# Visibility of Technology and Cumulative Innovation: Evidence from Trade Secrets Laws*

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**Abstract**

Innovative activity depends on the incentives to create new ideas as well as the visibility of and access to existing ones. We show that a relative strengthening of trade secrets protection has a disproportionately negative effect on patenting of processes – inventions that are not otherwise visible to society. We develop a structural model of initial and follow-on innovation to determine the welfare effects of such shifts in disclosure for industries characterized by cumulative innovation. While stronger trade secrets encourage investment in initial R&D, they may have negative effects on overall welfare by reducing opportunities for follow-on innovation.

**Keywords:** cumulative innovation; disclosure; intellectual property; Uniform Trade Secrets Act; visibility.

**JEL Codes:** D80; O31; O34

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*"[S]ociety is giving something for nothing ... [when] concealable inventions remain concealed and only unconcealable inventions are patented."*

Machlup and Penrose (1950)

# 1 Introduction

When better protection of intellectual property improves the appropriability of R&D investment returns, firms have stronger incentives to invest and innovate. The fruits of such innovation serve as the proverbial shoulders on which future innovators can stand, thus fostering technological progress through more follow-on (or cumulative) innovation.[1] However, granting the inventor a temporary monopoly through a patent can have negative, "anticommons" effects on follow-on innovation when exclusivity renders the shoulders less accessible (Heller and Eisenberg, 1998). A negative effect on follow-on innovation also arises when inventors decide to disclose fewer of their inventions through patents and instead keep them secret, especially in industries with technologies that are per se less visible or "self disclosing" (Strandburg, 2004). In those industries, the diffusion of knowledge relies on the disclosure function of patents. Diffusion would be hampered if inventors kept more secrets, and even more so when legal trade secrets protection is strong. We study these effects of intellectual propery policy and visibility of technology on patenting and cumulative innovation.

Secrecy is an important tool in a firm's intellectual property management toolbox. There is ample survey-based evidence that secrecy is widely used and often more important as an appropriability mechanism than patents (e.g., Levin et al., 1987; Cohen et al., 2000; Arundel, 2001). Mansfield (1986) reports survey results suggesting that one out of three patentable inventions is kept secret when inventors have a choice between secrecy and patenting. Importantly, choosing secrecy does not mean that the invention is without any protection. The laws governing trade secrets offer protection against *misappropriation* of secrets – that is, the

[1] In February 1675, Sir Issac Newton wrote in a letter to Robert Hooke: "If I have seen further, it is by standing upon the shoulders of giants." See Scotchmer (1991) for the economics of giants' shoulders.

acquisition of a trade secret by *improper means* or the disclosure of a trade secret without consent.[2] For example, in a well-publicized legal case, Waymo LLC (a self-driving car startup under Google's Alphabet) accused Uber Technologies of violating both California state and federal trade secret laws, alleging that a former employee secretly downloaded data around a key piece of technology from its servers before resigning and launching a self-driving truck startup.[3] However, while trade secrets laws provide protection against such misappropriation, unlike patents they do not grant general exclusivity: A trade secret is not protected if it accidentally leaks or is uncovered through independent discovery or reverse engineering (Friedman et al., 1991).

Stronger protection of trade secrets renders them more attractive relative to patents. In this paper, we ask how a change in the attractiveness of secrecy affects the diffusion of knowledge through the decision to invest in different types of innovation, the disclosure of these inventions, and the ability to build on them. We use exogenous variation across states and time from the staggered adoption of the Uniform Trade Secrets Act (UTSA) of 1979/1985, which changed the strength of trade secrets protection in individual states, to isolate the effects of trade secrets protection from other unobserved factors. Using the index of the strength of trade secrets protection introduced by Png (2017a) and new data on the type of a patented invention – product or process – to capture how visible or self-disclosing an invention is (Ganglmair et al., 2020), we show that stronger trade secrets protection results in a disproportionate decrease of process patents. Since patents provide insight into what is *not* kept secret, we interpret this change as a relative increase in the propensity to keep process inventions secret.[4] This, in turn, limits opportunities for follow-on innovation.

[2] Generally speaking, a trade secret is information (e.g., a customer list, a business plan, or a manufacturing process) that has commercial value the secret holder wants to conceal from others (Friedman et al., 1991). "Trade secret" is a legal term that applies when the conditions (as laid out in the law) for information to qualify as a trade secret are satisfied. We use the terms "secrecy" and "trade secrets" interchangeably.

[3] The startup was later acquired by Uber. See Waymo LLC v. Uber Technologies, Inc; Ottomotto LLC; Otto Trucking LLC. No. 3:17-cv-00939, N.D. Cal., San Francisco Division. The case settled in February 2018, only five days into the trial.

[4] Our assumption of the choice between secrecy and patents (as opposed to joint use (Arora, 1997)) comes without loss of generality as long as there is *some* degree of substitutability. We return to this issue below when we examine the effects of trade secrets protection across firm and technology types.

The welfare implications of such changes in intellectual property protection depend not only on the facilitation of follow-on innovation but also on the ex-ante incentives to innovate. To make inferences about these incentives, we need to estimate the distributions of both *realized* and *potential* inventions. We do so in a structural model of sequential innovation, in which we use simulation methods to infer potential inventions from realized inventions estimated from patent data and variation in trade secrets protection. We find that total welfare may in fact decline as trade secrets protection grows stronger, especially when the costs of R&D are relatively small and stronger trade secrets protection does little to incentivize innovation. In contrast, stronger trade secrets protection can increase welfare when R&D is more costly as protection can lead to increased investment in initial R&D.

We provide more institutional background, including details about the UTSA and a discussion of the disclosure function of patents, in Section 2. In Section 3, we develop a simple model of an inventor's decision to disclose a new invention through a patent. Among other factors, the value of the invention from a patent increases with the underlying invention's visibility: Visibility allows for easier enforcement of the patent, thus guaranteeing exclusive access to the technology. In contrast, the value of an invention that is kept secret decreases in its visibility, because secrecy (and therefore exclusive access) is more difficult to maintain. To derive predictions, we assume that *processes* are on average less visible than *products*, so that, on average, inventors of processes value secrecy more than inventors of products.[5] Our model predicts that, for a given baseline share of process *inventions*, the share of process *patents* decreases as trade secrets protection strengthens. This theoretical prediction serves as the basis for the empirical analysis in the rest of the paper.

In Section 5, we use the patent-level data introduced in Section 4 and the staggered adoption of the UTSA (from Section 2) to estimate the effect of stronger trade secrets protection on the likelihood that a patent covers a process innovation in a difference-in-differences setting. Consistent with results from our theoretical model, we find that stronger

[5] This is consistent with survey evidence (Levin et al., 1987; Cohen et al., 2000; Arundel, 2001; Hall et al., 2013).

legal protection of trade secrets leads to a disproportionate decrease of patenting of processes. Our estimated effects are largest among individual inventors and small firms and are driven by patents covering discrete rather than complex technologies.

Our structural model, developed in Section 6, adds the R&D decisions in a sequential innovation model to our simple framework from Section 3. It provides estimates for the visibility distributions of potential process and product inventions (and their respective shares), conditional on the assumed costs of R&D. These distributions allow us to calculate the probability of R&D investment and the shares and characteristics of the realized inventions that become trade secrets. Counterfactual analyses of the full sequential-innovation model show that the optimal level of trade secrets protection is increasing in the costs of R&D. When costs are low, stronger legal protection of trade secrets has little effect on initial R&D but carries the unintended consequence of impeding follow-on innovation. On the other hand, for R&D projects that are relatively more costly, stronger legal protection improves welfare by encouraging initial R&D. We further show that both positive and negative effects of trade secrets protection are more pronounced for processes than for products, and that the optimal level of trade secrets protection is lower when follow-on innovation is more important.

