report secrecy as the most effective mechanism for protecting inventions (Cohen et al. 2000, Arundel 2001, Jensen and Webster 2009, Hall et al. 2014, EU IPO 2017).[7] Recent survey evidence suggests that 52% of R&D-active U.S. firms consider trade secrets important for protecting their IP, more than twice the rate for patents (Mezzanotti and Simcoe 2023). Typical inventions protected, in whole or in part, as trade secrets include recipes (of which a successful example is that of Coca-Cola), chemical formulae (WD-40), algorithms (Google search), manufacturing processes (the Mistron 604AV production process by the Luzenac Group, the world's largest talc producer), and blueprints (the foldable Apple iPhone prototype).

As a form of IP protection, trade secrets have several distinguishing features. First, and fundamentally, capturing the profits from them relies on non-disclosure. To enjoy legal protection, firms must engage in ongoing, demonstrable effort to prevent disclosure. Second, firms need not wait for government agencies to grant IP protection to use inventions protected as trade secrets; firms can use and protect them immediately.[8] Third, there is no time limit on the legal rights associated with a trade secret (Almeling et al. 2010b, Schwartz 2013).[9] Last, the type of information that is potentially protectable using trade secrets is relatively broad: trade secrets can be invoked to protect "valuable information," which can include technological inventions, but also non-technological information such as customer or price lists. Patents protect only novel, non-obvious, and useful technological information (Lemley 2008). Our focus is on technological information protected by trade secrets. Importantly, firms cannot claim information

[7] Inventions are novel, uncertain ideas, processes, methods, or objects that satisfy a given need (Kline and Rosenberg 1985, Arthur 2007, Giuri et al. 2007).
[8] The lack of a need for governmental approval of trade secrets also means there is no registry and thereby (unfortunately for researchers) no database of trade secrets.
[9] The current limit on patent monopoly is generally a 20-year term from the filing date of the application. Copyrights are generally limited to life of the author plus an additional term. For instance, in the U.S. and most countries in Europe, the additional term is seventy years.

as a trade secret if it is "readily ascertainable," already publicly known, or previously disclosed (Uniform Law Commission 1985). Therefore, trade secrets must be useful and involve some form of novelty, uniqueness and/or non-obviousness.[10]

Much research examining when firms are likely to use secrecy to protect inventions has contrasted secrecy and patents. Whereas patents require inventors to publicly disclose the invention in exchange for legal protections (though disclosure quality can vary (Amore 2020, Dyer et al. 2020)), protection via secrecy relies on the inventor effectively concealing the crucial inventive steps. Thus, for inventors, the benefits of trade secrets may outweigh those of patents when reverse engineering is difficult (Png 2017b), when codification is challenging (Arora 1997), when the patent regime is weak (Katila et al. 2008), when firms are mandated to disclose other valuable information (Sofka et al. 2018), or when, because secrecy does not require approval, firms highly value speed to market (Zaby 2010, Gans and Stern 2017). Firms may seek to protect their more novel inventions via secrecy in order to completely avoid disclosure (Anton and Yao 2004) and to have the option to maintain protection indefinitely. Notably, firms may use secrecy to complement patents and other forms of IP. For instance, secrecy can be complementary to future patenting, given that the contents of patent applications are typically kept secret prior to disclosure (Graham and Hegde 2015, Hegde and Luo 2018). Secrets and patents can also be contemporaneously complementary, for example, when a particular technology requires know-how for its productive implementation (Parker 2015).[11]

Loss of protection of a trade secret can happen through three channels. First, the secret can be illegally misappropriated, via theft, bribery, breach of contract, espionage, or other illegal

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[10] As per the UTSA: "Trade secret […] derives independent *economic value*, actual or potential, *from not being generally known* [authors' italics] to, and not being readily ascertainable by proper means by, other persons who can obtain economic value from its disclosure or use"

[11] Taken to its extreme, this complementarity may mean that trade secrets are not valuable on their own but only through their use with related resources and/or capabilities. In such cases, leakage of the secret alone may be less material.

means (Schwartz 2013). Second, secrets may inadvertently leak if firms do not take "reasonable" precautions. Such precautions include labelling, physical locks, secure facilities (e.g., the Coca-Cola Vault), cybersecurity efforts, restricting access via need-to-know rules, and/or contracts including non-disclosure agreements (NDAs) and confidentiality agreements (Schwartz 2013).[12] Secrets are typically stolen or leak out via business partners, employees, or rival firms (Almeling et al. 2010a, b, Lemley 2008). For instance, in *Wyeth v. Natural Biologics*, a former employee was found to have divulged Wyeth's hormone therapy-related trade secret to a rival firm, who, within a year, replicated it.[13] Employees may also inadvertently share potential trade secrets, such as when Samsung engineers posted proprietary code on ChatGPT.[14] Additional examples of both misappropriation and inadvertent disclosure are in Appendix A. Third, other parties may independently discover or reverse engineer an invention (Cronin 2015). Trade secret law protects against illegal misappropriation—the definition of which varies under different legal protection regimes—but not against inadvertent disclosure or if the secret is independently discovered or reverse-engineered.

In sum, secrecy is commonly used to protect inventions and substantively differs from other forms of IP protection such as patents. Trade secrecy laws determine what constitutes illegal misappropriation as well as the degree of punishment associated with misappropriation. Legal trade secret protections affect firms' expectations of trade secret–related appropriability and should therefore influence their use of trade secrets.

Increased Trade Secret Protection and the Use of Trade Secrets

[12] An illustrative example: Chocolatier Mars "designs and builds its candy-making equipment within the company so outsiders never see the full process, and it blindfolds outside contractors coming in to make repairs" (Snyder *et al.,* 2012). Notably, NDAs are used ubiquitously when dealing with trade secrets in the Oil and Gas industry (Tosto and Nuttall 2012).
[13] https://casetext.com/case/wyeth-v-natural-biologies
[14] https://www.bloomberg.com/news/articles/2023-05-02/samsung-bans-chatgpt-and-other-generative-ai-use-by-staff-after-leak

We know that secrecy is a common and important means of appropriating value from invention (Cohen et al. 2000, Arundel 2001, Jensen and Webster 2009, Thomä and Bizer 2013, Sofka et al. 2018). Further, secrecy-protected inventions can be highly innovative (Anton and Yao 2004) and valuable.[15] Historically, in countries with weaker patent laws and more reliance on secrecy, inventions were more novel and impactful (Moser 2013). Stronger trade secret policies lead firms to increase their R&D investments, as evidenced by responses to the pre-DTSA Uniform Trade Secrets Act (UTSA)[16] (Ganglmair and Reimers 2024, Png 2017a). Also, in some sectors, increased secrecy protection is associated with lower rates of patenting (Contigiani et al. 2018, Contigiani and Testoni 2023, Png 2017b).

However, a direct link between legal trade secret protection and the use of trade secrets has not been established. To begin to fill this gap, we examine the relationship between stronger legal protection of trade secrets and the use of trade secrets. Simply put, because increased legal protection decreases the knowledge leakage risk associated with use, we expect use of trade secrets to increase. We also investigate trade secret-protected inventive activity and provide some indirect evidence of an uptick following increased legal protection of trade secrets. Finally, we explore the productivity-related consequences of using trade secret–protected inputs.

CONTEXT: U.S. HYDRAULIC FRACTURING

Our empirical context is hydraulic fracturing in the U.S. oil and gas industry from 2014 to 2018. During the 2010s, hydraulic fracturing grew significantly in scale and economic importance worldwide, but especially in the U.S. (Feyrer et al. 2017). Fracturing use in U.S. oil and gas

[15] Scholars have pointed to examples suggesting secrecy is one of the most effective forms of IP protection. Teece (1986) argues Coca Cola's secret recipe exemplifies strong IP protected via secrecy.
[16] The Uniform Trade Secrets Act (passed in 1979 and amended in 1985) was intended to introduce a common set of rules for what constituted trade secrets, their misappropriation, and associated penalties across the U.S. States remained free to adopt selected parts of the Act and did so to varying degrees and at different times, a fact helpful for identifying effects both in our study and prior research (see Png 2017a, 2017b). Pre-UTSA, trade secrets were governed only by common law which varied substantially across states.

wells increased from less than 5% in the early 2000s to over 75% by 2019, which contributed to the U.S. becoming a net exporter of oil in 2019 (US EIA 2018, 2020).[17]

Hydraulic fracturing enables extraction of “unconventional” oil and gas deposits, i.e., those highly dispersed in shale rock or in deep coalbed formations. Because it enables extraction of otherwise trapped oil and gas, fracturing has significantly expanded areas of oil and gas development. The fracturing process first involves inspecting the underlying geology and selecting and calibrating the ingredients of the fracturing fluid—comprised of water, proppant materials, and chemicals—used to stimulate the shale rock and enable the flow of oil and/or gas. Service firms then drill and perforate a several-miles-long horizontal well, into which they inject their selected fracturing fluid.

Typically, hydraulic fracturing service firms fracture wells for oil and gas producers, who hold leases and thus property rights over the extracted oil and gas (Ma and Holditch 2015). As service firms compete to gain contracts from producers, they aim to demonstrate a higher net output of their services, including through their use of technological advances that improve well productivity (Kellogg 2011). Although several important factors can impact well productivity—including for instance, well location—a key input is fracturing fluid ingredients (Ma and Holditch 2015). Service firms have actively experimented with fracturing inputs, including fracturing fluid ingredients, since hydraulic fracturing first became commercially viable in the late 1990s (Curtis 2016, Curtis 2017). Such experimentation continues today (Quosay et al. 2020).

Since the early 2010s, most U.S. states with measurable hydraulic fracturing activity have required firms to publicly disclose fracturing fluid ingredients at the well level, except for

[17] Monthly import/export data available through Energy Information Administration: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=pet&s=mttntus2&f=m

ingredients held as trade secrets (Fetter 2018). We limit our sample to wells in states that both (1) require detailed fracturing-ingredient disclosure,[18] and (2) require substantiation of the legal validity of trade secret claims by the fracturing firms to preclude disclosure of trade secret ingredients (as state requirements for claiming a trade secret vary (McFeeley 2012), with only some requiring detailed justification to state regulators).[19] We employ the first limit out of necessity, and the second because our study aims to examine the use of trade secrecy to protect valuable intellectual property, rather than secrecy for other strategic motives, such as potential obfuscation of known ingredients from competitors (Fisk 2013, Tang 2024) or concealment of harmful input use from government and the public.[20] Our included states are Arkansas, Colorado, Louisiana, Oklahoma, Pennsylvania, Texas, and Wyoming, which encompassed roughly 80% of U.S. fractured wells from 2014 to 2018—all the years following ingredient disclosure mandates and for which we have data access.

To measure increased legal protection, we use the Defend Trade Secrets Act (DTSA).[21] Enacted in May 2016, the DTSA increased trade secret protection by creating the first-ever federal jurisdiction for adjudicating trade secret disputes and establishing additional legal remedies for misappropriation (for instance, the seizure of assets and remedies for triple damages). At the time of its passing, legal experts considered the DTSA the most significant

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[18] Based on our literature review, interviews, and manual review of hundreds of disclosure forms, hydraulic fracturing service firms specialize in designing and applying fracturing fluids and are thus required to disclose them to the regulators. Our data include a service firm for each well in the sample. The forms are typically filled out by an engineer overseeing chemical compositions of the service provider. In a request for disclosure exemption due to a trade secret, the signer usually must ascertain, under penalties of perjury, that the information provided is true, correct, and complete. Authorities may carry out inspections on site to check all fluid ingredients used in a well were reported.

[19] Justification typically includes firms attesting to the following: the information has not been disclosed beyond those outside of strict confidentiality; disclosure would cause substantial harm to the competitive position of the company; no Federal or state law requires the information to be made public; and the chemical identity is not readily discoverable.

[20] We investigate if there is any evidence of firms using secrecy to conceal harmful behavior using measures of chemical toxicity and find nearly all wells in our sample contain toxic ingredients (98.8%), and the likelihood and amount of toxic ingredients is the same whether the well includes trade secret ingredients or not (details in Appendix I).

[21] We use the enactment date of the legislation (May 2016) as it is the relevant date for firm secret activity, after which trade secrets were more likely to be protected. The Act was first presented in the House of Representatives and the Senate on July 29th, 2015; however, the data suggest little change to trade secret use pre-enactment.

expansion of federal IP law for at least 30 years (Levine and Seaman 2018).[22] Using the state-level index constructed by Png (Png 2017a, 2017b),[23] we use pre-DTSA state-level variation in trade secret protection to explore heterogeneity in the effects of DTSA on use of trade secrets.[24] States have different levels of pre-DTSA trade secret protection through diverging state-level applications of the Universal Trade Secrets Act (UTSA) (Sandeen 2010) and state common law.

Our approach relies on pre-DTSA levels of secrecy protection being exogenous to other factors that might cause trade secret use to disproportionally increase following DTSA enactment in High Treatment States. Several pieces of evidence suggest that this is not a concern. First, Png found that state adoption of the UTSA was unrelated to state-level economic and policy-related drivers of inventive activity (e.g., R&D tax credits, state legislature composition). Second, in supplementary analyses, we find no evidence of a relationship between pre-DTSA variation in secrecy protection and various relevant fracking disclosure and other relevant policies that could otherwise be generating our results (see Appendix B).

KNOWLEDGE LEAKAGE IN HYDRAULIC FRACTURING

To motivate our empirical analyses, consider a typical fracturing service firm, with a portfolio of existing assets, including IP. As it performs a fracturing service on a given well, the firm faces a key choice: which ingredients to include in their fracturing fluid recipe.[25] In choosing whether to use a trade secret ingredient in a particular well, the service firm trades off the expected value of using the ingredient against the risk of knowledge leakage, i.e., the use-specific risk that the

[22] Notably, federal trade secret litigation increased by 30% following the enactment of the DTSA. See Appendix P for an account of trade secret-related court cases following the DTSA.
[23] See appendix O for a description of the Png index values used in this paper.
[24] We exploit a uniform federal policy change applied to heterogenous pre-existing state-level policies. This approach is in line with other research which uses the introduction of Medicare to assess how health insurance affects hospital spending across states with varying pre-existing coverage (Finkelstein 2007).
[25] Service firms may use their own ingredients (including trade secrets) or ingredients sourced from third party supplier firms. We include details on externally sourced ingredients and trade secret ingredients in Appendix N. We assume the trade-off between value and leakage risk follows the same general logic when using externally sourced ingredients.

secret will leak out to rivals, ending the ingredient's IP protection forever.[26] This trade-off suggests that service firms will only use trade secret fracturing fluid ingredients when the value of using them exceeds such risk.[27]

Within this simple setup, we consider the effect of the DTSA. Stronger legal protections for trade secrets expand what constitutes misappropriation and/or increase the penalties for misappropriation (Png 2017a). Such extensions discourage misappropriation by increasing the concomitant expected costs and the likelihood that firms will be able to recoup losses if misappropriation occurs.[28] Because the DTSA lowered knowledge leakage risk, the expected value threshold for use decreased. We would thus expect that the DTSA increased the use of trade secret ingredients. Further, we would expect the increase to be largest in states that had relatively lower trade secret protection pre-DTSA.

Knowledge leakage risk is not just a consequence of trade secret policy. Leakage commonly happens through ex-employees leaving for rivals or through business partners (like customer firms) stealing confidentially disclosed information, both across all industries (see Appendix A) and in hydraulic fracturing specifically (see Appendix Q). Relatedly, knowledge leakage risk is likely to be lower pre-DTSA depending on three related drivers. First, knowledge leakage risk was likely lower in states with other strong policies that protect against firm's confidential knowledge leaking to competitors via ex-employees, e.g., relatively strong non-compete enforcement laws (Starr et al. 2021). Second, given that firms build relationships and

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[26] Recall that legal trade secret protection is available only if the information is not "generally known". Besides the legal repercussions of losing a trade secret, knowledge leakage implies rivals can reach competitive parity with little investment.

[27] The costs of losing a fracturing-related trade secret are potentially quite high. For instance, the damages associated with misappropriating fracturing-related secrets were assessed at $15 million and $25 million in two recent cases (see Appendix Q for details). Such damages include loss of competitive advantages and related R&D expenditure.

[28] Firms protect secrets using both prevention (e.g., contracts, locks, etc.) and retribution (e.g., legal action). The policy change affects the latter directly, by making misappropriation more costly and less likely. If prevention is the main mode of protection, the change in law may have limited effect on secrecy use and invention. However, if misappropriation risks matter, the legal change should have detectable effects.

trust through repeated exchange, knowledge leakage risk would be mitigated when the service firm represented a relatively large share of the producer firm's business (Poppo et al. 2016, Poppo and Zenger 2002)). Third, given that proximity to rivals can facilitate leakage (Ryu et al. 2018, Tallman et al. 2004), pre-DTSA, the risk should have been lower in locations with fewer rival service firms.[29] Notably, these factors may also have competing implications for the value of trade secret use. For instance, higher local rivalry may lead to increased differentiation-related value of trade secret ingredients and thereby drive-up their use. We leave it to the empirics to parse the net effects.