Beyond a number of studies based on survey data, there is limited empirical work on trade secrets, though a small literature presents indirect evidence on secrecy. Moser (2012) documents a shift toward patenting (and away from secrecy) in the chemical industry as reverse engineering became easier with the publication of the periodic table of elements. Gross (2019) finds that a policy during World War II to keep certain patent applications secret resulted in fewer citations and slower dissemination of the patented technologies into product markets. Hegde and Luo (2018) show that a reduction of the duration of temporary secrecy of patent applications had a mitigating effect on licensing delays, and Hegde et al. (2020) find an acceleration in diffusion of knowledge and ideas.

A related strand of literature studies the effect of changes in legal trade secrets protection on innovation and patenting behavior. Png (2017a,b) finds that stronger trade secrets protection has a positive effect on firms' investment in R&D and renders patenting relatively less attractive. Related to this line of work, Contigiani et al. (2018) find that more employer-friendly trade secrets protection has a dampening effect on innovation, and Castellaneta et al. (2017) show a positive effect on firm value in industries with high mobility of skilled labor. Angenendt (2018) finds that patent applicants respond to stronger trade secrets protection by reducing the number of patent claims.

We add to these bodies of literature by accounting for the role of an invention's visibility in patenting and innovation decisions, as well as in providing opportunities for follow-on innovation. To our knowledge, this is also the first paper presenting welfare results for changes in trade secrets laws. We further uncover the mechanisms behind these effects, which highlight that insights gained from the effects of patents on innovation do not necessarily apply to trade secrets. This is particularly important in light of the U.S. Defend Trade Secrets Act and the EU Trade Secrets Directive 2016/943, for which impact evaluations are just now starting to become available. Results from the UTSA can thus inform an ongoing policy debate in both the U.S. and in Europe.

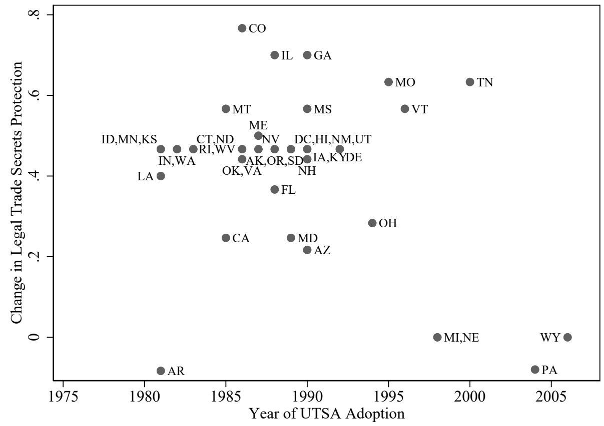
# 2 Institutional Background

## 2.1 Uniform Trade Secrets Act (1979/1985)

The UTSA was published and recommended to the individual U.S. states for adoption in 1979 (with a revision in 1985) by the National Conference of Commissions on Uniform State Laws. Since 1979, 47 states, the District of Columbia, Puerto Rico, and the U.S. Virgin Islands have adopted the UTSA, with adoption dates ranging from 1981 (5 states) to 2013 (Texas) (Sandeen and Rowe, 2013).

The objective of the UTSA was to clarify and harmonize across U.S. states the legal protection of trade secrets. Most prominently, it attempted to standardize the definition of a trade secret, the meaning of misappropriation, and remedies (including damages) for

**Figure 1:** Change in Legal Protection of Trade Secrets




*Notes:* This figure presents data from Table 1 in Png (2017a). For the states that adopted the UTSA between 1981 and 2006, it depicts the change in legal protection of trade secrets across states as a result of the UTSA.

trade secret holders in case of a violation. For example, with the adoption of the UTSA, the Commonwealth of Virginia dropped the requirement of actual or intended use for something to be considered a trade secret and increased the punitive damages multiplier from 0.5 to 2. Png (2017a) constructs an annual index that measures the strength of legal trade secrets protection at the state level for the years 1976 to 2008. The changes in Virginia – dropping the actual or intended use requirement and raising the punitive damages multiplier – represent increases in two of the six inputs into the index.[6]

Figure 1 illustrates the *change* in this index in individual states as they adopted the UTSA in a given year, with higher values implying larger increases in protection. In most states, the UTSA resulted in a strengthening of trade secrets protection, with the exception of Michigan, Nebraska, and Wyoming, where the UTSA had no effect, and Arkansas and Pennsylvania, where pre-UTSA trade secrets protection (under common law) was stronger. There is no obvious pattern in the size of these changes over time and across states, and Png (2017a) cites anecdotal evidence that suggests that passing of the bills often happened for "whimsical" reasons.

[6] In addition to these two factors, the index is higher (i) without a requirement that the trade secret holder have in place reasonable effort to protect the secret, (ii) without a requirement that the information is used or disclosed, (iii) without a statute of limitation, and (iv) with unlimited length of injunction.

## 2.2 Trade Secrets and the Disclosure Function of Patents

By using the UTSA to examine the effects of trade secrets and patents on follow-on innovation and welfare, we make two implicit assumptions. First, changes in the level of trade secrets protection affect firms' use and defense of trade secrets. Second, patents provide some disclosure of inventions.

The first premise, that the changes in trade secrets protection through the UTSA were sufficient to induce changes in behavior, is supported by the empirical evidence discussed in the introduction (e.g., Png, 2017a,b; Castellaneta et al., 2017). Moreover, Almeling (2012) attributes part of the rise of the litigation of trade secrets over the past few decades to the individual states' adoption of the UTSA, mostly because it raised awareness of the option to keep trade secrets.[7]

The second premise is that patents provide some disclosure of inventions that are not inherently visible. Legal scholars have called the disclosure function of patents into question. For example, Ouellette (2012) argues that patents have lowered the level of openness in science. While acknowledging that "patents disclose useful, nonduplicative technical information" (p.$\hat{5}$33), she notes they "could be even more informative." Others share these concerns (Roin, 2005; Fromer, 2009; Devlin, 2009; Seymore, 2009). In addition, Lemley (2008a) suggests that researchers do not pay attention to patents, perhaps for strategic reasons, a phenomenon observed more often in complex than in discrete technologies (Bessen and Meurer, 2009).

Nevertheless, both law and economics researchers seem to agree that patents provide *some* information. Exploiting variation across fields, Merges (1988) finds that many inventors do rely on published patents for technical information. Recent work by economists also finds that innovators use existing patents for inspiration and information (Furman et al., 2018; Gross, 2019; Hegde et al., 2020). Importantly, while in our modeling approach we assume

[7]For a comprehensive survey of trade secrets litigation in federal and state courts, see Almeling et al. (2010a,b).

perfect disclosure for tractability reasons, our results hold as long as there is *some* disclosure in patents.

# 3 A Model of Trade Secrets and Disclosure

In this section, we consider an inventor's decision whether to disclose a (patentable) invention through a patent or to keep the invention a secret.[8] This decision is embedded (as Stage 2) in a three-stage sequential model, where Stage 1 describes the inventor's decision to invest in R&D and realize the initial invention, Stage 2 describes the disclosure decision, and Stage 3 captures the market's engagement in follow-on innovation. We return to the full three-stage model when we present our welfare results in Section 6. For the patenting decision at Stage 2, we take a simple approach and focus on the roles of trade secrets and an invention's visibility. Many other factors that may play a role in the decision to patent are captured by a single parameter. The model serves two purposes: It derives predictions for the analyses in Section 5, where we examine the empirical relationships between trade secrets protection, visibility, and patenting; and it provides a benchmark against which we can assess the results from our structural estimations in Section 6.

## 3.1 An Inventor's Decision to Disclose

An invention $i$ at Stage 2 can be described by a tuple $(\phi, \Theta, v)$. It is characterized by its visibility $\phi \in [0,1]$, its type $\Theta$, and its private commercial value $v \geq 0$ (from exclusive use). We discuss each of the invention's characteristics below.

An inventor is given the choice to disclose an invention through a patent ($\tilde{d} = D$) or keep the invention secret ($\tilde{d} = S$).[9] We set the inventor's private returns $V_{\tilde{d}}$ equal to the

[8] Given that we use patent data for our empirical analysis, we restrict our model interpretation to inventions that are patentable. In the U.S., this means they must exhibit patentable subject matter (35 U.S.C. §101), be useful (35 U.S.C. §101), novel (35 U.S.C. §102), and non-obvious (35 U.S.C. §103).

[9] This assumption of mutually exclusive states $\tilde{d}$ is for convenience and does not pose any significant restrictions. For instance, instead of a singleton invention, we can think of an invention that comprises both product and process elements, and for which the decision to patent or keep secret is made for each individual

*exclusivity-weighted* commercial value $v$, where we interpret $v$ as the rents the inventor is able to appropriate from *exclusive* use of the invention. A lower degree of exclusivity means the inventor reaps a smaller fraction of these rents.

In both disclosure states $\tilde{d} = D, S$, the probability of exclusive use depends on the *visibility* of the invention.[10] Visibility is a two-way street. We refer to *disclosure-visibility*, denoted by $\phi_D$, as the ease with which an inventor $A$ can observe a firm $B$ using $A$'s (disclosed) invention. We refer to *secrecy-visibility*, denoted by $\phi_S$, as the ease with which a firm $B$ can observe inventor $A$ using $A$'s own (secret) invention. We will assume that, for a given invention, disclosure-visibility is higher than secrecy-visibility, $\phi_D \geq \phi_S$. A simple argument for this is that the inventor herself knows what to be on the lookout for, whereas firm $B$ has little prior guidance. We set $\phi_D = \phi$ and $\phi_S = \xi\phi$ with $\xi \in (0, 1]$.

A patent for a more disclosure-visible invention is easier to enforce, and exclusivity prevails.[11] We can write the expected commercial value the inventor is able to materialize as $\phi_D v = \phi v$. In addition, the inventor receives a patent premium $\lambda$.[12] It captures the benefits from patenting over trade secrets and may even include licensing revenues from follow-on innovation. Collecting terms, we can summarize the inventor's private value of disclosing the invention (i.e., the value from patenting) as $V_D(\phi) = \phi\,(1 + \lambda)\,v$.

While disclosure-visibility is important to determine the value of a *patent*, the value from *trade secrecy* is determined by secrecy-visibility, $\phi_S = \xi\phi$. Moreover, the value of secrecy increases with the level of trade secrets protection. We denote the exogenous probability that a trade secret is protected by $\tau \in [0, 1]$. Recall that trade secrets laws provide protection

component.

[10] In certain applications, higher visibility can also be interpreted as a higher probability that the invention can be reverse-engineered. Scotchmer and Green (1990) show that an inventor of a patentable technology might not want to patent and keep the technology off the market to avoid reverse engineering. For a general treatment of reverse engineering, see Samuelson and Scotchmer (2002).

[11] Active monitoring of infringement is said to be a major source of the costs of patent enforcement (Hall et al., 2014). Goldstein (2013:64) writes: "A patent claim whose infringement is very hard to discover is a claim with low or no value."

[12] Patents are of additional value because, for instance, they signal the quality of the invention (Hsu and Ziedonis, 2013), convey reputation (Graham et al., 2009; Sichelman and Graham, 2010), or simply improve an inventor's bargaining position in license negotiations (Hall and Ziedonis, 2001). Webster and Jensen (2011) further provide evidence for a premium from commercialization.

against misappropriation of trade secrets but not against simple copying. This means that, even with perfect trade secrets protection ($\tau = 1$), keeping the invention secret is of little value to the inventor if it is secrecy-visible. Conversely, weaker trade secrets protection reduces deterrence and results in more (unsanctioned) misappropriation of trade secrets (e.g., Friedman et al., 1991:68). We therefore assume that, without any trade secrets protection, the value of trade secrecy is zero even for non-visible inventions.[13] Collecting terms, we define the private value from secrecy as $V_S(\phi, \tau) = \tau\,(1 - \xi\phi)\,v$.

An implicit assumption in $V_S$ is that the secret holder can detect misappropriation, and this ability is independent of the underlying visibility of the technology. A positive probability of detection is consistent with empirical evidence: Many instances of trade secrets litigation involve former employees or business partners stealing the secret holder's information (Almeling et al., 2010a,b). The Waymo case described in the introduction provides one prominent such example. For tractability, we set the probability of detection equal to unity, so that the only variation in the enforcement of trade secrets is through $\tau$.[14]

The inventor chooses disclosure if, and only if, $V_D(\phi) \geq V_S(\phi, \tau)$, or

$$\phi \geq \frac{\tau}{1 + \lambda + \xi\tau} =: \bar{\phi}(\tau). \tag{1}$$

For a given $\phi$, we can summarize the decision to disclose, $\tilde{d} \in \{D, S\}$, as

$$\tilde{d} = \begin{cases} D & \text{if } \phi \geq \bar{\phi}(\tau) \\ S & \text{if otherwise.} \end{cases} \tag{2}$$

Observe that in our model, the inventor's decision to patent an invention is not a function of the potential commercial value of the invention but rather of the *effective* value (given

[13] While the lack of legal sanctions is likely to encourage misappropriation, firms are expected to erect safeguards when trade secrets protection is weak (Friedman et al., 1991; Lemley, 2008b). These safeguards are often inefficient and their costs increase in $v$ and decrease in $\tau$. Without trade secrets protection, the effective commercial value may thus in fact fully dissipate.

[14] An alternative interpretation of $\tau$ is the product of the detectability of misappropriation and the strength of legal trade secrets protection.

the invention's visibility).[15] From Equation (2) and the expression for $\bar{\phi}(\tau)$, we can conclude that an inventor is more likely to file for a patent (and thereby disclose her invention) as the degree of visibility $\phi$ increases, and she is less likely to patent as the degree of trade secrets protection $\tau$ increases. External sources provide corroborating evidence for these comparative statics. Moser (2012) provides empirical evidence for more patenting as visibility increases captured by the ease of reverse engineering an invention, and Png (2017b) shows that patenting decreases as trade secrets protection increases.

## 3.2 Value of Trade Secrecy by Invention Type

We assume that an invention's visibility $\phi$ is unobservable but distributed on the unit support with cdf $G_\Theta$. What is observable is an invention's *type* $\Theta$ that is correlated with its visibility. An invention is either a process (or method), $\Theta = M$, or a product, $\Theta = P$. The probability that the realized invention is a process is $\theta = \Pr(\Theta = M)$.

We assume that processes are on average less visible than products.[16] The (expected) values of secrecy $EV_{S|\Theta}(\tau)$ and disclosure $EV_{D|\Theta}(\tau)$ of an invention of type $\Theta$ are

$$EV_{S|\Theta}(\tau) = \int_0^1 \tau\,(1 - \xi\phi)\,v dG_\Theta \qquad \text{and} \qquad EV_{D|\Theta}(\tau) = \int_0^1 \phi\,(1 + \lambda)\,v dG_\Theta. \tag{3}$$

**Proposition 1.** *For a given level of trade secrets protection $\tau$, the value of secrecy is higher for processes than for products. Conversely, the value of disclosure is lower for processes than for products.*

The proofs of this and all other results are relegated to Appendix Section A.1. Evidence from survey data, finding that the propensity to patent is higher for products than processes

[15] While the theoretical literature is divided (e.g., Anton and Yao, 2004; Jansen, 2011), most empirical studies find a positive relationship between the value of an invention and the propensity to patent (e.g., Moser, 2012; Sampat and Williams, 2018).