Beyond choosing from their existing set of trade secret fracturing fluid ingredients, a firm also has the ongoing choice to invent (and use) new ingredients and to protect them as trade secrets. To become valid trade secrets, such ingredients must have an element of novelty and/or non-obviousness and derive value from being secret. The tradeoff is a simple extension of the one above for the service firm: does the expected value of developing and using new trade secrets outweigh the costs, including, importantly, the leakage risk across the service firm's expected future uses? If stronger laws decrease the knowledge leakage risk associated with trade secret use, a firm will expect to appropriate more value out of any investments in developing new secrecy-protected inputs (Teece 1986). The DTSA should again increase secrecy-protected inventive activity through lowering future leakage risk, and thereby lead to increased new trade

[29] This logic was articulated to us in an interview with the CEO of a hydraulic fracturing firm. While it is predictably difficult to interview firms about their trade secrets, we were able to interview the CEO of one of the service provider companies in our sample. Our reasoning for knowledge leakage considerations is congruent with concerns he raised: "The people, the movement between companies is always an issue. And the other issue is we're not working in a secure environment. You can go on to a pad and probably obtain a sample of a chemical per se, or the customer may obtain a sample of the chemical and give to another service provider to say, 'hey can you figure this out? Because we're paying a lot for this. And if you could find something as good for cheaper, we'll use that instead'. And unfortunately, our customers, they play the game very well. They're continuously encouraging us to compete against each other whether it's done on the up and up or not. Right? So, for the most part, our worries are having to report and our customers giving our competitors the information […] we tend to avoid the, 'hey, we'll work for this customer for three months'. Then when that project's done, it's up for grabs because that's a real potential for everything that we learned from an efficiency perspective, that customer is going to give to the next service provider. And so that's a real issue. […] whether we like it or not, our trade secrets are constantly getting passed around."

secret ingredient use.[30] There is one important caveat here: secrecy is generally believed to have a dampening effect on knowledge spillovers (Cohen 2010),[31] which are a key input into invention (Jaffe 1986, Harhoff 1996, Png 2017b). Thereby, increased use of secrecy might indirectly depress follow-on inventive activity (Gross 2019). However, if rather than disclosed invention (i.e., patents) the counterfactual is little to no invention and copying of disclosed productive practices, as it is in fracturing (Fetter 2018), there are few spillovers to lose from increased secrecy protection and trade secret use. We therefore expect the indirect negative effects relating to spillovers to be muted in our setting.

Last, we consider the relationship between trade secret use and productivity. Building IP and protecting it via secrecy involves upfront investment (e.g., R&D) and ongoing costly effort (e.g., confidentiality agreements, electronic protections). Given such added cost, we would expect trade secret–protected inputs to provide additional value.[32] Moreover, if trade secrets are protecting valuable IP, their use should be associated with higher productivity. Productivity linkages are typically difficult to show at a granular level; for patents, researchers have looked at the relationship between filings and firm-level returns (Bloom and Van Reenen 2002, Pakes 1985). We link trade secret use and productivity by examining output at the well level. It is not

[30] We observe trade secret use. We do not observe any new trade secret-protected inventions that go unused. Further, as described in more detail in the empirics, we can only observe "new" secrets at the level of new-to-the-firm categories or types of ingredients.

[31] "Of all the appropriability mechanisms, secrecy entails the clearest suppression of knowledge flows and thus its use may entail the sharpest trade-off between the appropriability incentive effect on R&D versus the complementarity and efficiency benefits of spillovers, pitting the private incentives of firms most clearly against the innovative performance of an industry as a whole" (Cohen, 2010).

[32] A senior engineer who files trade secret claim forms with various authorities for Halliburton, a large service firm, was interviewed about the use of fracturing fluids by a professor at Oklahoma University. When asked about the need to rely on proprietary knowledge, she said the following: "As in any industry, there are things that each company has that provides them a competitive advantage. That is what is deemed to be proprietary information. The company invests millions and millions of dollars to develop this and to bring this formulation to the operators. It allows them [the service firm] to get a leg up on their competition. If the proprietary information was made available, then the competition [of the service firm] would be able to take that and reverse engineer it. In a very short order, it would negate our investment in all our research and technology development and it is millions every year. That would stifle our company to bring more innovative products to the marketplace down the road to solve other problems. Because, if we're losing our competitive advantage, there's no reason for us to have that". The interview is available via University of Oklahoma here: https://www.youtube.com/watch?v=BWw1VVXcH2Q&t=398s

immediately clear what the DTSA-related impacts will be for the association between trade secret use and productivity. Under weaker protections pre-DTSA, firms likely had a higher threshold for trade secret productivity. Trade secret use induced by the DTSA may therefore be on average less productive than in the initial, first-best application cases. Further, given the experimental nature of fracturing activities, policy-driven use may not provide clear gains, especially over the short term, as firms experiment with new uses and new ingredients.

DATA

We use data on well fracturing from the Shale Well Database of Rystad Energy. Rystad Energy collects and compiles data on the oil and gas industry from governmental databases and archives, company presentations, and industry reports, and it has been used both by academics (Aguilera 2014, Krane 2017) and policymakers (EIA 2014, Department for Business 2019).[33] Our analytical dataset includes data for 47,500 wells fractured from 2014 to 2018.[34] Figure 1 maps our full analytical sample of wells across High and Low Treatment States.

-Insert Figure 1 about here-

We examine trade secret use, use of new trade secrets, and productivity outcomes using well-level data. Well-level analyses allow us to account for time-invariant characteristics of involved firms—both the focal service firms who hydraulically fracture the wells and the producer firms who are the customers of the service firms and who own the rights to the oil and/or gas produced. Such analyses also allow us account for geological formation differences and time-related variance by including well location (basin) and month fixed effects.

[33] Further, we compared Rystad's data with DrillingInfo (Enverus), a widely used database for well production, and found that Rystad data contained around 98.2% of the number of wells captured by DrillingInfo for the same period in the selected states.
[34] For our measure of "new" secrets, we use wells from 2013 and 2014 as reference and start our analyses in 2015 (described in more detail in the sections below). Note that 47,500 wells are the sample used in regressions with our full suite of fixed effects (service firm, producer firm, basin, well type, and month) from the full sample of 47,617.

ANALYSES

To analyze the effect of stronger legal protection on trade secret use and associated novelty, we take a repeated cross-section, difference-in-differences approach, with a well as the unit of analysis (Cunningham 2021, Hong 2013, Sequeira 2016).

The sample includes 46 service firms (such as Schlumberger, Halliburton, and Patterson-UTI) and 461 producer firms (such as EOG Resources, ExxonMobil, and Chevron). An average service firm is associated with 1033 wells and a producer with 103 wells. Service firms specialize in hydraulic fracturing and bid for projects (well contracts). Their customers (producer firms) allocate projects based on cost, service firm expertise, and other relevant characteristics. Because a producer typically works with multiple service provider firms in and across geographic areas, service firms may worry about their trade secrets leaking to competitors via producer firms or (ex-)employees.

Key dependent variables: Our dependent variables measure: (1) trade secret use, and (2) new trade secret use. Our measures capture the use of trade secret fracturing fluid ingredients.[35]

Trade secret use: We measure secret use in two ways. First, we use a binary variable indicating whether a well uses any trade secret ingredient (*Trade Secret*). We considered an ingredient "trade secret" if both the ingredient name and the Chemical Abstract Service (CAS) number, a generic chemical identifier, are not disclosed. We choose this conservative definition of a trade secret because for a portion of ingredients, the CAS number is not listed, but the ingredients are easily identifiable from their name (or vice versa) to experts, which contradicts the legal definition of a trade secret.[36]

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[35] We unfortunately cannot observe use of other types of trade secret inputs, which may also change following the policy changes and may also affect firm outcomes.

[36] For instance, per our measure, an ingredient listed as "Crystalline Silica", which is commonly understood as sand, would not be recorded as secret, but "Proprietary" or "Trade secret" would be recorded as a secret, even if all omitted the CAS number. As such, we are measuring secrets more strictly relative to some previous research. Please see Appendix C for a discussion of our

Second, to ensure that our results do not result from the DTSA increasing the number of ingredients used (and, proportionally, trade secret ingredients), we also include a measure of the *Share of TS ingredients*.

New trade secret use: We also attempt to measure new trade secret use (as an imperfect proxy for secrecy-protected inventive activities). Because trade secret ingredients are necessarily undisclosed and their specific details thereby unobservable to researchers, we must indirectly infer the novelty of trade secrets. However, for both disclosed and trade secret ingredients, firms disclose, and therefore we can observe, the ingredient's chemical purpose category (CPC). Our sample of wells encompasses more than 2,300 disclosed ingredients (e.g., hydrochloric acid, glutaraldehyde, sorbitol tetraoleate, crystalline silica (quartz), potassium metaborate) as well as trade secret ingredients, across 19 CPCs. The 19 CPCs are well-established by the beginning of our study period and remain stable throughout.[37]

As a first measure, we infer a trade secret is new-to-the-firm trade secret ingredient if it is in a CPC in which the service firm has not previously used a trade secret ingredient (*New secret category)*.[38] For example, if a firm did not use a trade secret ingredient in the category of Acids before July 2016, but did so in that month, this would count as a use of a new secret category in July 2016 (and as 0 in any subsequent month). To establish novelty, we use 2013 and 2014 as a lookback window and use 2015–2018 as our years in this analytical sample. Notably, this is a somewhat conservative measure, as it is likely (though unobservable) that firms also generate new trade secrets in CPCs in which they already had trade secret ingredients. Further, because the CPCs are relatively broad, and because, ultimately, we cannot know the content of the trade

measure and analyses using a measure based only on the CAS number, following Konschnik and Dayalu (2016). The results are qualitatively similar using either measure, although the CAS number-based results are not significant in certain specifications.

[37] They are detailed in Appendix L.

[38] This measure is therefore likely undercounting new-to-the-firm trade secrets, as we cannot know if secrets in existing categories are new or existing ingredients.

secrets, our novelty measure cannot capture universal novelty with certainty.[39] New-to-the-firm trade secret ingredients may represent new-to-the-world inventions or they may represent unknown duplicative efforts. Given that trade secrets are not observable to rival firms, it is impossible even for firms to know if their new trade secret ingredients are new to the world.

We include two additional measures of new trade secret ingredients leveraging the CPC information. First, we create a measure that captures a *New secret category combination*, that is, the first time a firm uses a secret ingredient from category A and category B together in the same well. Second, we create a measure that uses the number of secret ingredients in a category used in each well and that captures if a well represents an *Additional TS in category*. For example, if a firm has only ever used one "Buffer" trade secret ingredient in a well and then uses two "Buffer" trade secrets in a well, this would count as an *Additional TS in category*.

Key independent variables: We measure stronger legal protection via a binary variable that takes 0 for the months before the DTSA was enacted (i.e., before May 2016) and 1 thereafter (Post-DTSA).[40] We measure heterogeneous treatment based on variations in the pre-DTSA state-level trade secret regime, using an index created by Png (Png 2017a, 2017b). The Png index consists of six elements of trade secret law: three relating to substantive law (degree of use; protective effort; use/disclosure required for misappropriation); one to civil procedure (time limits for owner to take legal action); and two for remedies (injunction limits; damages multiple).

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[39] The measure captures 'new-to-the-firm' new secret categories. As such, it is a high bar for novelty at the firm level but does not necessarily capture 'new-to-the-world' type inventions (which would be impossible to identify for trade secrets). It also favors firms that a priori had secrets in relatively few categories. For larger firms or firms that had existing trade secrets across many categories, this measure will fail to detect novelty. However, given that we cannot see the precise content of trade secret ingredients, exploiting categories at least allows some measure of new-to-the firm trade secret use, which provides some indirect evidence of secrecy-protected inventive activity.

[40] The DTSA received bipartisan support. One concern may be that firms in our sample (and especially those in high treatment states) drove the passage of the DTSA, i.e., they lobbied the government into passing the law. We think this concern is minimal for several reasons. First, the DTSA is a federal-level legislation. Second, in the oil and gas industry, the primary lobbying firms are large integrated companies, while the bulk of firms we study are specialist oilfield service providers. Third, lobbying expenditure in the industry declined in the years prior to the passage of DTSA (2015 and 2016): https://www.opensecrets.org/federal-lobbying/industries/summary?id=E01.

The stronger the protection, the higher the (state-level) Png index.[41] We categorize states into High Treatment States (those that had below median level of trade secret protection prior to DTSA: Arkansas, Louisiana and Pennsylvania) and Low Treatment States (those that had above or equal to median level of trade secret protection prior to DTSA: Colorado, Oklahoma, Texas, and Wyoming).[42] Note that because we are using repeated cross-sections for our difference-in-difference analyses (Hong 2013, Cunningham 2021), we also investigated if activity moved from Low to High Treatment States Post-DTSA, i.e., if there is evidence of compositional changes driven by treatment. We find the share of wells across locations remains stable (see Appendix D). In addition, while we opt for a binary treatment variable for ease of presentation across our main analyses, we also run the analyses using indicator variables for each state separately and use a continuous index variable to measure treatment intensity instead of the binary variable (see Appendix E). Both provide consistent results. Because lawsuits are tied to the location of trade secret use and misappropriation, we use state-level policies tied to well location.[43]

Control variables: We include firm fixed effects (for both the service firm and the producer firm) to control for any time-invariant firm characteristics, such as quality or inventiveness, that may also drive use of trade secrets. We also control for the type of well (oil, gas, mixed oil and gas) and the location (basin) in which the well is completed; different output mixes and geological formations may require different inputs and thus more (or less) secret

[41] The lower the substantive requirements, the longer the time to take legal action, and the higher remedies, the higher the score on Png index. The score is the average across all six dimensions, and hence bounded between 0 and 1.
[42] We follow the public algorithm provided by Png (2017a, 2017b) to compute the index value for Texas, which adopted UTSA after the observation period in the Png articles and posted data. For all other states, we used existing Png index values. See Appendix O for more details on the index construction.
[43] As per LexisNexis database, "State courts generally have jurisdiction over trade secret disputes. In determining which state has jurisdiction, *courts consider where the alleged misappropriation and damage occurred* [authors' italics]." https://www.lexisnexis.co.uk/legal/guidance/trade-secrets-usa-q-a-guide. Also, we interviewed Prof. Mark Schultz, an expert in Trade Secret law, co-author of the OECD Trade Secret Index (Lippoldt and Schultz 2014). In response to a question about the likely location of trade secret lawsuits in our setting, he said "It's a fair statement to say that most of the time it's going to be the location of the well".

ingredients on average. Also, we include month fixed effects (e.g., June 2017) to capture economic and technological factors, which may affect secrecy use.[44]

Moderators: We contend that trade secrecy use will be driven in part by concerns around knowledge leakage risk, and that strengthening of legal protections of trade secrets increases use because it alleviates some of this risk. Therefore, we investigate whether firm response to the DTSA is muted in contexts where leakage concerns are less acute for reasons relating to other relevant policies, inter-firm trust, and/or rival proximity.[45] First, we use the non-compete enforceability (NCE) index of Starr et al. (2021) and separate states into those with *High NCE* and *Low NCE.*[46] As non-competes restrict the mobility of (former) employees, one key channel of secret loss, we expect that knowledge leakage risk will be lower when enforcement is higher. Second, we distinguish the service firm's customer firms (producers) based on *High customer trust* and *Low customer trust* based on the amount of the service firm's business the customer represents (with an above-median annual share of business proxying for higher trust). Higher inter-firm trust should lead to a lower expectation of knowledge leakage. Third, we examine how the number of proximate competitors relates to knowledge leakage risk. We denote *Many Rivals* as a binary variable if the number of firms in a county completing wells in the month of completion of the focal well was above the sample median (4 firms), and *Few Rivals* otherwise.

Econometric specification: The main specification is the following:

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[44] In Appendix F, we replace month fixed effects with oil price controls to estimate the role of changes to the competitive environment and time trends as an alternative control for the passage of time. The results remain similar.

[45] It is possible that the effect of the DTSA could be very low (or even non-existent) if other policies or contextual factors lowered knowledge leakage risk so much as to fully alleviate such concerns. We assume no existing policy or situation provides such protection in our context pre-DTSA. We thank a reviewer for pointing this out.

[46] Following Starr et al. (2021) index, high non-compete protection states are Louisiana, Colorado, Wyoming, and Pennsylvania, while low non-compete protection states are Texas, Oklahoma, and Arkansas. We categorize the first four states as high non-compete protection states because they rank closely together and provide a 4 and 3 state split for the two groups. There are both high and low treatment states in both groups.

$$Y_{ijklt} = \beta_1 PostDTSA + \beta_2 HighTreatment + \beta_3 PostDTSA * HighTreatment + \sigma_i + \omega_j + \theta_k + \lambda_l + \tau_t + \varepsilon_{ijklt},$$

where Y represents our well-level dependent variable, *HighTreatment* indicates well location in a state with lower state-level trade secret protection, and *PostDTSA X HighTreatment* captures the effects of DTSA in states with lower protection (and thus β_3 is the main coefficient of interest). We include fixed effects for well fracturing month (τ_t), service firm (σ_i), producer firm (ω_j), well type (θ_k), and location (basin) (λ_l); ε is the error term. We cluster standard errors at the state-level, i.e., the level of treatment assignment.[47] For ease of presentation and interpretation, we use linear models throughout.[48]

RESULTS

Table 1 includes the descriptive statistics at the well level for the entire 2014–2018 sample period. Of 47,500 wells, 56% contain at least one trade secret ingredient. On average, 5% of all ingredients are trade secrets. Also, 0.6% of wells include new-to-the-firm trade secrets, i.e., trade secret ingredients in categories in which the fracturing firm has not previously used a trade secret ingredient.[49]

In addition, we include sample statistics for the main outcome variables pre- and post-DTSA (Table 2). On average, trade secret use increased from 45% to 77% of wells, while new secret use rose from 0.4% to 0.8% of wells.

-Insert Tables 1 and 2 about here-

[47] In Appendix G, we cluster standard errors at the service firm level. In Appendix G we also include wild cluster bootstrap estimated p-values for all main coefficients to address concerns regarding relatively few states (clusters). Canay et al. 2021 highlight wild bootstrap as a suitable solution, in particular in cases where the number of clusters is small but the number of observations per cluster is large, such as ours. Our core results are robust to the different clustering specifications.
[48] We also ran logit (for binary dependent variable) and Poisson (for count dependent variable) models. We also ran firth logit models for the new trade secret analyses (since the outcome was somewhat rare). The results are qualitatively similar.
[49] Per this operationalization, 191 wells in the sample have new-to-the-firm trade secret ingredients between 2015 to 2018.