[16] We formally capture this by assuming *hazard-rate dominance* which implies first-order stochastic dominance (Krishna, 2010:276). The distribution $G_P$ hazard-rate dominates $G_M$ if $\frac{g_p(\phi)}{1-G_P(\phi)} \leq \frac{g_M(\phi)}{1-G_M(\phi)}$ for all $\phi$. Moreover, $G_P$ first-order stochastically dominates $G_M$ so that $G_P \leq G_M$ for all $\phi$.

and thus suggesting a higher value of secrecy for processes, comports with this theoretical finding (e.g., Levin et al., 1987; Cohen et al., 2000; Arundel, 2001; Hall et al., 2013).

### 3.3 Probability of Disclosure for Invention Types

For our main theoretical result and prediction, we derive the probability $\rho$ that a given patent covers a process invention. We first establish two auxiliary results. In Lemma 1, we show that the probability that a process is patented is weakly smaller than the probability that a product is patented. For this, let $d(\phi, \tau) = 1$ if $\tilde{d} = D$ and $d(\phi, \tau) = 0$ if $\tilde{d} = S$. The probability that an invention of type $\Theta$ is patented is

$$d_\Theta(\tau) = \int_0^1 d(\phi, \tau) dG_\Theta(\phi) = \int_{\bar{\phi}(\tau)}^1 1 \cdot dG_\Theta(\phi) = 1 - G_\Theta(\bar{\phi}(\tau)). \tag{4}$$

**Lemma 1.** *For a given level of trade secrets protection $\tau$, $d_M(\tau) \leq d_P(\tau)$.*

In Lemma 2, we establish the relationship between patenting probabilities and trade secrets protection.

**Lemma 2.** *The patenting probabilities for products $d_P(\tau)$ and processes $d_M(\tau)$ decrease in trade secrets protection $\tau$.*

Given the underlying distribution of invention types with $\theta = \Pr(\Theta = M)$, Bayes' rule gives us the probability that a given patent covers a process:

$$\rho(\tau) = \frac{\theta d_M(\tau)}{\theta d_M(\tau) + (1 - \theta)\, d_P(\tau)}. \tag{5}$$

**Proposition 2.** *Given the pool of inventions, the probability that a given patent covers a process is decreasing as trade secrets protection increases.*

The expression in Equation (5) can also be interpreted as the share of process patents in a sample of patents. Proposition 2 predicts that the probability that a given patent is a process patent decreases in response to an (exogenous) increase in trade secrets protection. In the next two sections, we take this prediction to the data.

# 4 Patent Data

In our empirical analyses, we estimate the probability that a patent includes a process innovation as a function of the trade secrets protection index described in Section 2, for patents with priority dates between 1976 and 2008 – the years for which we have trade secrets protection data. To do this, we (a) match a set of patents to the relevant level of trade secrets protection by identifying the timing and location of the patenting decision, and we (b) determine each patent's type (process or product) based on the language used in its claims. We supplement these data with additional patent characteristics.

## 4.1 Timing of the Disclosure Decision and Patent Location

To determine the timing of the disclosure (patenting) decision, we use the earliest priority date of the respective granted patent. The earliest priority date reflects the application date of the first patent application in a patent family (i.e., the *parent application*) from which a patent's ultimate application draws and applies to all its subsequent continuation and divisional applications.[17] The relevant disclosure decision was likely made at the time of the parent application, so that we use that application's priority date as the disclosure date for all related patents.

For the location of the patent, we consider only patents for which all U.S. inventors and U.S. assignees are from the same state, and we use that state as the patent's location. Our approach allows us to unambiguously identify a patent's location, and hence ensures that the patent applicant's decision was driven by only that state's level of trade secrets protection,

[17] For continuations, the applicant may not add new disclosures but may delete claims. Divisions involve separating an earlier patent application into two or more.

and not contaminated by laws in other states.[18]

For our final sample, we follow Strandburg (2004), who argues that business methods are highly visible "self-disclosing processes," and drop all business method patents (Lerner, 2006). With our assumption of single-state patents, we limit our overall sample to 1,451,311 patents (out of 2,433,317 patents by U.S. applicants, and 4,370,594 total), granted between 1976 and 2014 and with priority dates between 1976 and 2008.[19]

## 4.2 Indicators for Process and Product Patents

We use information about the type of the patented invention at the level of the patent's independent claims to construct our indicators of process and product patents.[20] A claim can be of one of three distinct types: (1) process (or method) claims describe the sequence of steps which together complete a task such as making an article; (2) product-by-process claims define a product through the process employed in the making of a product; and (3) product claims describe an invention in the form of a physical apparatus, a system, or a device.[21]

We aggregate the claim-level information to obtain an indicator for the invention type at the patent level. Specifically, we classify a patent as a *process patent* if at least one of its independent claims is either a process claim or a product-by-process claim, and as a *product patent* otherwise. We choose this rather aggressive indicator because we are interested in whether any process-related aspects of an invention are disclosed at all, regardless of the

[18] An identifying assumption, which is supported by Paolino v. Channel Home Centers, 668 F.2d 721 724 n.2 (3d Cir. 1982), is that trade secrets protection is determined by the state where the secret was developed and not where it was misappropriated ("the law of the state of residence of the person who initially developed and protected the secret appears to be the obvious starting point for its protection.")

[19] Our estimation sample slightly over-represents individual applicants and under-represents large firms. We show in the Appendix that this selection does not drive our results.

[20] A patent claim describes what the applicant claims to be the invention for which the patent grants exclusive legal rights. Each patent can hold multiple claims of different types. An *independent* claim stands on its own whereas a *dependent* claim is in reference to an independent claim, further limiting its scope.

[21] These data come from Ganglmair et al. (2020) who use for their text-based categorization of patent claims information from both the preamble of the claim (that names what the invention is about) and the body of the claim (that lists steps of a process or the components of a product).

**Table 1:** Summary Statistics

| | N | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|---|
| Process patent | 1451311 | 0.473 | 0 | 0.499 | 0 | 1 |
| Number of process claims | 1451311 | 0.871 | 0 | 1.407 | 0 | 60 |
| Number of product claims | 1451311 | 1.920 | 2 | 1.885 | 0 | 104 |
| Product-by-process claims | 1451311 | 0.042 | 0 | 0.288 | 0 | 30 |
| Independent claims | 1451311 | 2.883 | 2 | 2.286 | 1 | 116 |
| Length of first claim (words) | 1451311 | 169.194 | 148 | 106.034 | 1 | 7078 |
| Length of description (chars.) | 1451311 | 25992.144 | 15658 | 39439.832 | 4 | 3608036 |
| Generality | 1096154 | 0.638 | 0.719 | 0.244 | 0 | 1 |
| Originality | 1276719 | 0.626 | 0.694 | 0.244 | 0 | 1 |
| 4th year renewal | 1358663 | 0.826 | 1 | 0.380 | 0 | 1 |
| Observations | 1451311 | | | | | |

*Notes:* This table provides summary statistics for all granted utility patents (between 1976 and 2014) with priority dates between 1976 and 2008 for which all U.S. inventors and assignees are from the same state.

presence of product-related aspects.[22]

The top portion of Table 1 provides summary statistics for our patent-type indicators for all granted USPTO utility patents in our sample. Almost half of all patents include a process claim, although that number increased steadily over the time period of our study, from just under 30% in the 1970s to almost 60% in the 2000s.

## 4.3 Additional Variables

We collect and construct additional patent characteristics to capture the complexity and value of the patented technology. Table 1 summarizes these variables across all patents in our main sample. We proxy for a patent's breadth and complexity using the number of independent claims (see Lerner, 1994; Lanjouw and Schankerman, 2004) and the length (in words) of the first claim (see Kuhn and Thompson, 2019), where shorter claims are likely broader. As an additional measure of a patent's complexity, we include the length of the patent's detailed description text.