Moving to our main analyses, in Figures 2 and 3, we plot the raw patterns in trade secret use pre- and post-DTSA across High and Low Treatment States. Figure 2 shows the proportion of wells using any trade secret ingredient. In Figure 3, we depict the share of trade secret ingredients used per well. These figures show clear evidence of increases post-DTSA, with High Treatment States having a more pronounced increase in the use of any trade secret ingredient (Figure 2) and in the share of trade secret ingredients used (Figure 3).[50] These graphs also highlight similar trends for Low and High Treatment States pre-DTSA.

-Insert Figures 2 and 3 about here-

In Table 3, we depict the effect of increased secrecy protection on the use of trade secret ingredients. First, we investigate whether a well contained any secret ingredient (column 1). We find that, following the enactment of DTSA, the likelihood of using a trade secret ingredient increases by 22pp in High Treatment States relative to Low Treatment States (over the pre-DTSA baseline of 25% in High Treatment States).[51] Second, we find that the share of trade secret ingredients increases in High Treatment States by 3.7pp relative to Low Treatment States (over the baseline of 2.3% in High Treatment States (column 2)). Put simply, trade secret use increases disproportionately. Taken together, these results show that the use of trade secret–protected ingredients increased substantially with increased legal protection.[52]

Next, we study the use of new trade secret–protected ingredients. As outlined above, because we cannot observe the details of each secret ingredient to know with certainty if it is new to the world, we infer new trade secret ingredient use via three measures that leverage CPC

[50] While the increase in use of trade secrets is stable post-DTSA (Figure 2), the share of secret ingredients continues to increase (Figure 3). While speculative, given our other results which are consistent with secrecy-protected inventive activity ramping up post-DTSA, we interpret these results as reflective of this ramp up (e.g., newer ingredient use).
[51] We also ran the analyses using a continuous measure for secret protection level as well as by-state analyses and found results consistent with our main tables, see Appendix E.
[52] Appendix K collapses well-level results and presents similar findings at the firm level.

details and suggest firm-level novelty: *New TS category* (the strictest measure); *New TS category combination;* and *Additional TS in category.*

We present these results in columns 3–5 (Table 3). Post-DTSA, the likelihood of using a trade secret in a new category increased substantively—by 1pp in-High Treatment States. Though using a trade secret in a new category is a rare event (0.4% average likelihood pre-DTSA across all states and 0.1% chance in High Treatment States), the 1pp increase indicates a significant increase with respect to the pre-DTSA baseline. For *New TS category combination*, the likelihood increases by 0.9pp (from pre-DTSA average of 0.5% in High Treatment States). For *Additional TS in category*, the likelihood increases by 1.1pp from 0.4% pre-DTSA in High Treatment States. In sum, we find some indirect support for an increase in trade secret–protected inventive activities, as proxied by increased use of new-to-the-firm trade secret ingredients.

-Insert Table 3 about here-

In addition, we examine how knowledge leakage risk conditions the effects of increased legal protection on the likelihood of using trade secret ingredients. We would expect trade secret legal protection to have the strongest effects in situations in which firms had previously been more wary of using trade secret ingredients out of heightened fear of knowledge leakage. In Table 4, we find that post-DTSA, High Treatment States with lower non-compete enforcement (NCE) have a higher increase in the use of trade secrets (columns 1 and 2). Notably, the NCE analysis is based off state-level variation and should be interpreted with care. In columns 3 and 4, we show that the results are stronger for wells completed in situations of relatively low trust between service and producer firms. Wells fractured in High Treatment States post-DTSA in lower inter-firm trust contexts see a 30pp increase in trade secret use, while wells in higher inter-firm trust contexts do not experience such an increase. In other words, these results suggest that stronger legal protections create conditions amenable to using trade secrets, even when inter-firm relationships may be relatively weak. Finally, in columns 5 and 6, we see that wells in proximity to many rivals are more likely to contain secrets following the passage of DTSA in High Treatment States.[53] Being proximate to many rivals may drive higher use of trade secrets for value-related reasons (i.e., differentiation). However, we find having many nearby rivals is only associated with increased trade secret use post-DTSA (see Appendix M), which is consistent with knowledge leakage risk. Collectively, the Table 4 results are consistent with stronger legal protection attenuating knowledge leakage concerns.

-Insert Table 4 about here-

Alternative Explanations

We now turn to investigating alternative explanations for our results.

One main concern is that instead of measuring increased use of trade secret–protected IP, we are capturing "relabeling" effects, i.e., firms are labelling previously disclosed ingredients as "trade secret." Given that the details of trade secret ingredients remain secret to us, we cannot investigate this possibility directly. However, we consider it unlikely for several qualitative reasons, and because of wide-ranging indirect evidence inconsistent with relabeling.

First, it is not clear why incentives for relabeling would increase discretely in May 2016 and be particularly focused in states with lower pre-DTSA protection (and thus explain our results). Second, and more generally, firms can only legally defend trade secrets if the inventions have not been previously disclosed and are not publicly known (Johnson 2021). We expect this argument against relabeling to apply particularly strongly in our sample states, where firms incur costs in claiming trade secrets (including a high-ranking employee, typically engineer, signing a

[53] We include split sample analysis in the main paper for ease of presentation. A version of the results with triple interactions is included in Appendix M. The results are consistent with split sample results.

document that the trade secret ingredients have not previously been disclosed[54]). Third, given the disclosure requirements in our setting, we assume that competitors would be able to infer the re-labeled "secret" ingredients from previously disclosed recipes. Fourth, additional analyses suggest overall changes of the well-level recipes and contradict relabeling explanations. In terms of categories of ingredients, they increase overall as well as for trade secret categories, with no significant decline in disclosed categories in High Treatment States, while the likelihood of using a new disclosed ingredient actually increases (Table 5).[55] Fifth, service firms increase their external sourcing of trade secret ingredients (i.e., from third party chemical providers), which again is not consistent with relabeling.[56] Sixth, our analyses of productivity associations (see below) suggest that recipes with trade secrets are on average more productive than those without, suggestive of meaningful differences inconsistent with relabeling. In sum, the legal landscape of trade secret protection, the disclosure environment in our context, the requirements to claim trade secrets in our sample, and the broader findings of changes in fracturing fluid composition all fail to support the conjecture that firms' increased use of trade secrets is relabeling of previously disclosed ingredients.

-Insert Table 5 around here-

[54] The veracity of these submissions may be checked by government officials. Per the legal counsel of the service provider firm in our sample: "It's important that people know what is going down into the well site to know that if I'm putting something down there, I have thought through it, and I know what it is and I disclosed it and regulators can come and check, test it out and see that the components and ingredients that we said are the things that are contained in it […] They do that from time to time. It's not in every well that they do it, but they do samples from time to time."

[55] We measure *new disclosed ingredients* using the disclosed chemical identifiers (Chemical Abstract Service (CAS) numbers), noting when an ingredient (CAS) is first used by a service firm.

[56] Firms source a large portion of their inventions from outside the firm (Arora et al. 2016). To further investigate evidence for invention rather than relabeling, we investigate the sources of ingredients. Additional analyses on the sourcing of trade secret ingredients suggest ingredient recombination in recipes: we find that post-DTSA, service provider firms source more ingredients from third party suppliers, and in High Treatment States. See Appendix N for details.

A second alternative explanation is potential IP substitution. In other words, the strengthening of trade secrecy protection may cause firms to switch from protecting their fracturing fluid–related IP via secrecy to protecting it via other modes (for instance, patenting).

Two sets of analyses suggest that substitution is not driving our results. First, we find no evidence of decreases in new disclosed ingredient use (Table 5). Instead, our results are consistent with complementarity between disclosed and trade secret–protected invention. Second, to explore the potential of IP substitution further, we examine patterns in the relationship between the DTSA, associated increases in trade secret use, and firm-level patenting. It is important to note that most firms in our sample patent relatively little, either before or after the DTSA, which makes it doubtful that patent-related IP substitution drive our results. However, to investigate patenting more directly, we examined the relationship between fracturing-related patenting (Kapoor and Murmann 2023) and trade secret ingredient use at the firm-month level, pre- and post-DTSA (see Appendix H). While the analyses are descriptive associations, we find no evidence of a negative relationship between the firm patenting—whether we count all fracturing related patents, or just those covering chemicals (those most narrowly related to fracturing fluid ingredients). Further, we see larger increases in secrecy use post-DTSA among patenting firms, suggesting that our results are not due to firms changing IP protection type (i.e., IP substitution).

A third alternative explanation, given the environmental and policy stakeholder attention to the industry (Osborn et al. 2011), is that a firm's use of secrecy is driven not by protecting IP but instead by trying to conceal "bad" behavior, i.e., the use of environmentally damaging and toxic ingredients. We cannot directly observe if secret ingredients are more toxic than those disclosed, as such information is, by definition, secret. However, to examine this third alternative explanation, we explored patterns in the toxicity of disclosed ingredients. To do so, we use the Environmental Protection Agency (EPA) Toxics Release Inventory (TRI) list of toxic chemicals to identify toxic fracturing ingredients, as well as the subset of toxic ingredients that are environmental pollutants. We link these lists into our data using CAS number, which is a unique numerical identifier for chemical substances and is available for all disclosed ingredients. Across our sample, 98.8% of wells had at least one disclosed toxic chemical, which suggests both pervasive and public use of toxic ingredients. Further, on average 6 disclosed ingredients per well are toxic, and there is no difference across wells with and without trade secret ingredients. We ran regressions to explore if there is evidence that firms that use trade secret ingredients post-DTSA in High Treatment States decrease their relative use of disclosed toxic (or pollutant) ingredients. The results in Appendix I show no evidence of relative changes in line with cloaking. In other words, toxic ingredients are commonly and intensely used and similarly disclosed across wells with and without secret ingredients, and this pattern does not change with stronger secrecy protection. We also see no evidence of increases in court cases relating to fracturing toxicity and damages in High Treatment States (Appendix I), further supporting our contention that increases in trade secrets are not merely directed towards cloaking toxic ingredients.

Decomposing post-DTSA period

We explore if there is any evidence of potentially decreased opportunities for knowledge spillovers across firms post-DTSA. To do so, we decompose our post-DTSA indicator variable into four six-month periods (e.g., July-Dec 2016, Jan-June 2017, etc.). If a general increase in secrecy curtailed knowledge spillovers, we might expect to see some decreases over time. Yet, we find increases persist in High Treatment States, suggesting that spillover-related constraints are not (or at least not yet) binding (Table 6).[57] In terms of new trade secrets, in High Treatment States, firms use new trade secret ingredients more after about a year post-DTSA, which suggests some ramp-up is needed post-policy to invent and use new ingredients. This lag also provides additional corroborating evidence that our new trade secret analysis implies increased secrecy-protected inventive activity, rather than relabeling or copying. Overall, these additional analyses show little evidence of negative effects of reduced spillovers emerging during our study period.

-Insert Table 6 about here-

Trade Secret Use and Productivity

Finally, we investigate the association of the use of trade secrets with well productivity. We have argued that firms use trade secret ingredients to obtain a competitive advantage: in our case, hydraulic fracturing firms use and keep trade secret ingredients if they produce higher well productivity. In general, a service firm's ability to obtain lucrative contracts with a producer firm depends on its ability to demonstrate value, i.e., to extract more oil and/or gas for the producer. In this section, we explore the association between trade secret use and well productivity. If trade secret ingredients provide value, we should, on average, see a positive association between trade secrecy and well productivity. However, it is not clear whether the DTSA-induced use of trade secrets will be associated with increased productivity. If we assume that firms trade off the value from use against the risks of leakage as they decide when to use trade secret ingredients, we expect trade secrets to be used where they are most productive pre-DTSA. When the risk of leakage decreases post-DTSA, the productivity bar for use would also decrease. As a result, the effect of the DTSA on the association between trade secrets and productivity is somewhat ambiguous.

[57] A lack of a decrease also provides some support that these increases are policy-driven, as they and the DTSA persist over the full period.

To investigate these relationships, we first compare the productivity of wells that have a trade secret ingredient to those without. We use standard industry productivity measures: average daily production in the first 30 days of the well's productive life, also referred to as Initial Production in the first 30 days (or IP30), measured in barrels for oil and in thousands of cubic feet for gas. Figure 4 shows that, on average, use of trade secret ingredients is associated with a 26% increase in production of oil and a 6% in production of gas.[58]

-Insert Figure 4 about here-

Tables 7a and 7b include regression results for the relationship between use of trade secret fracturing fluid ingredients and well productivity, including DTSA-associated effects. The simple correlations (columns 1) suggest that a well with a trade secret ingredient produces around 96 more barrels per day in the first 30 days and 135,000 more cubic feet of gas.[59]

Table 7a includes results for oil productivity. In regressions that include service firm, producer firm, basin, well type and time fixed effects, the statistical significance of the trade secret–productivity association falls (Column 2). The relationship between trade secret use and productivity is positive post-DTSA (Column 3). If we split the post-DTSA period into 6-month periods, the results suggest that the surge is largest in the initial period, possibly as firms find the most fruitful opportunities to repurpose their existing trade secrets. The magnitude of the coefficient drops and then rises again towards the end of our observation period, which would be consistent with some of the new trade secrets (as per Table 6) being introduced into wells successfully. However, the result is not statistically significant.

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[58] These statistics are based on the entire sample of wells, without differentiating the predominant type of hydrocarbon produced. Wells may produce oil, gas, or both. We further study these associations in Appendix J. The raw associations hold for focused wells and when we control for service firm, producer firm, basin, well type, and time fixed effects.

[59] This is likely a conservative estimation. Another way to specify this regression is considering wells that only produce oil, and vice versa for gas. Note this categorization is only apparent ex-post, and thus we include the full sample in this analysis. If we focus on the different split samples, the association between trade secret use and productivity is substantially higher. See Appendix J.

Table 7b includes results for gas productivity. The raw correlation between the well using a trade secret and gas productivity in the whole sample is positive. The result is not statistically significant at conventional levels once fixed effects are introduced. As a result, we cannot conclude that the DTSA was associated with an increase in trade secret–driven well productivity in gas.[60]

-Insert Tables 7a and 7b about here-

DISCUSSION AND CONCLUSION

Trade secrets are highly valuable to firms and the economy. Thus, understanding secrecy-protected IP, and how different legal protection regimes alter it, is important in understanding firm performance and economic growth. In this paper, we have investigated when firms use this prevalent but understudied mode of IP protection. In the hydraulic fracturing context, we find not only that the use of fracturing fluid ingredient trade secrets is pervasive, as survey-based research would suggest (Levin et al. 1987, Cohen et al. 2000, Hussinger 2006, Sofka et al. 2018, Veugelers and Schneider 2018), but also that the use of trade secrets and novel trade secrets responds to trade secret policy.

Stronger trade-secret policies spur an increase in the use of trade secrets both across and within projects (in our setting, wells). Also, firms increase their use of new trade secret ingredients, which provides some indirect evidence for an increase in secrecy-protected inventive activity. At the same time, firms do not decrease their use of disclosed novel ingredients, or their fracturing-related patenting. Hence, this paper supplements existing research on the indirect effects of trade secrecy policy on R&D and patenting—which has implied that secrecy protection may lead to less disclosed inventive outputs—as well as other innovation-related outcomes like

[60] In additional analyses, we do not find evidence that the DTSA drove additional increases in productivity in High Treatment States relative to Low Treatment States.

M&A (Castellaneta et al. 2017, Png 2017a, 2017b, Contigiani et al. 2018). Our findings not only provide a first systematic and detailed empirical analysis of trade secret use but also provide additional nuance to literatures focused on patents-as-invention. In particular, the results appear to show that stronger trade secret protection enables experimentation, including novel recipes, broader sourcing, and a higher likelihood of novel (to the firm) disclosed inputs. The last result may suggest mild complementarity between secrecy and disclosure rather than IP substitution, consistent with evidence at the product level (Crass et al. 2019).

We focus our main analyses at the fracturing fluid ingredient level, both for pragmatic reasons (i.e., they are the trade secrets we observe) and because fracturing ingredients are important for productivity (Fetter, 2018). Our empirical results suggest fracturing fluid recipe compositions change and complexity appears to increase with trade secret protection as well (Table 5). As in other recipes and formulas, fracturing fluid ingredients interact with one another, and thus, it is not surprising that increased use of trade secrets leads to more complex recipes. These findings may also imply more follow-on innovation-related impacts of increased trade secrecy protection; however, we leave full investigation of these relationships to future research.

Our study has several limitations. First, while we can see trade secret use and see information about the purpose of the related ingredient, we still are unable to observe what exactly is kept secret. Hence, we must infer new secrecy-protected invention indirectly. Ultimately, without knowing the substance of the secret (which is highly unlikely given that trade secrets enjoy potentially perpetual protection, conditional on non-disclosure) and without access to the corpus of all trade secrets that predate a given trade secret, such limitations are unavoidable. Second, we are focused on just one industry, and it has features that likely lead to relatively high levels of secrecy use. As such, our findings are likely most generalizable to similar settings with features that support the use of secrecy. These include settings where the risk of reverse-engineering is relatively low (e.g., algorithms, chemical compounds, perfumes, plastics, production processes), where the pace of technological change is relatively quick, or where patenting is not the sole or default IP protection mechanism. Third, even though we can observe trade secret use, we are limited to one type of trade secret, i.e., fracturing fluid ingredients. We therefore cannot examine the full patterns of secrecy use in hydraulic fracturing (e.g., processes, techniques). Fourth, while we find suggestive evidence of an increase in secrecy-protected inventive activity—the use of new trade secret–protected ingredients—following increased trade secrecy protections, we observe a relatively short period following the change in policy. This short post-policy window limits our ability to detect any potential decreased knowledge spillovers that may emerge over the longer term as secrecy use increases. Furthermore, we cannot measure spillovers. However, because spillovers are unobservable, even patent measures using citation patterns are indirect and error-prone (Arora et al. 2018); moreover, unintended, market-unmediated spillovers are likely overestimated in the literature (Arqué-Castells and Spulber 2022, Fadeev 2023). Last, we focus on the use of trade secrets and secrecy-protected inventive activity. Building on this work, future research may explore substitution or complementarities of secrecy with other IP protection methods, such as patents or trademarks.

In sum, we have shown that stronger trade secret protection increases firms' secrecy use, and we provide some suggestive evidence that secrecy-protected inventive activity also increases without any measurable decrease to disclosed inventive activity. Our results highlight the importance of studying various forms of intellectual property protection due to their ubiquitous use in organizations.

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Table 1. Descriptive statistics: well level

Variable	Obs.	Mean	Std. Dev.	Min	Max
Trade secret (TS) (0/1)	47,500	0.56	0.5	0	1
Share of TS	47,500	0.05	0.08	0	0.75
New TS category (0/1)	30,468	0.01	0.08	0	1
New TS category combination (0/1)	30,468	0.01	0.11	0	1
Additional TS in category (0/1)	30,468	0.01	0.09	0	1
Number of categories	47,500	11.66	2.82	1	19
Number of secret ingredient categories	47,500	1.06	1.51	0	14
Number of disclosed ingredient categories	47,500	10.6	3.1	0	19
New disclosed ingredient (0/1)	30,468	0.07	0.25	0	1
Post-DTSA (0/1)	47,500	0.35	0.48	0	1
Well in High Treatment State (0/1)	47,500	0.11	0.32	0	1

Table 2. Descriptive statistics for main dependent variables pre- and post-DTSA by treatment, well level

		Pre-DTSA	Post-DTSA
Trade secrets	All wells	44.80%	76.90%
	High Treatment	25.20%	73.20%
	Low Treatment	47.40%	77.40%
Share of TS	All wells	3.80%	6.90%
	High Treatment	2.30%	8.40%
	Low Treatment	4.20%	6.80%
New TS category	All wells	0.40%	0.80%
	High Treatment	0.10%	1.40%
	Low Treatment	0.50%	0.70%
New TS category combination	All wells	0.90%	1.50%
	High Treatment	0.50%	1.40%
	Low Treatment	1.20%	1.50%
Additional TS in category	All wells	0.70%	1%
	High Treatment	0.40%	1.40%
	Low Treatment	0.60%	0.90%

Table 3. Trade secret use and stronger appropriability

	(1)	(2)	(3)	(4)	(5)
	Trade Secret	Share of TS	New TS category	New TS category combination	Additional TS in category
High Treatment State	-0.083	-0.014	0.003	0.011*	-0.009
	-0.076	-0.017	-0.007	-0.005	-0.009
Post X High Treatment State	0.220***	0.037**	0.010***	0.009**	0.011***
	-0.032	-0.012	-0.002	-0.003	-0.002
Observations	47,500	47,500	30,436	30,436	30,436
R-squared	0.408	0.614	0.110	0.080	0.060
Producer Firm FE	Yes	Yes	Yes	Yes	Yes
Service Firm FE	Yes	Yes	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes	Yes	Yes
Basin FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Notes: Each column represents a separate regression examining well-level fracturing fluid trade secret use. The dependent variables are indicated at the top of each column: Trade secret is a binary variable for whether there are any trade secret in the well, Share of TS is the number of trade secrets over the total number of ingredients, New TS category indicates the introduction of a new-to-the-firm category of trade secrets in the well; New TS category combination signifies a new combination of trade secret categories used in a well; Additional TS in category captures additional trade secrets in a category. High Treatment State refers to the key independent variable of interest in the analysis. Post X High Treatment State is an interaction term between a post-period indicator (Post-DTSA) and the High Treatment State indicator. In columns 3-5, the sample is based on the years 2015-2018, since we use 2013 and 2014 as a lookback window to begin identifying novel ingredients for 2015 and subsequent years. Robust standard errors are in parentheses below each coefficient estimate and are clustered at the state level. Statistical significance levels are denoted as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Trade secret use and knowledge leakage risk: non-compete enforcement, inter-firm relationships, and rival location

	(1)	(2)	(3)	(4)	(5)	(6)
	Low Non-Compete Enforcement	High Non-Compete Enforcement	Low Customer Trust	High Customer Trust	Few Rivals	Many Rivals
	Trade secret					
High Treatment State	0.391***	-0.091	-0.196***	-0.053	-0.074	-0.058
	(0.010)	(0.064)	(0.042)	(0.114)	(0.072)	(0.040)
Post X High Treatment State	0.501***	0.236	0.296***	0.019	0.186***	0.390***
	(0.001)	(0.101)	(0.036)	(0.058)	(0.039)	(0.049)
Observations	34,604	12,892	23,690	23,788	19,684	27,762
R-squared	0.407	0.467	0.464	0.491	0.479	0.410
Operator Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Supplier Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Basin FE	No	No	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable for all columns is Trade Secret, indicating the presence of any trade secret in the well. Columns 1 and 2 present results on trade secret use under different non-compete enforcement regimes. Columns 3 and 4 present results on trade secret use under different levels of trust with customer firms, captured by a binary variable above and below the median share of business carried out with a particular customer. Columns 5 and 6 present results on trade secret use under different rival levels within a county, captured by a binary variable based on the number of competitor firms contemporaneously operating in the county, split at the median. High Treatment State refers to the key independent variable of interest in the analysis. Post X High Treatment State is an interaction term between a post-period indicator (Post-DTSA) and the High Treatment State indicator. Robust standard errors are provided below each coefficient estimate and are clustered at the state level. Statistical significance levels are denoted as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Recipe changes post-DTSA

	(1)	(2)	(3)	(4)
	Number of categories	Number of secret categories	Number of non-secret categories	New disclosed ingredient
High Treatment State	-1.526**	-0.417	-1.109***	-0.008
	(0.454)	(0.368)	(0.199)	(0.007)
Post X High Treatment State	0.760*	1.154**	-0.394	0.022**
	(0.324)	(0.372)	(0.646)	(0.008)
Observations	47,500	47,500	47,500	30,436
R-squared	0.601	0.388	0.575	0.126
Operator Firm FE	Yes	Yes	Yes	Yes
Supplier Firm FE	Yes	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes	Yes
Basin FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

Notes: This table presents an analysis of overall recipe changes. The dependent variables are described as follows: Number of categories indicates all distinct categories of ingredients present in a well; Number of TS categories represents the distinct categories of ingredients that are trade secrets; Number of disclosed categories represents the distinct categories with no trade secret ingredients; and New disclosed ingredient represents the introduction of a new-to-the-firm ingredient that is not kept as a trade secret. High Treatment State refers to the key independent variable of interest in the analysis. Post X High Treatment State is an interaction term between a post-period indicator and the High Treatment State indicator. Robust standard errors are provided below each coefficient estimate and are clustered at the state level. Statistical significance levels are denoted as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Trade secret use and novelty: decomposing the Post-DTSA effect

	(1) Trade Secret	(2) Share of TS	(3) New TS category	(4) New TS category combination	(5) Additional TS in category
High Treatment State (HTS)	-0.080	-0.013	0.003	0.012*	-0.009
	(0.075)	(0.017)	(0.007)	(0.005)	(0.009)
Post 1 X HTS	0.206**	0.016**	0.018	0.006	0.008
	(0.076)	(0.005)	(0.010)	(0.004)	(0.006)
Post 2 X HTS	0.157**	0.031**	0.002	0.001	0.011***
	(0.057)	(0.011)	(0.007)	(0.003)	(0.002)
Post 3 X HTS	0.232***	0.046**	0.008**	0.012***	0.011**
	(0.039)	(0.018)	(0.003)	(0.003)	(0.004)
Post 4 X HTS	0.292***	0.054***	0.011***	0.014**	0.016***
	(0.026)	(0.013)	(0.003)	(0.004)	(0.003)
Observations	47,500	47,500	30,436	30,436	30,436
R-squared	0.408	0.615	0.110	0.080	0.060
Operator Firm FE	Yes	Yes	Yes	Yes	Yes
Supplier Firm FE	Yes	Yes	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes	Yes	Yes
Basin FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Notes: This table decomposes the post-DTSA effect on trade secret use and novelty over distinct 6-month periods. Each column represents a distinct regression. The dependent variables are the same as in Table 3: Trade secret captures the utilization of trade secrets; New TS category signifies the introduction of novel categories of trade secrets; New TS category indicates the introduction of a new-to-the-firm category of trade secrets in the well; New TS category combination signifies a new combination of trade secret categories used in a well; Additional TS in category captures additional trade secrets in a category. The series of Post-DTSA variables (1-4) represent the effects in successive 6-month periods after the introduction of the DTSA. High Treatment State is the key independent variable of interest in the analysis, and the interaction terms between Post and High Treatment State capture the differential effects of the DTSA in high treatment states over time. Robust standard errors are provided below each coefficient estimate and are clustered at the state level. Statistical significance levels are denoted as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table 7a. Trade secret use post-DTSA and average daily oil production, bbl (IP30)

	(1)	(2)	(3)	(4)
	No FEs	Full FEs		
	Oil IP30			
Trade secret	95.821***	12.436	-0.920	1.928
	(3.932)	(9.580)	(14.217)	(14.363)
Post X Trade Secret			45.950*	
			(19.723)	
Post 1 X Trade Secret				60.620*
				(27.313)
Post 2 X Trade Secret				33.608
				(23.912)
Post 3 X Trade Secret				15.246
				(23.961)
Post 4 X Trade Secret				50.940
				(30.724)
Observations	42,031	42,025	42,025	42,025
R-squared	0.013	0.494	0.494	0.494
Operator Firm FE	No	Yes	Yes	Yes
Supplier Firm FE	No	Yes	Yes	Yes
Well Type FE	No	Yes	Yes	Yes
Basin FE	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes

Notes: Tables 7a investigates the association between trade secret use Post-DTSA and well productivity in barrels of oil. We use a standard industry productivity measure, namely, average daily production in the first 30 days of the well's productive life, also referred to as Initial Production in the first 30 days (IP30 as a shorthand) in barrels of oil. Each column represents a distinct regression. Column 1 includes no fixed effects, columns 2-4 include the full suite of fixed effects. The series of Post-DTSA variables (1-4) represent the effects in successive 6-month periods after the introduction of the DTSA. Robust standard errors are provided below each coefficient estimate and are clustered at the state level. Statistical significance levels are denoted as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table 7b. Trade secret use post-DTSA and average daily gas production, mcfd (IP30)

	(1)	(2)	(3)	(4)
	No FEs	Full FEs		
	Gas IP30			
Trade secret	135.259***	53.594	108.260	112.026
	(36.974)	(73.838)	(138.254)	(135.045)
Post X Trade Secret			-187.361	
			(216.242)	
Post 1 X Trade Secret				-108.817
				(129.656)
Post 2 X Trade Secret				-329.521
				(322.877)
Post 3 X Trade Secret				19.430
				(94.394)
Post 4 X Trade Secret				-462.608
				(413.719)
Observations	46,791	46,783	46,783	46,783
R-squared	0.000	0.642	0.642	0.642
Operator Firm FE	No	Yes	Yes	Yes
Supplier Firm FE	No	Yes	Yes	Yes
Well Type FE	No	Yes	Yes	Yes
Basin FE	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes

Notes: Tables 7b investigates the association between trade secret use Post-DTSA and well productivity in thousands of cubic feet of gas. We use a standard industry productivity measure, namely, average daily production in the first 30 days of the well's productive life, also referred to as Initial Production in the first 30 days (IP30 as a shorthand) in in thousands of cubic feet of gas (mcfd). Each column represents a distinct regression. Column 1 includes no fixed effects, columns 2-4 include the full suite of fixed effects. The series of Post-DTSA variables (1-4) represent the effects in successive 6-month periods after the introduction of the DTSA. Robust standard errors are provided below each coefficient estimate and are clustered at the state level. Statistical significance levels are denoted as follows: *** p<0.01, ** p<0.05, * p<0.1.