To capture the external value (or technological impact) of a patent, we construct measures

[22]We treat product-by-process claims as process claims because what they disclose is a process more than a product. Dropping these patents leaves our results unchanged.

of *patent generality* and *patent originality* as proposed by Trajtenberg et al. (1997). Patent generality captures the diversity of patents (measured by their respective patent classes) in which a given patent is (forward)-cited. A higher generality score implies more widespread impacts (Hall et al., 2001). Patent originality, on the other hand, captures the diversity of technologies from which a given patent (backward)-cites. A higher originality score means that the patented invention is combining ideas from different areas to create something new (or "original"). We construct these measures for each patent using the first USPC main class listed on the patent.[23] As a measure of a patent's internal or private value, we use information on whether the patent holder paid the patent maintenance fee during the 4$^{\text{th}}$ year of the patent term (see, e.g., Pakes, 1986; Schankerman and Pakes, 1986).

# 5 Empirical Estimation and Results

## 5.1 The Impact of the Protection of Trade Secrets

We take advantage of the staggered adoption of the UTSA across U.S. states to estimate the likelihood that a patent includes a process (Proposition 2). In our main specification, we estimate the probability that a patent covers a process invention as a function of the patent's characteristics and the state's trade secrets protection index. Formally, we estimate

$$process_{jst} = \beta_1\, protection_{st} + \beta_2 X_{jst} + \nu_s + \mu_t + \eta_j + \epsilon_{jst}, \tag{6}$$

where the dependent variable is an indicator that is 1 if patent $j$ filed in year $t$ by an entity in state $s$ is a process patent; $protection_{st}$ is the trade secrets protection index in state $s$ and year $t$ according to Png (2017a). To control for any events that occur in all states simultaneously and for any state-specific characteristics that do not vary over time, we include priority-year ($\mu_t$) and location-state ($\nu_s$) fixed effects, respectively. In our preferred specification, we also

[23]There are about 450 main classes and about 150,000 subclasses in the United States Patent Classification (USPC) system.

include dummy variables for patent $j$'s first USPC main class ($\eta_j$).[24] Our specification at the patent level is equivalent to an analysis at the state level where the states are weighted by the number of patents. It further allows us to directly control for patent-specific measures of complexity and value, $X_{jst}$, as described in Section 4.[25]

## 5.2 Baseline Results

Table 2 shows the coefficients from the baseline specifications, including different sets of control variables.[26] All specifications show a statistically significant, negative effect of a UTSA-related strengthening of trade secrets protection on the probability that a patent is a process patent. We are most interested in the specifications including control variables on both patent complexity and value measures (Columns (4) and (5)). Column (4), which does not include USPC main class dummies and therefore allows the coefficient of interest to capture technology-wide changes in patenting, suggests that patents are 4.1 percentage points less likely to include a process innovation if the trade secrets protection index rises by a full point. Column (5) includes USPC main class dummies and therefore identifies changes in patenting propensities *within* technologies. It reports a 2.6 percentage point decrease. At a baseline process patent share of 42.3% before UTSA adoption, and with a mean increase in the trade secrets protection index of 0.36 points across all patents, our results correspond to respective mean decreases of 3.5% and 2.2% in the probability that a patent is a process patent when a state adopts the UTSA. These effects correspond to economically significant changes in patenting decisions.[27]

[24] Note that our year fixed effects control for nationwide policy changes such as the *Uruguay Round Agreements Act* of 1995 (extending the maximum validity of a patent to 20 years from filing) and the *American Inventors Protection Act* of 1999 (introducing pre-grant publication of patent applications).

[25] While some of the control variables are likely endogenous, we include them regardless because we are interested in the impact of $protection_{st}$ on the probability of a process patent, and these covariates are likely correlated with this probability.

[26] We report results of a linear probability model for ease of interpretation, noting that logit estimations provide qualitatively identical results.

[27] As we explain below, we can interpret these results as lower bounds of the effects on the disclosure decisions.

**Table 2:** Baseline Results – Impact of Trade Secrets Protection

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Trade secrets protection | -0.023** | -0.025** | -0.047*** | -0.041*** | -0.026*** |
| | (0.011) | (0.010) | (0.012) | (0.011) | (0.007) |
| Log(indep. claims) | | 0.244*** | | 0.232*** | 0.231*** |
| | | (0.004) | | (0.003) | (0.002) |
| Log(length of first claim) | | -0.094*** | | -0.104*** | -0.052*** |
| | | (0.003) | | (0.002) | (0.001) |
| Log(length of description) | | 0.057*** | | 0.060*** | 0.001 |
| | | (0.001) | | (0.001) | (0.001) |
| Originality | | | 0.134*** | 0.090*** | 0.011*** |
| | | | (0.003) | (0.003) | (0.003) |
| Generality | | | 0.094*** | 0.052*** | 0.039*** |
| | | | (0.005) | (0.005) | (0.003) |
| 4th year renewal | | | 0.128*** | 0.078*** | 0.025*** |
| | | | (0.003) | (0.002) | (0.001) |
| State FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| USPC Mainclass FE | No | No | No | No | Yes |
| $\overline{R}^2$ | 0.062 | 0.142 | 0.065 | 0.145 | 0.335 |
| N | 1451311 | 1451311 | 894960 | 894960 | 894956 |

*Notes:* Linear probability models at the patent level with 1[process patent] as the dependent variable, and the index of trade secrets protection as the independent variable of interest. Robust standard errors, clustered by state and year, in parentheses. Additional controls in all columns include indicator variables for the patent's location state and priority year. Column (5) also includes dummy variables for the patent's first listed USPC main class.

## 5.3 Discussion of Identification

Our identification strategy relies on two assumptions. First, the relative number of process and product *inventions* (rather than patents) does not vary systematically in response to the implementation of the UTSA. We explain below that our results are inconsistent with the most likely changes in innovation behavior due to the strengthening of trade secrets protection as documented by Png (2017a). Second, the adoption of the UTSA is not affected by an expectation that certain types of inventions will be more prevalent in the future. Png (2017a) provides evidence of the exogeneity of the UTSA with regard to firms' decisions to invest in R&D. We further provide evidence from a set of randomization and placebo tests to examine whether the adoption of the UTSA was motivated by changes in innovation and patenting behavior, and if the results are otherwise driven by chance.[28]

### 5.3.1 Innovation of Products and Processes

Png (2017a) shows that investment in R&D increases when trade secrets protection becomes stronger, which could change the pool of realized inventions.[29] While we are unaware of empirical evidence, it is likely that investment in process inventions is affected disproportionately, because less visible inventions benefit the most from secrecy. Thus, if a strengthening of trade secrets protection affected the *creation* of different types of innovation differently, then stronger trade secrets protection would likely lead to a relative *increase* in process patents absent changes in patenting behavior of existing inventions.[30] That is, because we observe a relative *decrease*, our results can be interpreted as a lower bound of the effect of trade secrets protection.