Figure 1. Well locations in the analytical sample

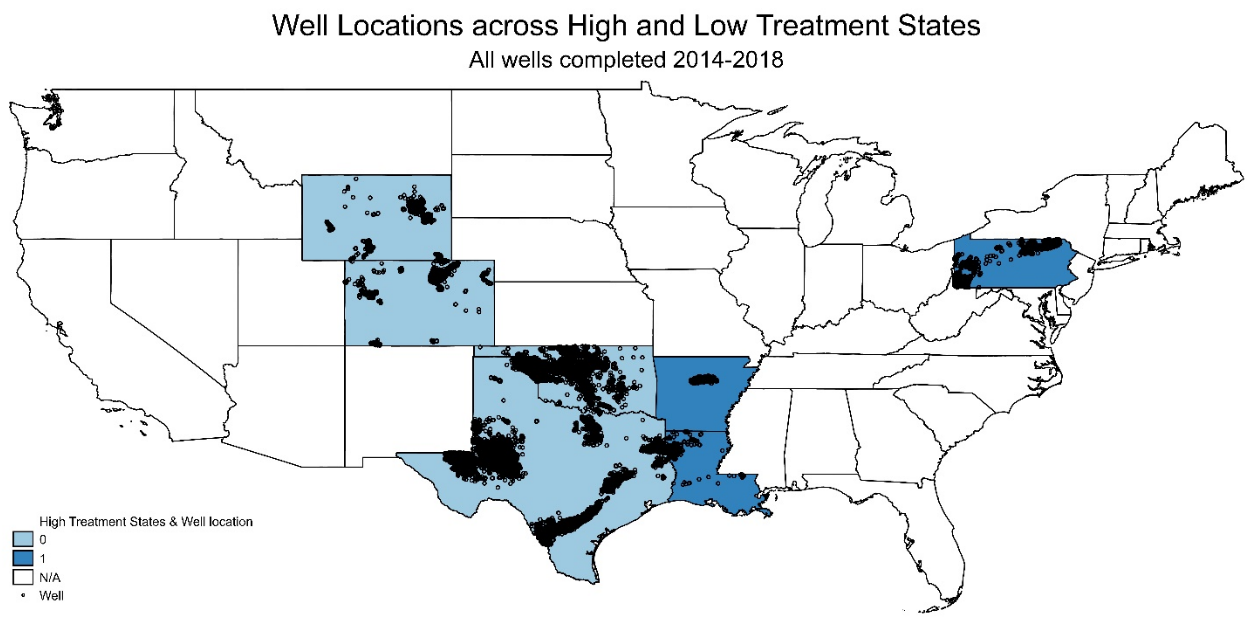


Figure 2. Share of wells with secret ingredients pre- and post-DTSA

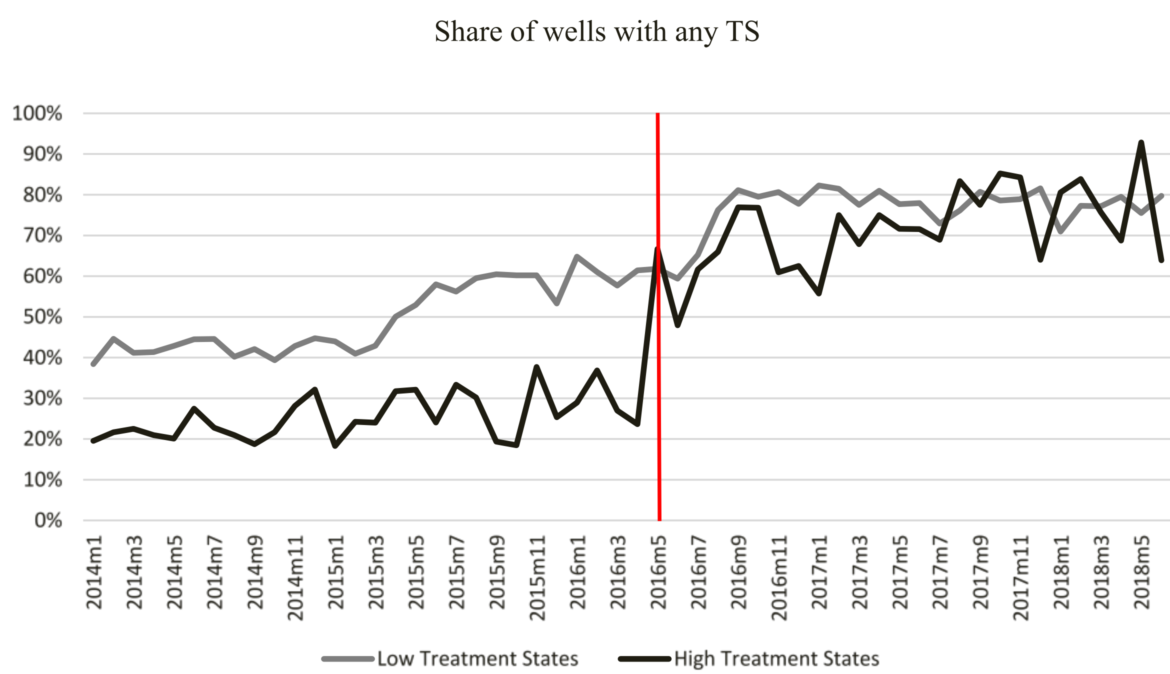


Figure 3. Share of secret ingredients per well pre- and post-DTSA

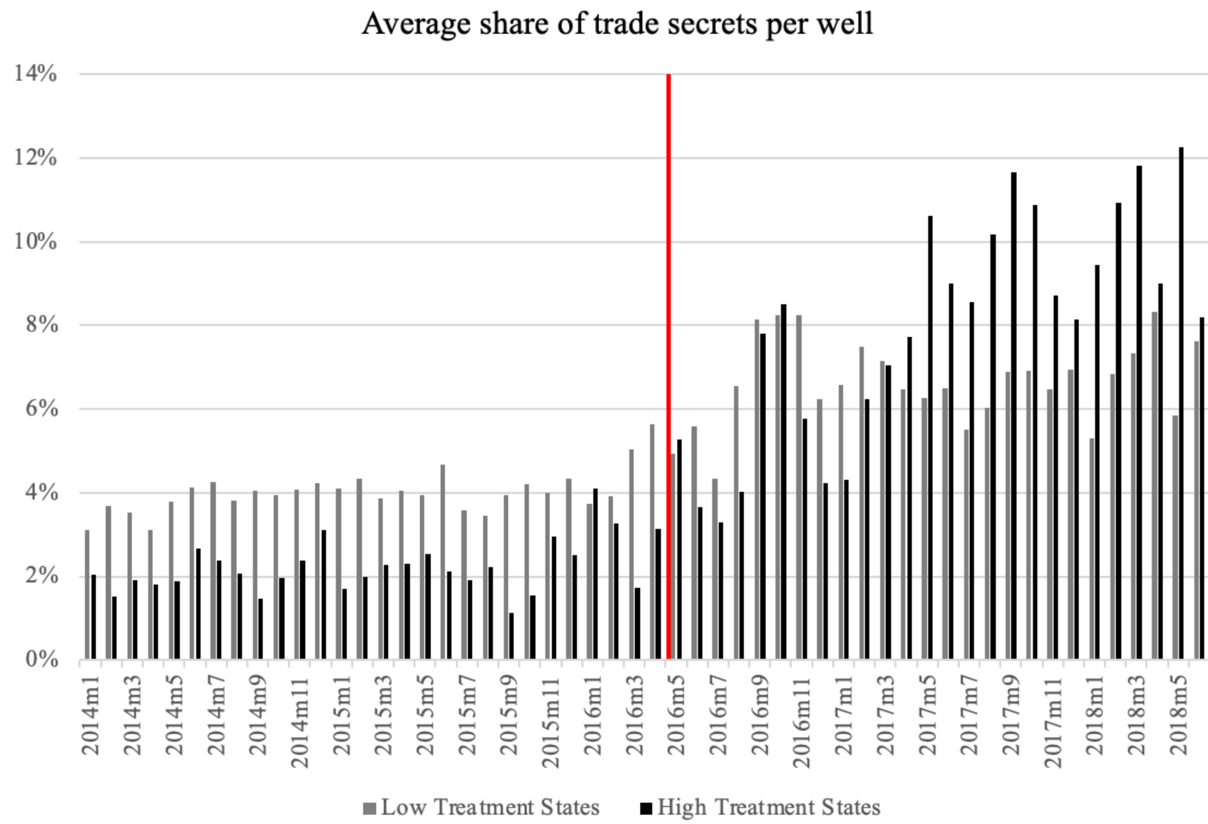
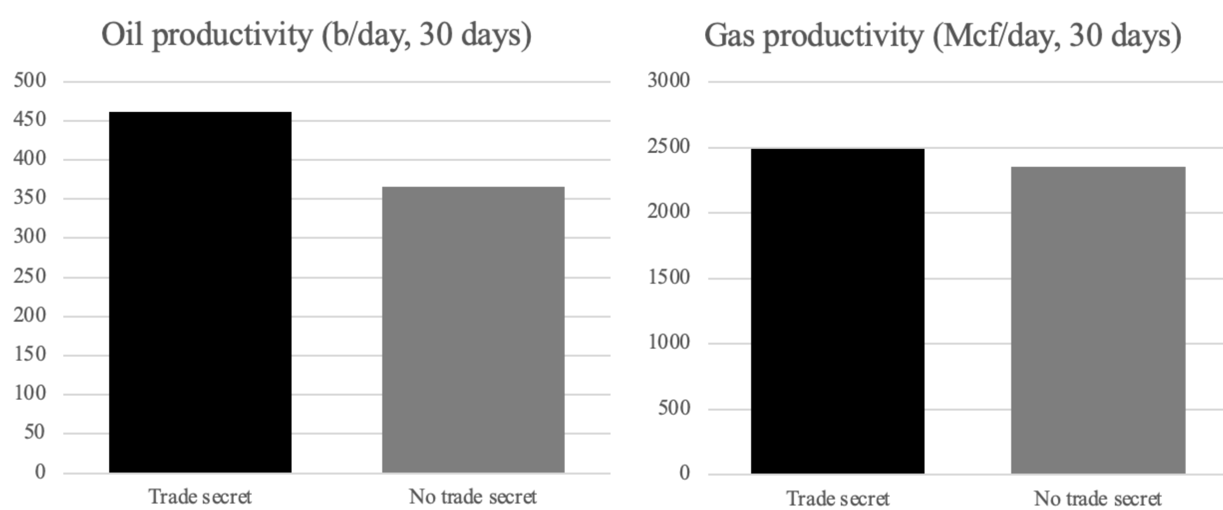


Figure 4: Average well productivity (30-day output), TS and non-TS wells



APPENDIX A: Examples of Trade Secret misappropriation

Loss of a trade secret can happen through three main channels: illegal misappropriation, inadvertent disclosure, and reverse engineering (or independent discovery). This appendix provides some examples of these.

Trade secret cases involving claims of illegal misappropriation largely involve rivals, business partners, or employees (Almeling et al. 2010a, b, Lemley 2008). An example of misappropriation via rivals (via competitive intelligence) is the case of E.I. du Pont de Nemours & Co. v. Christopher, wherein Rolfe and Gary Christopher took aerial photographs of an under-construction DuPont methanol plant, from which their highly secret process could be deduced (Lemley, 2008).

An example of misappropriation via business partners is the first case brought under the DTSA. It involved the stealing of a secret recipe (for fig jam), from Dalmatia Import Group by their former distributors Foodmatch and Lancaster Fine Foods (Songer and Tehrani 2017).

An example of claimed misappropriation via an employee is the case of Waymo (an Alphabet subsidiary) who sued Uber for misappropriation claiming a former Waymo employee had stolen trade secrets and shared them with Uber. This case was settled for $245 million. The alleged theft was detected in an interesting way: "Waymo claims that it caught wind of the alleged misappropriation recently when one of its LiDAR component vendors inadvertently copied Waymo on an email depicting Uber's LiDAR circuit board. According to Waymo, Uber's LiDAR circuit board "bears a striking resemblance to Waymo's own highly confidential and proprietary design and reflects Waymo trade secrets."[61]

Examples of inadvertent disclosure are harder to observe since firms are often loath to confirm leaked information is a "trade secret" as doing so confirms its validity, value, and leakage. One prominent example involves an Apple software engineer mistakenly leaving a disguised pre-release iPhone 4 in a California bar (Lam 2010, Nosowitz 2010, Sandoval and McCullagh 2011), which was eventually acquired by technology website who subsequently published a detailed description of the device.[62] Apple confirmed the leak by requesting the phone's return.

Finally, using a trade secret also implies risking losing it through reverse engineering, which is again very hard to observe on a case-by-case basis. One general example: since the advancement of chemical analytic technologies, reverse-engineering of fragrances has become common. As a result, controlling fragrance-related IP and maintaining trade secrets in the fragrance industry has become more difficult. For instance: "Once Chanel sells a bottle of its well-known No. 5 the company has virtually no legal means of controlling how the buyer uses it." (Cronin 2015, p. 300).

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[61] Details here: https://blogs.orrick.com/trade-secrets-watch/2017/02/24/trade-secret-misappropriation-in-the-world-of-driverless-cars-google-versus-uber/

[62] Entitled "This is Apple's Next Phone". Available here: https://gizmodo.com/this-is-apples-next-iphone-5520164

APPENDIX B: Investigating potential endogeneity of treatment heterogeneity

Our main objective is to identify the effects of stronger (or increased) trade secrecy protection, using pre-DTSA variation in protection to segment wells into high and low treatment. This relies on the assumption there are not underlying systematic difference across high and low treatment states that endogenously drives differences in pre-DTSA secrecy protection and/or differential reactions to DTSA.

To investigate this, we examine two potential sources of concern. First, across all states, what explains variation in pre-DTSA trade secrecy policy, and is it related to factors that may otherwise drive secrecy use? Second, among our sample of states and at the time of DTSA enactment, are there systematic differences in socio-economic and industry-related regulatory characteristics, or systemic changes at the same time as the DTSA enactment, that strongly correlate with high versus low treatment states and thereby might cloud our estimates? The goal of these analyses is to investigate, as best we can, the concern that something other than pre-DTSA variation in secrecy protection at the state level is driving our main results.

To measure pre-DTSA variation, we use the Png index measures (Png 2017a, b), which rely both on pre-Uniform Trade Secrets Act (UTSA) enactment state-level common law standards and UTSA levels. In using the UTSA to estimate the causal relationship between secrecy protection and R&D (Png 2017a), Png includes several analyses to prove UTSA enactment is not endogenous to R&D investment. He shows: (1) No evidence of a relationship between legislative lag of UTSA (lag between first tabling of the bill and enactment) and R&D spending dynamics preceding UTSA enactment. Hence, it does not appear that the law was enacted because of pressure from firms intending to increase R&D investment. (2) Enactment of UTSA is not related to gross state product, population, the value added of key industry sectors, state-level R&D expenditure, or R&D tax credit policy. Further, he found no relationship between percent Republicans in state legislature (arguably a measure of pro-business orientation) and UTSA. Overall, Png's analyses suggest the enactment of the UTSA was not significantly related to state industrial structure, R&D, policies to support R&D, or pro-business orientation. His results provide us with helpful evidence that the enactment of UTSA policy, a key element in our treatment variation variable, is not endogenous to inventive activity.

Building from Png's analyses, we investigated whether, across all U.S. states (plus DC), there was any evidence of a relationship between the level of pre-DTSA secrecy protection and other state-level factors that might otherwise drive secrecy use. In the table below, we predict pre-DTSA secrecy protection as a function of the following characteristics in 2013, i.e., the year preceding our analyses: (column 1) macro-economic factors: state personal income, state population; (columns 2-4) invention-related factors: state-level R&D expenditure, state R&D tax credits; (5) pro-business orientation: percent Republicans in state legislature, (6) pro-business sentiment: percent of state population voting Republican for president (in 2012); or (7) percent income growth. We do not find any significant patterns.

Relating specifically to secrecy use, prior literature has argued that non-compete agreements affect employee outcomes via reduced job mobility (Starr et al. 2018, 2021), and specifically that lower mobility due to employer-friendly non-disclosure policies depress inventor incentives to patent, because the signaling value of patenting declines (Contigiani et al. 2018). Since non-competes target knowledge leakage, it's plausible they could drive trade secret outcomes. Thus, we also examine if there is a relationship between the non-compete enforceability index (Starr et al. 2021) and pre-DTSA secrecy protection. We do not find evidence of a significant relationship. Related literature has also looked at state-level variation in the Inevitable Disclosure Doctrine (IDD) as a form of trade secret protection (Castellaneta et al. 2016, Chen et al. 2021, Contigiani et al. 2018, Klasa et al. 2018). Precedent in favor of IDD suggests a firm may obtain a court injunction prohibiting a departing employee from joining a competing firm (where they might inevitably disclose trade secrets). For most states, and nearly all of our focal states, however, there is no clear IDD rule (Klasa et al. 2018).

Table B1. Pre-DTSA trade secrecy protection as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Macro	RD	RD credit (%)	RD credit	State Repub	Repub Pres	Income growth	Non-compete
Income (ln)	-0.132	-0.135	-0.132	-0.101	-0.114	-0.134	-0.117	-0.130
	(0.108)	(0.118)	(0.109)	(0.111)	(0.125)	(0.129)	(0.113)	(0.111)
Population (ln)	0.134	0.135	0.135	0.116	0.118	0.137	0.117	0.133
	(0.107)	(0.110)	(0.109)	(0.108)	(0.125)	(0.127)	(0.114)	(0.110)
R&D (ln)		0.001						
		(0.019)						
R&D credit (%)			-15.155					
			(75.375)					
R&D credit				-0.048				
				(0.041)				
State legislature Repub (%)					0.086			
					(0.103)			
Repub president votes (%)						-0.006		
						(0.171)		
Bills introduced								
Income growth (%)							0.000	
							(0.000)	
Non-compete enforcement								0.001
								(0.017)
Constant	0.037	0.048	0.029	-0.037	0.029	0.034	0.115	0.042
	(0.395)	(0.425)	(0.401)	(0.398)	(0.454)	(0.412)	(0.428)	(0.403)
Observations	51	51	51	51	49	51	51	51
R-squared	0.032	0.032	0.033	0.060	0.047	0.032	0.037	0.032

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We also explored whether there is evidence *within our sample states* for systematic differences between High and Low Treatment States that might drive changes in secrecy use and innovation post-DTSA. The table below includes time-invariant characteristics specific to state secrecy policy and to state-level fracturing disclosure mandates, as well as economic and policy characteristics in 2016, i.e., the year of enactment of DTSA. As we only have seven states in our sample, these analyses are necessarily descriptive and qualitative.

Overall, there is little evidence that High Treatment States are systematically different in observable ways for factors that might drive secrecy use. First, both high and Low Treatment States have early and late adopters of UTSA. Second, there is no clear pattern in the details of fracturing disclosure policies across High and Low Treatment States. This is important to examine because specifics of the disclosure policy—how long it's been in place, when in the fracturing process firms are required to disclose, and to whom (whether directly to the State regulators or instead to Fracfocus, a disclosure registry)—may shape patterns of disclosure, and firm's sensitivity to policy changes in ways that might affect our estimates. Third, there is no clear relationship between the levels of non-compete enforcement and pre-DTSA secrecy protection.

Finally, we do not observe clear demarcations between High and Low Treatment States in selected socio-economic variables in 2016. Further, patterns of income growth and changes in legislatures and voting do not appear to be systematically related to treatment intensity. One apparent exception may be that all Low Treatment States decreased their share of Republican votes in 2016, while High Treatment States either did not change or increased their share. However, two facts suggest this likely does not represent a significant systematic difference: first, none of the states changed in terms of majority, and second, the patterns across Democrat votes are not consistent across states by treatment, suggesting this was not about changes in latent policy attitudes.

Table B2. Characteristics of Sample states in 2016

	Colorado	Texas	Wyoming	Oklahoma	Arkansas	Louisiana	Penn-sylvania
High Treatment State	0	0	0	0	1	1	1
Pre-DTSA Png trade secret protection index[63]	0.77	0.69	0.50	0.47	0.40	0.40	0.13
Year of UTSA enactment	1986	2013	2006	1986	1981	1981	2004
Fracturing disclosure:							
Disclosure law date	01/04/2012	01/02/2012	01/09/2010	01/01/2013	01/01/2011	01/10/2011	01/04/2012
Basis for disclosure timing	Frac job	Drilling permit	Frac job	Frac job	Drilling permit	Drilling permit	Frac job
Reporting requirement	FracFocus	FracFocus	State Agency	FracFocus	State Agency	Either	FracFocus
Non-compete enforceability index	0.38	-0.28	0.23	-0.94	-0.98	0.50	0.14
2016 socio-economics:							
Income per capita	52251	46445	54522	42399	40720	42763	51700
Income per capita Δ (%)	0.00	-0.02	-0.06	-0.06	0.02	-0.01	0.03
State legislature, % republican	0.49	0.66	0.86	0.74	0.65	0.60	0.58
Δ % republican (pp)	0.04	0.03	-0.01	0.01	0.11	0.01	0.04
President votes, % Republican	0.43	0.52	0.67	0.65	0.61	0.58	0.49
Δ % Republican (pp)	-0.03	-0.05	-0.01	-0.01	0.00	0.00	0.02
Δ % Democrat (pp)	-0.03	0.02	-0.06	-0.04	-0.03	-0.02	-0.04

[63] Png (2017a) Secrecy and Patents: Theory and Evidence from the Uniform Trade Secrets Act. *Strategy Science* 2(3):176-193.

APPENDIX C: Trade secret measurement robustness

There are two potential ways to measure trade secret use in this context: one less conservative (using CAS number) and one more conservative (using both CAS number and chemical ingredient name).

The less conservative version involves labelling as a trade secret any ingredient that lists the Chemical Abstract Service (CAS) Number as “Proprietary/Not Available” (Konschnik and Dayalu 2016). While the benefit of this approach is that there is a clear decision rule, a drawback is that for some ingredients, even when the CAS number is not disclosed, the name of the ingredient is disclosed. Consider for example well 35-073-25542-00-00 with an ingredient marked as unavailable or proprietary in the CAS Number cell, but the Ingredient Name listed as Crystalline Silica, which is also known as quartz (sand), a widely used and easily identifiable proppant. Another example is well 42-255-33561-0000 with an ingredient marked as proprietary with the name Na2Co3, or sodium carbonate. In such cases, even though the CAS number is marked as proprietary, the actual name of the ingredient reveals crucial details of the identity of the ingredient. Thus, considering all ingredients marked as “Proprietary/Not Available” in the CAS Number cell may overstate the number of genuine trade secrets.

We use a second, more conservative approach. It involves examining each ingredient name and deducing whether the name reveals the chemical compound, which would be identifiable by experts in the industry. The benefit of this approach is that the true rate of trade secrets is more likely to be captured. The drawback is that the decision rule is not as clear. To get as precise measures as possible, we hired a chemical engineer to implement the categorization we used in the paper.

In this Appendix, we examine how our more conservative measure results compare to the less conservative measure. We report the result below in the table below. Because the incidence of secrecy is significantly higher with this measure (92% of wells contain at least one ingredient for which CAS number is marked “Proprietary/Not Available”), there is less variation in terms of both the incidence and the number of secrets per well. We replicate the results from Table 3 in the main body of the paper (corresponding to *Any Secret* and *Number of secrets* dependent variables) with the Chemical Abstract Service proprietary number variables that were also constructed as either a binary variable (columns 1-3) or counts of proprietary CAS components (columns 4-6). The coefficient for the interaction term of interest between post-DTSA and High Treatment State variables for the binary dependent variable has the expected (positive) sign but is not statistically significant (column 3). The lack of statistical significance may be explained by the near certainty of “secrets” in wells when measured with the CAS number. Next, we find the number of CAS proprietary components increased post-DTSA, and the coefficient for the interaction term of interest has the expected sign but is not statistically significant (column 6). Thus, the results are broadly consistent even with this less conservative measure.

Finally, because of the low variation in terms of non-proprietary component wells using the CAS measure, we also use categorical variables of above median levels (> 7) and a top quartile (>12) measures of non-disclosed CAS numbers as the dependent variable. The results are overall aligned with those in the paper when using the preferred measure of trade secrets: there is more use of secret ingredients post-DTSA for High Treatment States.

Table C1. Alternative measure of trade secrets: Chemical Abstract Service Number

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Proprietary CAS number (0/1)	Proprietary CAS number (0/1)	Number of CAS proprietary components	Number of CAS proprietary components	Above median CAS proprietary components	Above median CAS proprietary components	Top quartile CAS proprietary components	Top quartile CAS proprietary components
High Treatment State	0.052	0.050	-2.475	-2.553	-0.240*	-0.284*	-0.121*	-0.147*
	(0.036)	(0.036)	(1.307)	(1.451)	(0.108)	(0.119)	(0.061)	(0.069)
Post X HTS		0.007		0.295		0.165***		0.099***
		(0.017)		(0.659)		(0.035)		(0.026)
Observations	47,500	47,500	47,500	47,500	47,500	47,500	47,500	47,500
R-squared	0.423	0.423	0.532	0.532	0.422	0.424	0.417	0.418
Producer Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Service Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Basin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered at state level
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX D: Balanced sample checks

Our main analyses use well-level data on completions and are therefore constructed as a repeated cross-section rather than a panel. As a result, one may ask whether our sample is changing in composition in ways that may affect our results (c.f. Cunningham 2021). A key potential concern is that firms may be move their activity away from Low Treatment States into High Treatment States when protection of trade secrets increases in the latter states more than in the former post-DTSA. We think such compositional changes are unlikely to affect our results, first, because firms' inventions are partially based on local geological knowledge and are not low cost to move across geographies. Also, the fixed costs of hydraulic fracturing activities are high and justified only over longer periods of time, making the relatively quick and sizable moves that could explain away our main results unlikely. However, we also wanted to investigate this possibility empirically. To do so, first, we tabulated the share of wells across High and Low Treatment States pre- and post-DTSA. We find that the distribution of wells remains similar across the types of states pre- and post-DTSA, suggesting there is not a disproportionate movement towards High Treatment States.

Table D1. Well distribution by treatment state and across time

Proportion of wells	High Treatment States	Low Treatment States
Pre-DTSA	11.7%	88.3%
Post-DTSA	10.4%	89.6%

Second, we reran our main analyses on a sample that includes only those firms that are present in both pre- and post-DTSA periods. Our sample drops by around 2% but the results are robust. In sum, we find little evidence of firms selecting (i.e., moving into or increasing activity in) states based on treatment heterogeneity.

APPENDIX E: Alternative treatment: Continuous and State-by-State analyses

In the main paper, for simplicity, we exploit heterogeneity in treatment by creating a binary variable that splits affected states into High and Low Treatment States. To investigate whether our results are robust to this categorization of treatment, we first rerun the main analyses using a continuous treatment variable, using the Png index which is based on the pre-DTSA level of secrecy protection. As the index measures the level of state level trade secrecy protection before the passage of DTSA (ranging from 0.13 to 0.77): the higher the value on the index, the more protection a state had before DTSA. Thus, the expected sign of the main variable of interest in the table below is negative. Overall, these results are consistent with the argument that following the passage of DTSA the use and novelty of trade secrets increased more in High Treatment States relative to Low Treatment States.

Second, we also include state-by-state regressions in Table E2. We find that when decomposed, the High Treatment States coefficients are generally higher than those of Low Treatment States. We also find that no single state, whether low or high treatment, drives the results. Note that we include a time trend instead of month fixed effects in these regressions to estimate the coefficient for the Post variable given these are individual state samples and our treatment variable is at the state level. We do not include regressions for novelty DVs because of the low incidence of our novelty measures in some states in the state-by-state split samples.

Table E1. Continuous treatment operationalization

	(1)	(2)	(3)	(4)	(5)
	Trade secret	Share of TS	New TS category	New TS category combo	Additional TS in category
TS Protection pre-DTSA	0.131	0.020	0.022*	0.002	0.009
	(0.104)	(0.023)	(0.011)	(0.017)	(0.011)
Post X TS Prot. pre-DTSA	-0.350***	-0.072**	-0.019***	-0.019*	-0.023***
	(0.085)	(0.020)	(0.004)	(0.008)	(0.005)
Observations	47,500	47,500	30,436	30,436	30,436
R-squared	0.407	0.615	0.110	0.080	0.060
Producer Firm FE	Yes	Yes	Yes	Yes	Yes
Service Firm FE	Yes	Yes	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes	Yes	Yes
Basin FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E2. State level analyses: Any trade secret

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	High Treatment State			Low Treatment State			
	Pennsylvania	Louisiana	Arkansas	Oklahoma	Wyoming	Texas	Colorado
Post-DTSA	0.359***	0.230***	0.309***	0.012	0.111**	0.089***	0.102***
	(0.032)	(0.053)	(0.092)	(0.025)	(0.045)	(0.012)	(0.020)
Observations	3,640	858	826	5,958	2,076	27,815	6,311
R-squared	0.475	0.620	0.947	0.467	0.490	0.388	0.464
Producer Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Service Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Basin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX F: Oil price and alternative time controls

In the oil and gas industry, the period following end of 2014 was marked by a low-price environment. The decline followed a November 2014 OPEC meeting and decision to not cut (and to later increase) production across OPEC members. Since our observation period overlaps with these developments, one may be concerned that the secrecy patterns we observe are somehow due to the oil price fluctuation (albeit delayed) rather than DTSA. Several empirical patterns make this unlikely to be the case. First, while the price declined most sharply within a few months following November of 2014 (from around 100 USD/barrel to around 50 USD/barrel), we only observe changes in trade secret use following May 2016, or a year and a half after later. Second, it is unlikely that trade secret increases, if driven by the oil price, would be stronger in High Treatment States vs. Low Treatment States as defined by prior trade secret protection.

To investigate this more directly, we re-run the main results (Tables 3 and 5) including oil price controls below. We find that there is a high correlation between a (monthly) time trend variable and the (monthly) oil price. This is expected, because the price was high in the beginning of the observation period and relatively low following the year 2014. Indeed, the correlation between the time trend and the oil price (WTI) is at -0.72. Here we include the main results on use and secrecy-protected invention (from Tables 3 and 5) using oil price rather than time controls since month fixed effects and monthly price effects cannot be jointly estimated. The results are consistent with those in the main tables.

Table F1. Oil price controls

	(1)	(2)	(3)	(4)	(5)
	Trade Secret	Share of TS	New TS category	New TS category combination	Additional TS in category
Post-DTSA	0.297***	0.029***	-0.000	0.001	0.001
	(0.013)	(0.003)	(0.001)	(0.002)	(0.002)
High Treatment State	-0.101	-0.016	0.002	0.011*	-0.009
	(0.073)	(0.017)	(0.008)	(0.006)	(0.009)
Post-DTSA X HTS	0.216***	0.037**	0.010***	0.009**	0.011***
	(0.029)	(0.012)	(0.002)	(0.003)	(0.001)
Oil price	-0.002***	-0.000**	-0.000**	-0.000***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	47,500	47,500	30,436	30,436	30,436
R-squared	0.395	0.607	0.106	0.077	0.058
Producer Firm FE	Yes	Yes	Yes	Yes	Yes
Service Firm FE	Yes	Yes	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes	Yes	Yes
Basin FE	Yes	Yes	Yes	Yes	Yes
Month FE	No	No	No	No	No

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Another way to account for time-dependent changes is including a time trend instead of time fixed effects. Such specification also allows identifying the main effect of the Post-DTSA variable, shedding light on the general change in outcomes of interest following the passage of the DTSA. Below, we report the same models as in Table F1 but with a time trend. The results remain highly consistent with the main results, with some additional information provided by the Post-DTSA variable: following the passage of the DTSA, there was a general increase in the use of trade secrets and the use of new-to-the-firm trade secrets, with the effects concentrated in High Treatment States.

Table F2. Time trend controls

	(1)	(2)	(3)	(4)	(5)
	Trade Secret	Share of TS	New TS category	New TS category combination	Additional TS in category
Post-DTSA	0.083***	0.007**	0.005*	0.011**	0.008*
	(0.010)	(0.003)	(0.002)	(0.003)	(0.004)
High Treatment State	-0.087	-0.014	0.001	0.010	-0.010
	(0.072)	(0.017)	(0.009)	(0.007)	(0.010)
Post-DTSA X HTS	0.222***	0.037**	0.010***	0.009**	0.011***
	(0.032)	(0.012)	(0.002)	(0.003)	(0.001)
Observations	47,500	47,500	30,436	30,436	30,436
R-squared	0.402	0.611	0.106	0.078	0.059
Producer Firm FE	Yes	Yes	Yes	Yes	Yes
Service Firm FE	Yes	Yes	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes	Yes	Yes
Basin FE	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX G: Error clustering: firm level and wild cluster bootstrap

In the main analyses, we cluster errors at the state level. We do so because this is the level at which treatment is assigned, and clustering at the assignment level is suggested standard practice (Abadie et al. 2022). However, to investigate robustness, in this appendix, we further probe the results clustering at the firm level rather than treatment level. We present the results in Table G1 below. The results remain statistically significant at conventional levels.

Table G1. Clustered errors at firm level

	(1)	(2)	(3)	(4)	(5)
	Trade Secret	Share TS	New TS category	New TS category combination	Additional TS in category
High Treatment State	-0.083	-0.014	0.003	0.011	-0.009
	(0.060)	(0.016)	(0.013)	(0.013)	(0.009)
Post-DTSA X HTS	0.220**	0.037*	0.010**	0.009*	0.011***
	(0.095)	(0.019)	(0.005)	(0.005)	(0.003)
Observations	47,500	47,500	30,436	30,436	30,436
R-squared	0.408	0.614	0.110	0.080	0.060
Producer Firm FE	Yes	Yes	Yes	Yes	Yes
Service Firm FE	Yes	Yes	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes	Yes	Yes
Basin FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Further, because we have a relatively small number of clusters (states), we also ran the results using the wild cluster bootstrap (WCB) method (Canay et al. 2021, Choudhury et al. 2023, MacKinnon et al. 2023). Table G2 below includes the p-values from both the state clusters and the WCB for state clusters. For our focal coefficients, Post X HTS, the p-values are typically slightly larger than in our main analyses. However, all but the new trade secret category combination remain significant at typical levels.

Table G2: Wild Cluster Bootstrap

	(1)	(2)	(3)	(4)	(5)
	Trade Secret	Share TS	New TS category	New TS category combination	Add TS in category
High Treatment state	-0.083	-0.014	0.003	0.011	-0.009
p-value, state cluster	0.316	0.439	0.723	0.540	0.342
p-value, WCB	0.552	0.676	0.784	0.076	0.184
Post-DTSA X HTS	0.220	0.037	0.010	0.009	0.011
p-value, state cluster	0.000	0.021	0.001	0.023	0.000
p-value, WCB	0.000	0.058	0.082	0.218	0.078
Observations	47,500	47,500	30,436	30,436	30,436
Producer Firm FE	Yes	Yes	Yes	Yes	Yes
Service Firm FE	Yes	Yes	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes	Yes	Yes
Basin FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

APPENDIX H: Patent Analyses

In this appendix, we provide additional analyses exploring the relationship between trade secrecy use, firm patenting, and the DTSA, to investigate if there is any evidence that the firms in our sample are increasing trade secret use at the expense of patenting (i.e., that inventive activity is changing IP form, rather than increasing).

Patenting is very rare among firms in our sample, making estimating patent as the outcome noisy (i.e., just 13 firms have any fracturing patents, and 7 have 5 or fewer) Therefore, in the below analyses, we run firm level regressions predicting the intensity of trade secret use as a function of patenting across pre- and post-DTSA period. If patenting substitutes for trade secrecy, firm patenting would be negatively associated with trade secret use in response to the policy (*Post-DTSA X Patents*). The patenting data we use are from PatentsView. We match firms to patents using assignee names and use S&P Capital IQ to capture firm parent and subsidiary patents to ensure as inclusive a match as possible. Our fracturing patent classifications follow Kapoor and Murmann (2023), who built a list of fracturing associated patent classes in consultation with industry experts (classes listed below).

We find that post-DTSA, the share of wells with a trade secret ingredient (column 1-3 of Table H1a) and the % of trade secrets per well (column 4-6) both increase at the *Service Firm* level, which is consistent with our *well* level analysis in the main paper. In contrast with the idea that some of the increase in trade secret use may be due to substituting away from patenting, we do not find the increase in trade secret use is lower for firms with higher rates of patenting. Specifically, *Post-DTSA X Patents* is positive and/or not significant, even when including both firm and month fixed effects (columns 3 and 6). When we consider *chemical fracturing patents* as a subset, as such patents are the most likely to directly substitute for fracturing ingredient trade secrets (Table H1b), again we see no evidence of substitution. If anything, higher chemical patenting is associated with a *higher* use of trade secrets, post-DTSA, at least in terms of share of wells with a trade secret, columns 1-3.

We also regressed patenting as an outcome to see if firms who use secrets tend to patent less, and if that changed post-DTSA. While such results are quite noisy due to the rarity of patenting, we do not find a significant negative relationship between trade secret use (whether measured in terms of share of wells with any trade secrets, or the average share of secrets per well) and patenting.

Table H1a. Trade secrets and patents, firm-month-level, all fracturing patents

	(1)	(2)	(3)	(4)	(5)	(6)
	Trade Secret wells (share)			% secrets per well		
Post-DTSA	0.104*	0.130**		0.021**	0.018*	
	(0.060)	(0.061)		(0.010)	(0.009)	
Patent count	-0.001	-0.009***	-0.009***	-0.001	-0.001***	-0.001***
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Post-DTSA X Patents	0.026***	0.012	0.011	-0.001	0.000	-0.000
	(0.005)	(0.008)	(0.009)	(0.002)	(0.001)	(0.001)
Observations	1,494	1,490	1,490	1,494	1,490	1,490
R-squared	0.027	0.530	0.544	0.015	0.779	0.785
Service Firm FE	No	Yes	Yes	No	Yes	Yes
Month FE	No	No	Yes	No	No	Yes

Robust standard errors in parentheses clustered at firm level
*** p<0.01, ** p<0.05, * p<0.1

Note: The CPC classes used to identify fracturing patents (per Kapoor and Murmann 2023) are: B63B 35/00; B63B 35/44; C09K 8/46; C09K 8/58; C09K 8/60; C09K 8/62; C09K 8/64; C09K 8/66; C09K 8/68; C09K 8/70; C09K 8/72; C09K 8/74; C09K 8/76; C09K 8/78; C09K 8/80; C09K 8/82; C09K 8/84; C09K 8/86; C09K 8/88; C09K 8/90; C09K 8/92; C09K 8/94; E21B 10/00; E21B 10/02; E21B 10/04; E21B 10/56; E21B 17/00; E21B 17/10; E21B 17/16; E21B 23/00; E21B 23/04; E21B 29/06; E21B 33/12; E21B 33/13; E21B 33/14; E21B 34/00; E21B 34/06; E21B 34/10; E21B 34/14; E21B 43/12; E21B 43/16; E21B 43/17; E21B 43/26; E21B 43/267; E21B 47/12; E21B

47/24; E21B 7/06; E21B 7/08; G01N 27/30; G01S 15/00; G01V 1/00; G01V 1/28; G01V 1/40; G01V 11/00; G01V 3/00; G01V 3/18; G01V 3/20; G01V 3/24; G01V 3/26; G01V 3/32; G01V 5/10

Table H1b. Trade secrets and patents, firm-month-level, fracturing chemical patents

	(1)	(2)	(3)	(4)	(5)	(6)
	Trade Secret wells (share)			% secrets per well		
Post-DTSA	0.110*	0.133**		0.021**	0.018*	
	(0.060)	(0.061)		(0.010)	(0.009)	
Patents	-0.004	-0.035***	-0.034***	-0.002	-0.002***	-0.002***
	(0.005)	(0.004)	(0.005)	(0.001)	(0.001)	(0.001)
Post-DTSA X Patents	0.072***	0.034***	0.039***	0.001	0.002	0.002
	(0.011)	(0.010)	(0.012)	(0.003)	(0.001)	(0.002)
Observations	1,494	1,490	1,490	1,494	1,490	1,490
R-squared	0.024	0.529	0.543	0.014	0.779	0.785
Service Firm FE	No	Yes	Yes	No	Yes	Yes
Month FE	No	No	Yes	No	No	Yes

Robust standard errors in parentheses clustered at firm level
*** p<0.01, ** p<0.05, * p<0.1

Note: The CPC classes used to identify CHEMICAL fracturing patents (per Kapoor and Murmann 2023) are: C09K 8/60; C09K 8/62; C09K 8/64; C09K 8/66; C09K 8/68; C09K 8/70; C09K 8/72; C09K 8/74; C09K 8/76; C09K 8/78; C09K 8/80; C09K 8/82; C09K 8/84; C09K 8/86; C09K 8/88; C09K 8/90; C09K 8/92; C09K 8/94

APPENDIX I: Toxicity analyses: (1) Disclosed toxicity and (2) Fracturing (tort) cases

In this appendix, we provide additional analyses exploring the relationship between trade secrecy use, the use of toxic ingredients, and the DTSA. We do so to investigate if there is any evidence that increasing trade secret use that coincides with treatment is being used to cloak increased use of toxic ingredients. While it is unclear why increased toxic ingredient use would be driven by the DTSA (and especially for wells in High Treatment States) or some co-occurring structural change that caused toxicity (and the desire to hide it) to increase substantially, we run the analyses below to attempt to rule out this alternative explanation.

A notable fact is that practically all wells (98.8%) have at least one disclosed toxic ingredient (on average, 6.4 disclosed toxic ingredients). Hence, firms do not typically cloak toxicity. Further, 98.7% have a pollutant ingredient (on average, 5.2 pollutant ingredients). In other words, firms very commonly disclose such behaviors.