### 5.3.2 Randomizing Treatment

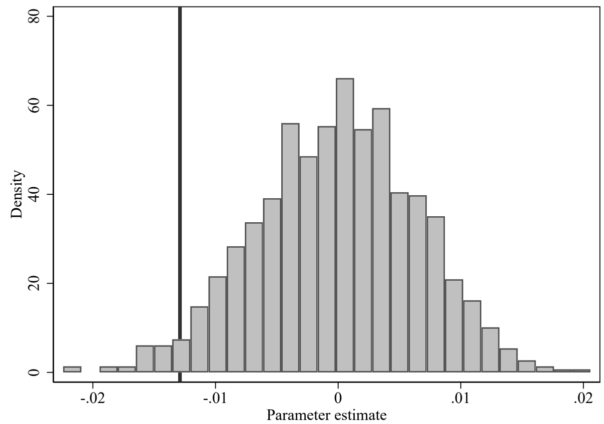
The negative coefficients in our main analyses could be the result merely of chance. We examine this possibility in a perturbation test similar to DeAngelo et al. (2017) and Alsan et al. (2019). We randomize the timing of UTSA adoption across states based on the true distribution of adoption dates. Then, we randomly assign these dates to the U.S. states and estimate the impact of this pseudo-adoption on the probability that a patent includes a process claim. Unlike the main analyses, which use a trade secrets protection index, our explanatory variable of interest here is an indicator variable that is 1 after (pseudo-)adoption, and 0 before.

[28]Our results are also supported in an instrumental variables estimation similar to Png (2017b), which addresses concerns about the causal relationship between trade secrets protection and patenting. We present results in the Online Appendix.

[29]The pool could also change if firms and inventors move to states with stronger trade secrets protection. As shown by Png (2012), however, the adoption of the UTSA had no significant effect on inventors' mobility.

[30]Formally, consider the expression for the share of process patents in Equation (5). Assume that $d_M$ and $d_P$ do not change with $\tau$, but let $\theta = \theta(\tau)$. If $\theta'(\tau) > 0$, then the share of process patents increases ($\rho'(\tau) > 0$).

**Figure 2:** Permutation Test – Randomized Dates of UTSA Adoption




*Notes:* This figure presents coefficients on an indicator variable that equals 1 after a state's pseudo-adoption of the UTSA. Pseudo-adoption dates are randomized across states 1000 times. The vertical line shows the coefficient based on the true adoption dates.

Figure 2 plots the coefficients from 1000 such permutations. As expected, they are centered around zero, with relatively little variation. Using the true adoption dates, the coefficient of interest is -0.0129, as indicated by the vertical line in the figure. Of the 1000 coefficients from the permutations, 975 are larger than the coefficient from the true adoption dates, suggesting that the UTSA indeed affected patenting of products and processes differently.

### 5.3.3 Placebo Tests

One might be concerned that each state's decision to adopt the UTSA was motivated by changes in innovation and patenting behavior, rather than the other way around. To the extent that patents are the results of investments made in the past, this would imply a change in the likelihood that a patent covers a process invention *before* a state adopts the UTSA. We examine this possibility in a set of placebo tests. Instead of the *true* UTSA adoption date for each state, we set an earlier date, dropping all patents with priority dates after the true UTSA adoption to avoid confounding our placebo effects with true ones.[31]

[31] We also drop all patents that were applied for more than ten years before the state's true UTSA adoption to create a closer comparison group.

We then estimate the effect of placebo UTSA adoption – one, two, three and four years before the true adoption – on the probability that a patent is a process patent, in regressions that mirror Column (5) of Table 2. For all four placebo adoption dates, the coefficient of interest is small and statistically insignificant, ranging from -0.007 (se=0.004) for placebo adoption two years earlier to +0.004 (se=0.004), four years earlier. These results suggest that states adopted the UTSA exogenously with respect to changes in the distribution of product and process patents.

## 5.4 Heterogeneous Effects

Next, we examine whether the effects of trade secrets protection on the probability of a process patent vary across firm sizes and different complexities of technology.

First, we repeat the estimation from Column (5) of Table 2, interacting the trade secrets index with three different sizes of patent applicants: individuals, small firms, and large firms. The estimated decrease in the probability that a patent is a process patent is largest for individuals. At the means of the change in trade secrets protection and the initial share of process patents for individuals, the estimated coefficient (-0.047, se=0.008) corresponds to an average decrease in the probability of a process patent of 5.9% (compared to an estimated average effect of 2.2% from Table 2). The (negative) coefficient is smaller for small firms (-0.021, se=0.009, avg. effect=1.6%), and statistically insignificant for large firms (-0.013, se=0.011, avg. effect=0.8%).

Our findings confirm our expectations, providing additional support for our empirical design. First, trade secrets are more important as a means to protect intellectual property for small firms than large firms (Hall et al., 2014). Second, each individual state is only a small part of a large firm's overall market, and the adoption of the UTSA in just one of these states may not have a strong impact on patenting. Third, findings by Crass et al. (2019) suggest a stronger degree of substitutability between secrecy and patents for small applicants, which should in turn yield a stronger effect of trade secrets protection.

We explore this issue of substitutability between patenting and trade secrets more directly by allowing the effects to vary between "complex" and "discrete" technologies. Complex technologies (such as in electrical engineering, telecommunications, semiconductors, or machine tools) are more likely protected by a combination of patents and trade secrets, whereas discrete technologies (such as in chemicals, pharmaceuticals, or materials) are more likely to rely on just one IP strategy. Thus, the effect of stronger trade secrets protection should be most pronounced among discrete technologies. To test this, we assign a complexity indicator to each patent based on von Graevenitz et al. (2013).[32] Interacting this indicator with the trade secrets index in our main specification, we find that the probability of a process patent decreases by 4.6% at the baseline (coef=0.064, se=0.011) among discrete technologies, whereas the effect is very small and statistically insignificant among complex technologies (coef=-0.008, se=0.008).

### 5.5 Robustness Analysis

Our data construction and empirical approach are based on a number of assumptions. In Appendix Section A.2, we present a set of sensitivity analyses to these assumptions. In short, we find that our results are robust. First, we vary the timing of the disclosure decision. Instead of assigning a patent's priority date, we use each patent's application date. We also limit our sample to the parent patents – the first patents in a patent family. Second, we examine if the results are driven by our sample restriction to single-state patents. We consider both a broader definition of patent location (based on the first U.S.-based assignee) and two narrower definitions (limiting the analysis to U.S.-only patents and to single-assignee patents). Third, we examine our definition of a process patent. We consider two less stringent definitions, and we drop software patents.[33] Fourth, we include state-specific linear time

[32] In our data, 73% of patents represent complex technologies.

[33] When dropping software patents, the share of process patents drops from 47.2% to 39.9% in our overall sample.

trends before UTSA adoption to account for possible time-varying differences across states.[34]

# 6 Welfare Implications

In addition to affecting an inventor's patenting decision, strengthening trade secrets protection can incentivize investment in initial R&D, but it may also retard knowledge diffusion by reducing disclosure of less visible inventions. In what follows, we first introduce a three-stage model of sequential innovation that endogenizes an inventor's initial R&D decision (Stage 1) and accounts for the effect of the inventor's disclosure decision (Stage 2) on the intensity of follow-on innovation (Stage 3). We then evaluate the total welfare effects of this trade-off.

## 6.1 An Augmented Model of Cumulative Innovation

### 6.1.1 Stage 1 (Initial R&D)

An inventor observes a *potential* invention (idea) $i$ with characteristics $(\phi, \Theta)$. The invention's visibility $\phi$ is drawn from an invention-type specific distribution with cdf $F_\Theta$. We assume that disclosure-visibility and secrecy-visibility are the same (so that $\xi = 1$). Invention types $\Theta$ (product or process) are binary, and the probability that a potential invention is a process is $\theta^F = \Pr(\Theta = M)$. Before any investment is made, the inventor observes R&D costs $C_i$ and forms expectations of the invention's commercial value $v_i$ based on a known distribution. She undertakes the R&D project if the expected payoffs from the invention (including the value and licensing revenues from both the invention and potential follow-on innovation) outweigh its cost. We refer to $F_\Theta$ and the distribution of invention types as *unconditional* distributions, that means, *before* the R&D decision is taken.

[34] We also repeat our analysis after separately dropping each U.S. state to examine whether the effects are driven by changes in individual states. We do not find any evidence of this. Results are available upon request.