In the first set of analysis (Table I1), we examine disclosed toxicity and pollutants. To measure toxic ingredients, we link the CAS number (Chemical Abstract Service) of disclosed ingredients to the EPA's Toxic release inventory (TRI) database of toxic chemicals (via https://www.epa.gov/toxics-release-inventory-tri-program/tri-data-and-tools, file "TRI Chemical List w/ Groupings for Analysis"). Chemicals covered by the TRI cause one or more of: (1) cancer or other chronic human health effects, (2) significant adverse acute human health effects, (3) significant adverse environmental effects. We flag ingredients of any type on the TRI as "toxic". We also flag the subset of "pollutants" (based on whether the chemical is on environmental pollutant lists, including CERCLA, EPCRA, CAA and/or CWA).

Table I1 Disclosed toxic and pollutant ingredient use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Disc. Toxic #	Disc. Toxic #	Disc. Toxic (any)	Disc. Toxic (any)	Disc. Pollutant #	Disc. Pollutant #	Disc. Pollutant (any)	Disc. Pollutant (any)
Trade secret	0.142	0.208***	-0.001	0.003	-0.026	0.042	-0.009*	-0.004
	(0.089)	(0.026)	(0.002)	(0.004)	(0.064)	(0.045)	(0.004)	(0.003)
Trade secret X Post	-0.733***	-1.130***	-0.017	-0.021	-0.533**	-0.849***	-0.005	-0.009
	(0.114)	(0.107)	(0.011)	(0.015)	(0.195)	(0.111)	(0.010)	(0.012)
High Treatment State	-0.244	0.945***	-0.011*	0.004	-0.197	0.676*	-0.008	0.009
	(0.272)	(0.249)	(0.005)	(0.007)	(0.388)	(0.310)	(0.009)	(0.015)
TS X HTS	-0.917**	-0.802*	0.003	0.011	-0.610*	-0.545	0.008	0.017
	(0.293)	(0.340)	(0.002)	(0.008)	(0.276)	(0.320)	(0.004)	(0.013)
Post X HTS	0.764	0.246	0.003	-0.008	0.726*	0.312	0.007	-0.003
	(0.443)	(0.358)	(0.015)	(0.014)	(0.366)	(0.307)	(0.016)	(0.015)
TS X Post X HTS	0.815**	0.841	0.012	-0.000	0.918**	0.954	-0.001	-0.012
	(0.237)	(0.609)	(0.009)	(0.011)	(0.265)	(0.522)	(0.008)	(0.011)
Observations	47,500	47,397	47,500	47,397	47,500	47,397	47,500	47,397
R-squared	0.428	0.601	0.145	0.253	0.429	0.595	0.145	0.252
CPC FE	No	Yes	No	Yes	No	Yes	No	Yes
Basin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Producer Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Service Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses clustered at state level
*** p<0.01, ** p<0.05, * p<0.1

In regression analyses, (Table I1) we find that post-DTSA, for wells with a secret ingredient in High Treatment States (*TS X Post X HTS)*, there is no decrease in disclosed toxic or pollutant ingredient use, whether in number (columns 1, 2 and 5, 6) or likelihood (columns 3, 4 and 7, 8). Note that in the most stringent of these analyses, we include chemical purpose category (CPC) fixed effects in addition to our full set of fixed effects from the main analyses in the paper, as toxic/pollutant ingredient likelihood varies significantly by CPC, and as such well toxicity may derive from CPC choices. For instance, nearly 90% of Acid ingredients are toxic/pollutants, whereas there are no Base Fluid ingredients that are toxic/pollutants. Note also that results that use trade secrets as a continuous variable are consistent.

Overall, the Table I1 results do not support the idea that some of the increase in trade secret use may be a means to cloak increasing toxic or pollutant ingredient use. We see little evidence of cloaking, and no differential change in toxicity or pollutant disclosure for highly treated wells that have trade secrets.

A remaining issue with these analyses is that we still cannot directly identify if the trade secret ingredients are toxic since they are (by definition) not disclosed. Thus, we also explored whether there was any indirect evidence for toxicity increases associated with policy treatment. To do so, we estimated if there was an increase in tort cases relating to hydraulic fracturing post-DTSA. If toxic or pollutant chemical use was behind the increased use of trade secrets in High Treatment States, we would expect that filings of lawsuits might increase post-DTSA, especially in High Treatment States. We use data on Hydraulic Fracturing Litigation from Watson (2022), grouped into state-month filing rates.

We find no evidence of such an increase. Table I2 shows that fracturing-related tort filings did not increase in high treatment states post-DTSA. Note that these results should be interpreted cautiously as there are relatively few filings in analysis period: zero in Arkansas, Colorado, and Louisiana; one in Wyoming; four in Texas; eleven in Pennsylvania; and twenty-eight in Oklahoma.

Table I2. Hydraulic fracturing-related court (tort) filings, by state-month

	(1) Court filings	(2) Court filings
Post-DTSA	0.083	
	(0.090)	
High Treatment State	-0.003	
	(0.100)	
Post-DTSA X High Treatment State	-0.142	-0.142
	(0.104)	(0.112)
Observations	420	420
R-squared	0.012	0.227
State FE	No	Yes
Month FE	No	Yes

Robust standard errors in parentheses clustered at state level
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX J: Productivity analyses

Firms use trade secrets to protect valuable information which confers a commercial advantage over rivals (Risch 2007). In our setting, service firms seek to attract producers for repeat business (i.e., future fracking jobs) by generating a higher output from a well over which the producer owns the rights.

If trade secrets in fracking fluid ingredients confer a commercial advantage, we may observe that fracking ingredient trade secret use provides productivity advantages in fracturing. To explore this, we study oil output in average barrels per day (bd) and gas output in average thousand cubic feet per day (Mcfd), both over the first 30 production days. These are common measures of well productivity (Curtis 2016) provided by Rystad Energy. We have some productivity information for 99.7% of our main sample of 47,500 wells.

Table J1 includes raw mean production values, by well type, for firms with and without trade secrets. It showa higher mean productivity for wells with trade secret ingredients. Table J2 includes regression analyses for the full sample of wells. Using a trade secret is associated with an increase in production of oil of around 26% in the whole sample relative to sample average (366 bd) of wells without a trade secret (Column 1). Using a trade secret is associated with an increase in production of gas by around 6% in the whole sample relative to the sample average (2,352 Mcfd) of wells without a trade secret (Column 3). These associations remain significant even with firm, location, and time fixed effects.

Table J3 includes separate analyses by the type of wells. Rystad Energy categorizes wells into types: oil, gas (each defined as more than 75% of the hydrocarbon produced being oil or gas, respectively), and mixed wells, where the hydrocarbon produced is no more than 75% oil or gas. Again, trade secret use is associated with productivity increases. In Table J4, we examine highly productive wells (those in the top 10% of either oil or gas distributions) and again find a positive association between productivity and trade secret use.

Last, we include the raw distributions of the oil and gas productivity measures in Figure J1 (up to the 99th percentile for presentability). A visual inspection of the raw data would suggest that the use of a trade secret is associated with distributions shifting to the right. We also conducted Kolmogorov-Smirnov (K-S) tests, which indicate a statistically significant difference between the distributions with a maximum deviation of $D = 0.116$ (oil wells) and $D = 0.090$ (gas wells), and a p-value less than 0.001 in both cases.

Finally, in the main paper we examine whether the use of fracking fluid ingredient trade secrets affects productivity differently post vs. pre-DTSA (Table 7a and 7b). As we outline in the main paper, we would expect firms are balancing off the benefits of using trade secret ingredients in each well against the (long run) costs. Paramount in these costs is the risk that secrets leak to rivals, diluting the value of the trade secret ingredients in the future. DTSA decreases leakage risk. Thus, we expect firms will use trade secrets more often, but their added value may decrease.

The results for oil productivity appear to indicate an increase in oil production, in particular earlier in the post-DTSA period. We do not find any conclusive evidence for gas production. As a result, we are unable to conclude that the DTSA-induced increase in trade secret use unequivocally increased productivity. Below, in Figures J2 and J3 we plot the effect of trade secret use on productivity (in the whole sample), taking account of the full suite of fixed effects (month, service provider firm, producer firm, basin, and well type). First, it is evident that the average productivity increased over time generally. Second, there is a perceptible increase for oil production following the DTSA, but the results are noisy. Last, there is not a clear pattern of trade secret wells producing more gas post-DTSA.

Table J1. Trade secret use and mean well output

		Mean production	
		TS	No TS
Oil, barrels per day (first 30 days)	All wells	461	366
	Oil-only wells	587	467
	Mixed wells	553	460
Gas, Cubic ft per day (000) (first 30 days)	Gas - all wells	2487	2352
	Gas - gas-only wells	5701	4395
	Gas - mixed wells	3311	2926

Table J2. Trade secret use and well output, full sample (all well types)

	(1)	(2)	(3)	(4)
	Oil (bbl)		Gas (mcfd)	
Trade secret	95.821***	12.436***	135.259***	53.594*
	(3.932)	(3.729)	(36.974)	(30.843)
Observations	42,031	42,025	46,791	46,783
R-squared	0.013	0.494	0.000	0.642
Producer Firm FE	No	Yes	No	Yes
Service Firm FE	No	Yes	No	Yes
Well Type FE	No	Yes	No	Yes
Basin FE	No	Yes	No	Yes
Month FE	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table J3. Trade secret use and well output, by well type

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Oil wells		Gas wells		Mixed wells			
	Oil (bbl)	Oil (bbl)	Gas (mcfd)	Gas (mcfd)	Oil (bbl)	Oil (bbl)	Gas (mcfd)	Gas (mcfd)
Trade secret	119.38***	18.346**	1306.77***	77.276	69.956***	24.658***	74.388***	5.245
	(7.811)	(8.097)	(89.032)	(89.967)	(6.060)	(5.880)	(18.504)	(17.477)
Observations	13,266	13,202	16,714	16,661	17,385	17,328	17,345	17,289
R-squared	0.016	0.474	0.013	0.600	0.007	0.447	0.001	0.439
Producer Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
Service Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
Well Type FE	No	No	No	No	No	No	No	No
Basin FE	No	Yes	No	Yes	No	Yes	No	Yes
Month FE	No	Yes	No	Yes	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table J4. Trade secret use and top production wells, all FEs

	(1)	(2)	(3)	(4)
	Oil wells	Gas wells	Mixed wells	
	Top 10% production			
Trade secret	0.021***	-0.000	0.032***	0.007***
	(0.007)	(0.007)	(0.005)	(0.002)
Observations	13,271	16,699	17,354	17,354
R-squared	0.263	0.563	0.264	0.090
Producer Firm FE	Yes	Yes	Yes	Yes
Supplier Firm FE	Yes	Yes	Yes	Yes
Well Type FE	No	No	No	No
Basin FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure J1. Distribution of productivity by trade secret use

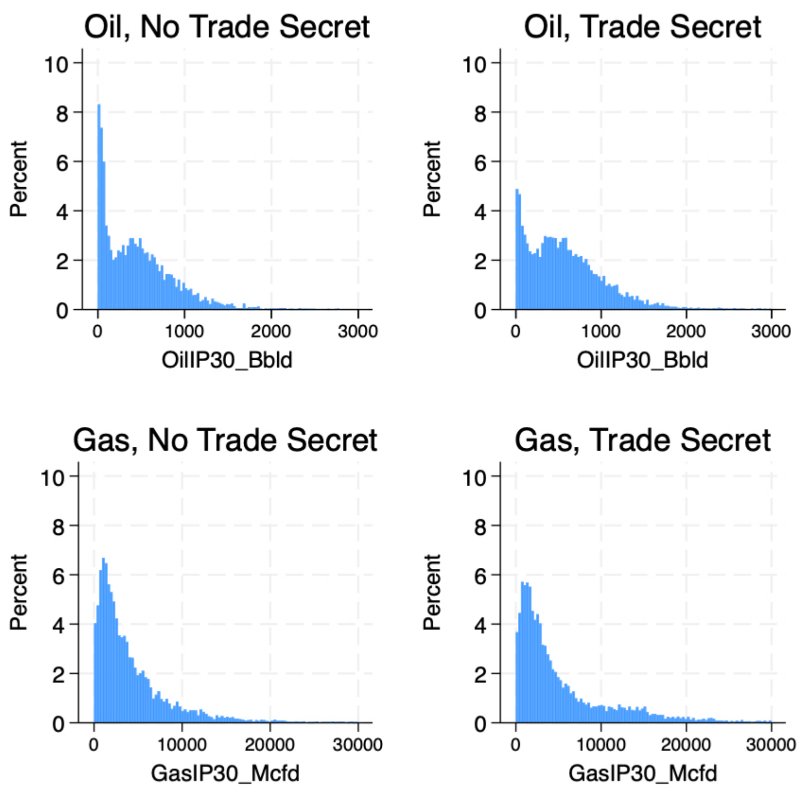


Figure J2. Dynamic oil production by trade secret use

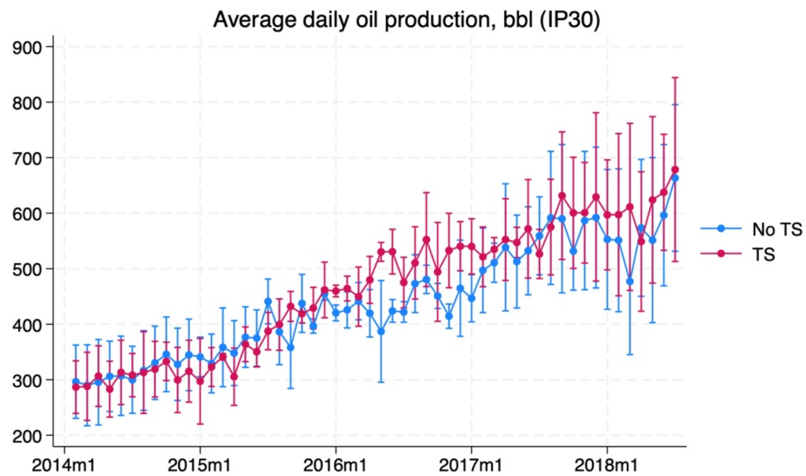
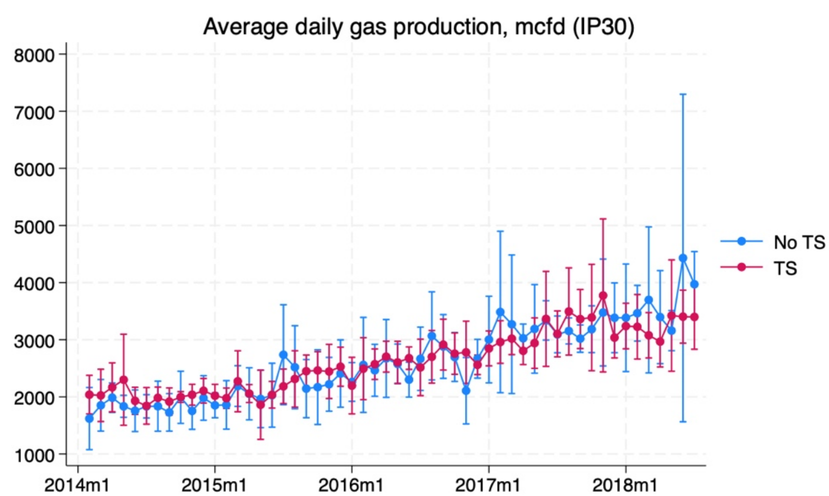


Figure J3. Dynamic gas production by trade secret use



APPENDIX K: Firm-state-level analyses

In this Appendix, we collapse our well-level observations of trade secret use by firm-state-month. These analyses reinforce our main findings. However, as we give up the ability to account for well-related heterogeneity driving ingredient choices when aggregating, we include these results to serve as robustness for our main well-level analyses. As these are at the firm-state-month level, our dependent variables are aggregate measures.

In the raw data, the overall proportion of wells with at least one trade secret is 48% prior to the DTSA and 75% post-DTSA. In Table K1, we first measure the proportion of (firm-state) wells with at least one trade secret ingredient. We estimate the effect of the DTSA on firm-state level use of trade secrets across High vs. Low Treatment States. In columns 1-3, we see High Treatment States experience a substantially higher increase in the proportion of wells with fracking fluid ingredient trade secrets following the DTSA (around 17-19pp higher relative to Low Treatment States, over the pre-DTSA average of 48%). We also consider the average share of trade secrets per well, and again see similar increases (columns 4-6). Overall, these aggregated results are consistent with our main analyses at the well level.

Table K1. Firm-State trade secret use

	(1)	(2)	(3)	(4)	(5)	(6)
	Trade Secret wells (share)			% secrets per well		
Post-DTSA	0.175***	0.112		0.027***	-0.026**	
	(0.016)	(0.196)		(0.004)	(0.012)	
High Treatment State	-0.201***	-0.197***	-0.201***	-0.022***	-0.022***	-0.008***
	(0.022)	(0.022)	(0.022)	(0.003)	(0.003)	(0.003)
Post X High Treatment State	0.191***	0.189***	0.173***	0.013**	0.012**	0.016***
	(0.036)	(0.036)	(0.033)	(0.006)	(0.006)	(0.005)
Observations	3,161	3,161	3,160	3,161	3,161	3,160
R-squared	0.094	0.106	0.364	0.038	0.048	0.675
Service Firm FE	No	No	Yes	No	No	Yes
Month FE	No	Yes	Yes	No	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX L: Hydraulic fracturing ingredient distribution

Table L1 below presents the nineteen chemical purpose categories capturing the general function of each ingredient as a part of fracturing fluid. Trade secret share column specifies the variance in reliance on trade secrets across the various categories. The share represents trade secrets by category across our entire sample of wells. The categories are stable: all nineteen exist throughout our study period, and disclosed ingredients fall within only one CPC.