#### 6.1.2 Stage 2 (Patent or Trade Secret)

The second stage of our augmented model is the disclosure model in Section 3. Conditional on a positive R&D decision, the disclosure decision depends on the strength of trade secrets protection $\tau$ and the invention's realized visibility $\phi_i$, where $\phi_i$ is drawn from the invention type specific *conditional* distribution of realized inventions with cdf $G_\Theta$ (*after* the R&D decision).

#### 6.1.3 Stage 3 (Follow-on Innovation)

For any realized initial invention $i$, we model follow-on innovation as one representative invention $i_F$ with random value $v_{i_F}$ and cost $C_{i_F}$.[35] Follow-on innovation can only happen if it is profitable (i.e., $v_{i_F} \geq C_{i_F}$). If it is, the realization then depends on how much of the initial invention $i$ is visible after the inventor's disclosure decision. We refer to this measure as *effective visibility* of initial invention $i$ and denote it by $\tilde{\phi}_i$. It is equal to

$$\tilde{\phi}_i = \begin{cases} \phi_i & \text{if R\&D in Stage 1 and trade secret in Stage 2;} \\ 1 & \text{if R\&D in Stage 1 and patent in Stage 2.} \end{cases} \tag{7}$$

Effective visibility is equal to the invention's visibility $\phi_i$ if the invention is realized but kept as a trade secret. We assume, without loss of generality, that the invention is fully disclosed through patenting so that effective visibility of a patented invention is equal to 1.[36]

In addition to the effective visibility, the probability that follow-on innovation is successful also depends on barriers to access to the initial invention. We capture how much patents (and their potential anticommons effect) lower the success probability of follow-on innovation by a scale parameter $\psi_D < 1$. For secrets, we normalize this parameter to $\psi_S = 1$. The success probability of follow-on innovation is then $\tilde{\psi}_{i_F,\tilde{d}} = \psi_{\tilde{d}}\tilde{\phi}_i$ following a realized initial

[35] The value of this representative invention can be interpreted as capturing the present discounted value of a stream of follow-on innovation triggered by invention $i$.

[36] The assumption of perfect disclosure through patenting is to simplify the analysis. Our results hold as long as patents provide more disclosure than does secrecy.

invention with disclosure state $\tilde{d} \in \{S, D\}$.

This model of follow-on innovation is simple but nonetheless consistent with stylized facts and other models proposed in the literature. We address this in more detail in Section A.3.1.

## 6.2 Structural Estimation and Simulation

Estimation of this model faces an obvious data challenge: we only observe inventions that are patented, not those that are kept secret or never developed. Still, we can estimate the conditional and unconditional distributions of invention types $\Theta$ and visibilities $\phi$ for given costs of R&D by making simple assumptions about their functional forms. We first estimate the *conditional* distributions by maximizing the log-likelihood of observing the empirical distributions of process and product patents in Stage 2. We then estimate the unconditional distributions by matching simulated moments of the distributions of visibilities and invention types with those estimated in Step 1. Finally, in Step 3 we use the estimated distributions to simulate follow-on innovation. We present a short description of our estimation procedure below and summarize the ingredients of each step in Table 3.[37]

**Step 1:** To calculate the log-likelihood of the observed distributions $G_\Theta$ and the distribution of invention types with $\theta$, we take advantage of variation in the trade secrets protection index and the share of process patents across states and time, and we make three main assumptions. First, we set the patent premium $\lambda = 0.1$, a value in line with Schankerman (1998), who finds that patent rights account for 5–15% of the returns of an invention.[38] Second, the type-specific visibilities $\phi$ follow triangular distributions. We hold the mode for the distribution for products constant at 0.5 and estimate the distribution for processes without imposing hazard rate dominance as in our theoretical framework in Section 3. Third, the probability $\theta_t$ that a realized invention at time $t$ includes a process innovation takes on

[37] We provide a formal description of the estimation details in Appendix Section A.3, and we report detailed results, for all estimations, in the Online Appendix.

[38] We provide model estimates for different values of $\lambda$ in the Online Appendix. Our results are consistent for $\lambda > 0$.

**Table 3:** Estimation Strategy

| | | |
|---|---|---|
| **Step 1** | **ML estimation of conditional distributions (given realized R&D)** | |
| Estimate | conditional visibility distribution $G_M$ for processes ($\phi \sim$ triangular$(\gamma_M)$)<br>conditional invention-type distributions $\theta_t$ | |
| Data | trade secrets protection index $\tau \in [0, 1]$<br>share of process patents | |
| Calibration | patent premium $\lambda$<br>visibility for products ($G_P$) | fixed ($= 0.1$)<br>$\sim$ triangular(0.5) |
| **Step 2** | **SMM estimation of unconditional distributions (given R&D costs)** | |
| Estimate | unconditional visibility distributions $F_\Theta$ with $\Theta = M, P$ ($\phi \sim$ triangular$(\cdot)$)<br>unconditional invention-type distributions $\theta_t^F$ | |
| Moments | mean & variance of estimated and simulated conditional visibility distributions<br>mean of estimated and simulated conditional invention-type distributions | |
| Data<br>From Step 1 | trade secrets protection index $\tau \in [0, 1]$<br>estimated conditional distributions $G_\Theta$ and $\theta_t$ | |
| Calibration | patent premium $\lambda$<br>value $v_i$<br>costs $C_i$ | fixed ($= 0.1$)<br>$\sim$ exp(0.1)<br>$\sim$ logistic$(C, 0.5)$ |
| **Step 3** | **Simulation of realized follow-on innovation** | |
| Simulate | $N =$ 1,000,000 potential inventions of full 3-stage sequential innovation model | |
| From Step 2 | unconditional distributions $F_\Theta$ and $\theta_t^F$ | |
| Calibration | patent premium $\lambda$<br>value $v_i$ and $v_{i_F}$<br>costs $C_i$ and $C_{i_F}$<br>baseline success probabilities $\psi_D$ and $\psi_S$ | fixed ($= 0.1$)<br>independently $\sim$ exp(0.1)<br>independently $\sim$ logistic$(C, 0.5)$<br>fixed ($\psi_D = 2/3$ and $\psi_S = 1$) |

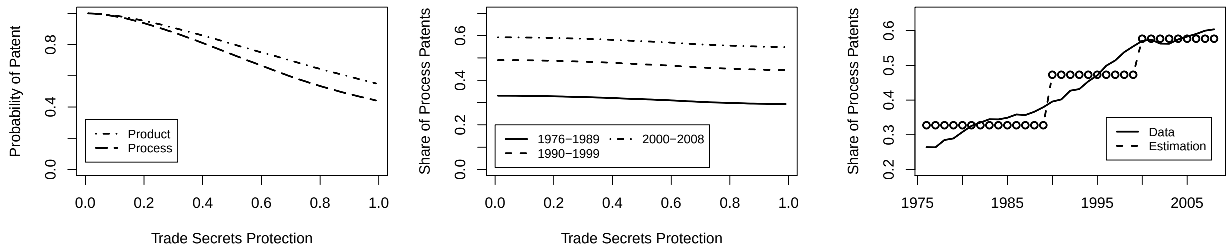
different values over time.[39]

The estimated parameters are illustrated in Figure 3 and comport with our theoretical predictions. We obtain a lower mode of the triangular distribution for processes than for products (0.374 vs. 0.5).[40] Patenting probabilities for processes are therefore lower than for products (Lemma 1), decreasing in $\tau$ (Lemma 2), and the share of process patents decreases as trade secrets protection increases (Proposition 2). Finally, together with the empirical distribution of the trade secrets protection index, the estimates of the time-variant innovation

[39]We assume $\theta_t$ takes on three values, with $\theta_1$ for all inventions with disclosure decisions from 1976 through 1989, $\theta_2$ for 1990 through 1999, and $\theta_3$ for 2000 through 2008.