Table L1. Fracturing ingredient categories and trade secret ingredients

Category	Purpose	Example ingredient	Trade secret share
Acid	Dissolve minerals and clays	Hydrochloric acid	2%
Biocide	Reduce bacteria	Chlorine dioxide	3%
Breaker	Decrease fluid viscosity	Ammonium persulfate	3%
Buffer	Optimize performance of fracturing fluids	Ammonium acetate	4%
Carrier/base fluid	Fluid into which additives are mixed	Water	0%
Clay control	Reduce swelling of clays	Choline chloride	11%
Corrosion inhibitor	Protect iron and steel equipment	Cinnamaldehyde	2%
Crosslinker	Create a more viscous gel	Ethylene glycol	5%
Diverting agent	Divert fluid to untreated zones	Polylactide resin	12%
Friction reducer	Allowing fluid to move efficiently	Sorbitol tetraoleate	3%
Gelling agent	Increase fluid viscosity	Guar gum	3%
Iron control	Control rust sludges and scale	Sodium erythorbate	1%
Multipurpose	Several purposes	Diutan gum	36%
Non-emulsifier	Separate hydrocarbon from flowback fluid	Ethoxylated nonylphenol	6%
Other/Unknown	Other purpose	Walnut hulls	3%
Ph control	Facilitate the crosslinking of gels and use of breakers	Sodium hydroxide	1%
Proppant	Hold the fractures open after hydraulic fracturing	Crystalline silica quartz	12%
Scale inhibitor	Prevent the formation of mineral scales	Calcium chloride	8%
Surfactant	Reduce the surface tension at the interface between two liquids	Naphthalene	4%

APPENDIX M: Knowledge leakage risk: triple interaction regressions

The table below summarizes the results presented in Table 4 in the main paper in triple-interaction form: the effects of the DTSA are lower where non-compete protection is stronger and customer trust is higher, and the effects are larger where the number of local rival firms is high. This is consistent with the interpretation that firms anticipate knowledge leakage risks, adjust to policies with such risks in mind, and deploy trade secrets accordingly.

Table M1. Triple interactions with moderators

	(1)	(2)	(3)
	Non-Compete Enforcement	Customer Trust	Co-located Rivals
	Trade secret		
High Treatment State	-0.080	-0.065	-0.070
	(0.097)	(0.081)	(0.074)
Post X High Treatment State	0.426***	0.289***	0.176***
	(0.070)	(0.039)	(0.038)
High NCE	0.008		
	(0.014)		
Post X High NCE	0.040		
	(0.066)		
High Treatment State X High NCE	-0.070		
	(0.061)		
High Treatment State X High NCE X Post	-0.238**		
	(0.085)		
High Customer Trust		-0.013	
		(0.042)	
Post X High Customer Trust		-0.030	
		(0.050)	
High Treatment State X High Customer Trust		-0.062*	
		(0.031)	
High Treatment State X High Customer Trust X Post		-0.200*	
		(0.087)	
Many Rivals			0.031
			(0.018)
Post X Many Rivals			-0.077
			(0.044)
High Treatment State X Many Rivals			0.016
			(0.016)
High Treatment State X Many Rivals X Post			0.144*
			(0.066)
Observations	47,500	47,500	47,500
R-squared	0.400	0.411	0.409
Operator Firm FE	Yes	Yes	Yes
Supplier Firm FE	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes
Basin FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX N: External sourcing

This appendix details the relationship between the change in trade secret protection and the sourcing of specific ingredients in the hydraulic mix recipes. At the ingredient level, we analyze whether an ingredient was listed as "own" (provided by the service provider firm performing the hydraulic fracturing job) or supplied by a third party. We then summarize our sourcing variable to the well level. More specifically, we flag wells with own, third-party, and mixed sourcing of ingredients in general and for trade secret ingredients specifically.

The well-level descriptive statistics are presented in Table N1. Next, in Table N2, we replicate the analyses of Table 3 in the main paper but with the dependent variables from Table N1. The regression analyses nuance the main findings, suggesting that both own and third-party trade secret ingredient incidence increased (Columns 2 and 4). In addition, the likelihood that all trade secret ingredients were externally sourced increased significantly (Column 3). The starkest increase relative to the baseline, however, is the increase in combining own and third-party trade secret ingredients within the same well (Column 5), which suggests an increase in recombinatorial sourcing activity. Finally, Table N3 replicates the same analyses for all ingredients (trade secret and non–trade secret ingredients combined). In this sample, as expected, we no longer see an increase in external sourcing. This is consistent with the DTSA driving externally sourced trade secret ingredients rather than market transactions in general.

Table N1. Descriptive statistics for ingredient sourcing (N=47,500)

Variable	Mean	Std. dev.	Min	Max
All own ingredients	0.06	0.25	0	1
All own TS ingredients	0.24	0.42	0	1
Any own TS ingredients	0.34	0.47	0	1
All third party ingredients	0.24	0.43	0	1
All third party TS ingredients	0.22	0.41	0	1
Any third party TS ingredients	0.33	0.47	0	1
Mixed ingredient provenance	0.69	0.46	0	1
Mixed TS provenance	0.11	0.31	0	1

Table N2. Regression analyses for TS ingredient sourcing

	(1)	(2)	(3)	(4)	(5)
	All own TS ingredients	Any own TS ingredients	All third party TS ingredients	Any third party TS ingredients	Mixed TS provenance
High Treatment State	0.005	-0.106	0.023	-0.088	-0.111
	(0.059)	(0.079)	(0.023)	(0.116)	(0.120)
Post X HTS	-0.028	0.151***	0.069**	0.248***	0.179**
	(0.058)	(0.023)	(0.021)	(0.033)	(0.050)
Observations	47,500	47,500	47,500	47,500	47,500
R-squared	0.375	0.471	0.399	0.361	0.282
Operator Firm FE	Yes	Yes	Yes	Yes	Yes
Supplier Firm FE	Yes	Yes	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes	Yes	Yes
Basin FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors clustered at state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table N3. Regression analyses for overall ingredient sourcing

	(1) All own ingredients	(2) All third party ingredients	(3) Mixed ingredient provenance
High Treatment State	-0.016	0.074***	-0.058
	(0.030)	(0.020)	(0.044)
Post X HTS	-0.013	-0.020	0.032
	(0.025)	(0.022)	(0.026)
Observations	47,500	47,500	47,500
R-squared	0.508	0.599	0.546
Operator Firm FE	Yes	Yes	Yes
Supplier Firm FE	Yes	Yes	Yes
Well Type FE	Yes	Yes	Yes
Basin FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes

Robust standard errors clustered at state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX O: Png Index

The Png index (Png 2017a, b) evaluates how the UTSA affected trade secret protection across different U.S. states. It collapses numerical evaluations along the following dimensions: law (statute), scope, limitations, procedure, and remedies. The existing Png index provides a value for 6 out of 7 states covered in our study: Arkansas, Colorado, Louisiana, Oklahoma, Pennsylvania, and Wyoming. Texas adopted the UTSA in 2013 and was thus not covered in the Png (2017a, 2017b) studies. We followed the methodology by Png to calculate the index value for Texas since 2013 based on the values provided in his online documentation.[64]

The main source for establishing trade secret protection in Texas following the UTSA adoption was the Texas Uniform Trade Secrets Act,[65] the state-specific interpretation of the UTSA. It was complemented with a report by Beck Reed Riden,[66] a law firm specializing in trade secret law.

The Texas index calculation was carried out following Png 2017b, Table S2 ("Index of Legal Protection of Trade Secrets"). The final index score is the <u>average of the six relevant dimensions</u>. The table below is an adaptation of Png 2017b, Table S2, and summarizes the index score for Texas:

Dimension	Item	Coding	Relevant Excerpt	TX post-UTSA score
Substantive law	Whether information must be in actual or intended business use to be protected as trade secret.	= 0 if information must be in actual or intended use, = 1 otherwise.	"[…] the information derives independent economic value, actual or potential, from not being generally known"	1
Substantive law	Whether reasonable efforts are required to maintain secrecy.	= 0 if reasonable efforts required, = 1 otherwise.	"[…] the owner of the trade secret has taken reasonable measures under the circumstances […]"	0
Substantive law	Whether information must be used or disclosed for it to be deemed to have been misappropriated.	= 0 if information must be used or disclosed, = 1 if includes mere improper acquisition or no requirement.	"[…] actual or threatened misappropriation may be enjoined […]"	1
Civil procedure	Limitation on the time for the owner to take legal action for misappropriation.	Number of years divided by six.	"An action for a misappropriation must be brought within 3 years after the misappropriation is discovered […]"	3/6

[64] In conversations with us, Png, instructed us to use the secrecy_index.doc file from his website to update the Texas measure, available here: https://sites.google.com/site/iplpng/research/stata?authuser=0

[65] https://statutes.capitol.texas.gov/Docs/CP/htm/CP.134A.htm. Last accessed on August 28, 2024

[66] https://www.faircompetitionlaw.com/wp-content/uploads/2018/08/Trade-Secret-50-State-Chart-20180808-UTSA-Comparison-Beck-Reed-Riden-2016-2018.pdf. Last accessed on August 28, 2024

Remedies	Whether an injunction is limited to eliminating the advantage from misappropriation.	= 0 if yes, = 1 otherwise	"[…]an injunction shall be terminated when the trade secret has ceased to exist […] In exceptional circumstances, an injunction may condition future use upon payment of a reasonable royalty […] In appropriate circumstances, affirmative acts to protect a trade secret may be compelled by court order."	1
Remedies	Multiple of actual damages available in punitive damages.	Number divided by three.	"[…] may award exemplary damages in an amount not exceeding twice any award made under Subsection (a)"	2/3
Score				**0.69**

With the final score of 0.69, Texas ranked as a "Low Treatment State" in this study, along with Colorado (score of 0.77), Oklahoma (score of 0.47), and Wyoming (score of 0.5). The remaining states — Arkansas (0.4), Louisiana (0.4), and Pennsylvania (0.13)[67] — were considered "High Treatment States" due to their lower scores of trade secret protection pre-DTSA. State-by-state analyses are in the Appendix E.

[67] For consistency with prior studies using the Png idnex, we adopt the same values as Png 2017a, 2017b for the 6 states where the index values are available and calculate the Texas value as per the Online Supplemental in Png 2017b. Besides the 2017 papers and associated online supplements, we also explored other documents on the Png website, including dofile "index.do", which suggests a normalization exercise. This would change the Texas index value from 0.69 to 0.63. Note that whether we follow Png2017b Table S2 or the personal website dofile, the ordinal values of the index remain the same, and thus do not affect our results. Since a normalization is not detailed in Png 2017a and 2017b papers or supplements, in our main analyses we follow the Png 2017b Supplement Table S2.

APPENDIX P: DTSA and Trade Secret Litigation

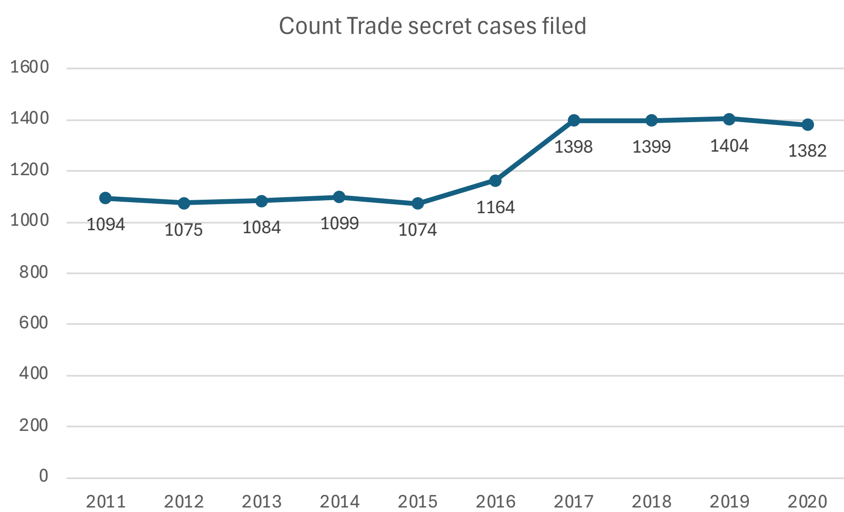
The purpose of this appendix is to summarize some high-level descriptive patterns in trade secret litigation associated with the DTSA. Using a trade secret involves trading off its value in a particular use (e.g., a well) against the costs of using it, particularly the likelihood and associated costs of leakage. The DTSA decreases both the costs of leakage (by increasing detectability and punishment) and the uncertainty in the legal environment (Mordaunt et al. 2020). Thus, DTSA should increase the use of trade secrets. Furthermore, we would expect DTSA to be associated with increased case filings, especially in federal district courts (e.g., Eastern District of Texas, Western District of Oklahoma). Note that state court data is not systematically available (Mordaunt et al. 2020).

Filing of trade secret cases increased by 30% in the year immediately following the passage of DTSA (Bailey 2018, 2021). Further, this increase appears to represent a shift rather than a temporary blip. Below are the federal district court cases involving trade secrets per year for 2010 to 2020, in Figure P1.

A few other facts about trade secret litigation (Bailey 2018, 2021):

1. DTSA is invoked in more than 70% of post-DTSA federal district court cases.
2. Most trade secret cases involve other claims, namely breach of contract. Other IP claims are also often involved, e.g., copyright (11% of TS cases), trademark (22%), and patent (6%).
3. Most cases (67%) end in settlement; 16% of cases have procedural resolution (e.g., dismissal). Trial outcomes are rare: claimants win 14% of the time versus 3% for defendants.

Figure P1: TS Cases (US Federal District Court) filed 2011–2020



APPENDIX Q: Trade Secret Cases from the U.S. Hydraulic Fracturing Industry

This appendix provides details on some example legal cases involving claims of trade secret misappropriation by firms involved in the hydraulic fracturing industry.

Legal cases claiming misappropriation of trade secrets are likely to represent a small and selected sample of misappropriation events. Our investigation of trade secret cases suggests four main reasons for the relatively rarity of misappropriation reaching legal action. First, claimant firms need to prove the existence and scope of the trade secret and that reasonable measures were taken to protect it, all of which can be hard to prove. Second, unlike patents that are disclosed, trade secret value depends on being kept secret. Yet, legal filings draw attention to their existence and divulge some amount of information about their characteristics, which risk further leakage of the secret. Third, proving misappropriation involves demonstrating that trade secrets were stolen, which can require detail forensic computer evidence, for instance. Finally, trade secret law has long been decentralized and heterogenous across jurisdictions within the U.S. making the filing risky in terms of leakages but also uncertain in terms of expected outcomes for plaintiffs.

Our interviews with hydraulic fracturing industry insiders suggested tat firms are loathe to bring trade secret related issues to court, as doing so may destroy a key firm relationship (see related quotes in main manuscript). In short, there is a limited number of opportunities in a highly competitive space, which makes firms highly value ongoing relationships.

Below are the details of 11 example trade secret cases from the period 2010 to 2024 (including ongoing). These cases were sourced via firm name searches in Lex Machina (which only provides details on only a limited set of federal cases via the public interest license) and searches for “Hydraulic Fracturing” and “Trade Secret” in CaseText.

Case	Year	Source of alleged misappropriation	State	Outcome	Secret
Baker Hughes v. Varel Int'l.	2010	Employee	Texas	Damages: $25 million	Design
TXCO Res. v. Peregrine Petroleum	2012	Business partner (rival)	Texas	Damages: $15 million	Data
Baker Hughes v. Homa	2013	Employee + Business partner (customer)	Texas	Dismissed	Technology; Process
Legacy Separators v. Halliburton Energy Servs.	2014	Business partner (supplier)	Oklahoma	Settlement	Process
Core Labs v. Spectrum Tracer Servs.	2016	Employee	Oklahoma	Other	Software
Trican Well Services v. Preferred Proppants	2017	Business partner (supplier)	Texas	Settlement	Data; Recipes
Downhole Tech. v. Silver Creek Servs.	2017	Employee + Business partner (customer)	Texas	Settlement	Design
Baker Hughes Oilfield Operations v. Packers Plus Energy Servs.	2018	Espionage by rival	Texas	Settlement	Technology; Process; Recipes
Synergy Indus. v. Nat'l Oilwell Varco & Schlumberger	2019	Business partner (customer)	Texas	Settlement	Technology
KLX Energy Servs. v. Magnesium Mach.	2023	Business partner (supplier)	Oklahoma	Settlement	Technology
U.S. Well Services v. Liberty Energy	ongoing	Business partner (rival)	Texas	Ongoing	Technology; Process

The key sources of misappropriation are former employees going to rivals or starting a new company, or via business partners (whether suppliers, customers, or potential rivals via collaboration explorations). Here are more details on one example of each.

1. **Ex-employee:** In Baker Hughes v. Varel Int'l Energy Services (2010), Varel managers who formerly worked at Baker Hughes were accused of stealing design specifications from Baker Hughes and ordering a Varel engineer to use them to copy a 7 7/8-inch tricone drill bit. In this case, misappropriation was found and $25 million in damages were awarded to Baker Hughes. Interestingly, Baker Hughes subsequently granted a license to Varel (terms of the licensing deal were confidential).
2. **Ex-business partner (customer):** An example is Synergy v. National Oilwell Varco (NOV) and Schlumberger (2019). Since 2012, Synergy was a supplier of wireline truck associated technology for Schlumberger. Synergy claimed that Schlumberger contracted with NOV to duplicate the wireline technologies. Synergy produced photo evidence of the use of the technology, which they claimed violated the purchasing agreement and misappropriated trade secrets. The case was settled.
3. **Ex-business partner (rival)**: In TXCO v. Peregrine (2012) involved the two firms meeting in 2009 to evaluate a sale relating to TXCO's Maverick Basin properties. They didn't reach an agreement. Peregrine subsequently leased land in the basin. The claim of trade secret misappropriation was that Peregrine used TXCO's land subsurface data, production data, and operations data to acquire oil and gas leases formerly held by TXCO. The use of the TS was proven via PowerPoint slides used internally in Peregrine including TXCO's confidential and protected data.
4. **Rival espionage:** This case followed on from a patent infringement suit, Baker Hughes v. Packers Plus (2016). Packers Plus filed a countersuit claiming a password protected folder of "commercially sensitive information and trade secrets relating to its various products, including its FracPort products" was accessed by a computer forensically linked to a Baker Hughes IP (and McKool Smith (law firm)). The patent infringement suit was how Packers Plus learned BH had possession of their trade secrets. The associated cases were all settled.

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