[40]The mode is estimated very precisely, based on 800 bootstrap replications. For more details, see the Online Appendix. The triangular distribution for visibilities of products likelihood-dominates, implying that it also hazard-rate dominates the triangular distribution for visibilities of processes, as is our distributional assumption in Section 3.

**Figure 3:** Results from Structural Model (Conditional Distributions)




**(a)** Patenting Probability **(b)** Process Patents (by $\tau$) **(c)** Process Patents (year)

*Notes:* We depict the estimation results from Step 1. For Panel (a), we plot the patenting probabilities $d_\Theta(\tau)$ (by invention type $\Theta$) as a function of trade secrets protection $\tau$. For Panel (b), we plot the share of process patents $\rho(\tau)$ as a function of trade secrets protection ($\tau$) for three different estimates of $\theta_t$. For Panel (c), we plot the share of process patents $\rho(\tau)$ over time. The solid line depicts annual process patent shares from the data, the dash-dotted line depicts the estimated values given $\theta_t$ and the empirical distribution of $\tau$ for the respective $t$. Graphs are based on $N$ = 100,000 potential inventions.

type distributions with parameters $\theta_t$ (increasing over time) imply that the share of process patents is increasing over time from 0.33 to 0.58. This is in line with the positive time trend we observe in the data.

**Step 2:** We estimate the unconditional distributions of invention types and visibilities through simulated method of moments. Specifically, we find the unconditional visibility and type distributions for which the moments of the simulated *conditional* distributions match the moments of the estimated conditional distributions (from Step 1).[41] These simulated conditional distributions are for all potential inventions that the inventor decides to develop at Stage 1. In addition to the potential invention's visibility and type, this R&D decision is also driven by its value $v_i$ and the costs of R&D $C_i$ (both of which are simulated), as well as the strength of trade secrets protection $\tau$, which is observed in the data and informs the disclosure decision at Stage 2. Like we did for the conditional distributions, we assume visibilities follow triangular distributions, but unlike in Step 1, we estimate the unconditional distributions for both invention types.

**Step 3:** Given our results from Steps 1 and 2, we simulate follow-on innovation as described in Stage 3 of the full model. We assume a baseline success probability of follow-on innovation

[41] We use the means and variances of the visibility distributions and the means of the invention-type distributions.

of $\psi_D = 2/3$ for patented Stage-1 inventions (so that $\tilde{\psi}_D = 2/3$) and $\psi_S = 1$ for secret Stage-1 inventions (so that $\tilde{\psi}_S = \phi$). The invention values $v_i$ and $v_{i_F}$ are independent draws from the same distribution, as are R&D costs $C_i$ and $C_{i_F}$.

**Model Results:** We calibrate our model for no R&D costs, low average costs, and high average costs for $N$ = 1,000,000 simulated potential inventions.[42] For all three cost levels, the results continue to satisfy our distributional assumption of hazard-rate dominance. Moreover, for both invention types, we observe a selection of higher-visibility inventions into development in Stage 1. The distributions of costs and values further imply relatively large R&D investment probabilities – ranging from 0.59, or 59% of all possible inventions, for high R&D costs to 1, or 100%, without any costs – in Stage 1. In Stage 2, over 79% of realized inventions are patented. These results are in line with survey evidence reported by Mansfield (1986) who finds that between 66% and 84% of patentable inventions are indeed patented. Finally, in Stage 3, up to one half of all realized initial inventions lead to follow-on innovation (with the share decreasing in R&D costs).

## 6.3 Welfare Effects of Trade Secrets Protection

Our estimates of the unconditional visibility and invention-type distributions allow us to assess the welfare effects of trade secrets protection in a number of counterfactual exercises. We begin by defining our welfare measure.

### 6.3.1 Welfare Measure

We use the *expected total value added* of a given idea, denoted by $W(\tau)$, as our welfare measure. It is calculated as the weighted sum of the aggregate surplus from the realized initial invention, $W_i$ (which depends on its disclosure state, $\tilde{d}_i$), and the aggregate surplus from realized follow-on innovation, $W_{i_F}$. The expected total value added of a potential idea

[42] For the low costs and high costs scenarios, the means of R&D costs are equal to 40% and 80% of the expected R&D project values, respectively.

$i$ is equal to

$$\overline{W}(\tau) = E_{(\Theta_i, \phi_i, \tilde{d}_i, v_i, v_{i_F})} \left[ \mathbf{R}_i(\tau) \left( W_i + \tilde{\psi}_{i_F, \tilde{d}_i} \mathbf{R}_{i_F} W_{i_F} \right) \right], \tag{8}$$

where expectations $E_{(\cdot)}$ are over the invention type $\Theta$, visibility $\phi$, disclosure state $\tilde{d}$, and commercial values $v_i$ for initial and $v_{i_F}$ for follow-on innovation. Further, $\mathbf{R}_i$ ($\mathbf{R}_{i_F}$) is an indicator that is equal to 1 if the inital (follow-on) R&D project is undertaken, and $W_i$ and $W_{i_F}$ are measures of aggregate surplus from initial and follow-on innovation, respectively.

We determine $\mathbf{R}_i$ and $\mathbf{R}_{i_F}$ as follows. Denote by $EV_i$ the expected gross value of the invention to the inventor: the maximum between the expected value of secrecy ($EV_{S|\Theta}(\tau)$) and disclosure through patenting ($EV_{D|\Theta}(\tau)$). The inventor decides to undertake the initial R&D project ($\mathbf{R}_i = 1$) if $EV_i \geq C_i$. Similarly, the follow-on invention is realized ($\mathbf{R}_{i_F} = 1$) if it is profitable and successful. It is profitable if the commercial value covers the costs, $v_{i_F} \geq C_{i_F}$ and successful with probability $\tilde{\psi}_{i_F, \tilde{d}}$.

For the measures of aggregate surplus $W_i$, we assume that $2v_i$ is the *potential* aggregate surplus that materializes when there are no barriers to access to the invention. Because the barriers to access depend on the inventor's disclosure decision, the realized aggregate surplus is the potential aggregate surplus net of the disclosure-state specific deadweight loss.[43] For patented inventions, barriers to access increase in visibility $\phi$, and the aggregate surplus, $W_D$, as a function of visibility is equal to

$$W_D(\phi) = 2v_i - \frac{\phi v_i}{2} - C_i, \tag{9}$$

where $C_i$ is the cost of R&D of the potential idea. For inventions kept as trade secrets, barriers to access decrease in $\phi$ and increase in trade secrets protection $\tau$. As discussed in

[43]For instance, in the textbook case of linear demand with unit market size (and zero marginal cost), non-price discriminating monopoly profits ($=v_i$) are one half of the aggregate surplus ($=2v_i$), and consumer surplus and deadweight loss are one quarter each ($=v_i/2$). This value represents the maximum deadweight loss (from a scenario with full barriers to access). In the Online Appendix, we provide a simple competition model to derive the reduced-form aggregate surplus from invention $i$.

Section 3, the probability that the inventor has exclusive access, implying full monopolistic deadweight loss, is equal to $\tau(1-\phi)$. Aggregate surplus, $W_S$ for an invention that is kept secret is therefore equal to

$$W_S(\phi,\tau) = 2v_i - \frac{\tau(1-\phi)\,v_i}{2} - C_i. \tag{10}$$

To summarize, using the disclosure condition in Equation (1), the aggregate surplus of the initial invention is $W_i = W_D(\phi)$ if $\phi \geq \bar{\phi}(\tau)$ and $W_i = W_S(\phi,\tau)$ otherwise. For the aggregate surplus of any realized follow-on innovation, we assume free access, so that $W_{i_F} = 2v_{i_F} - C_{i_F}$.

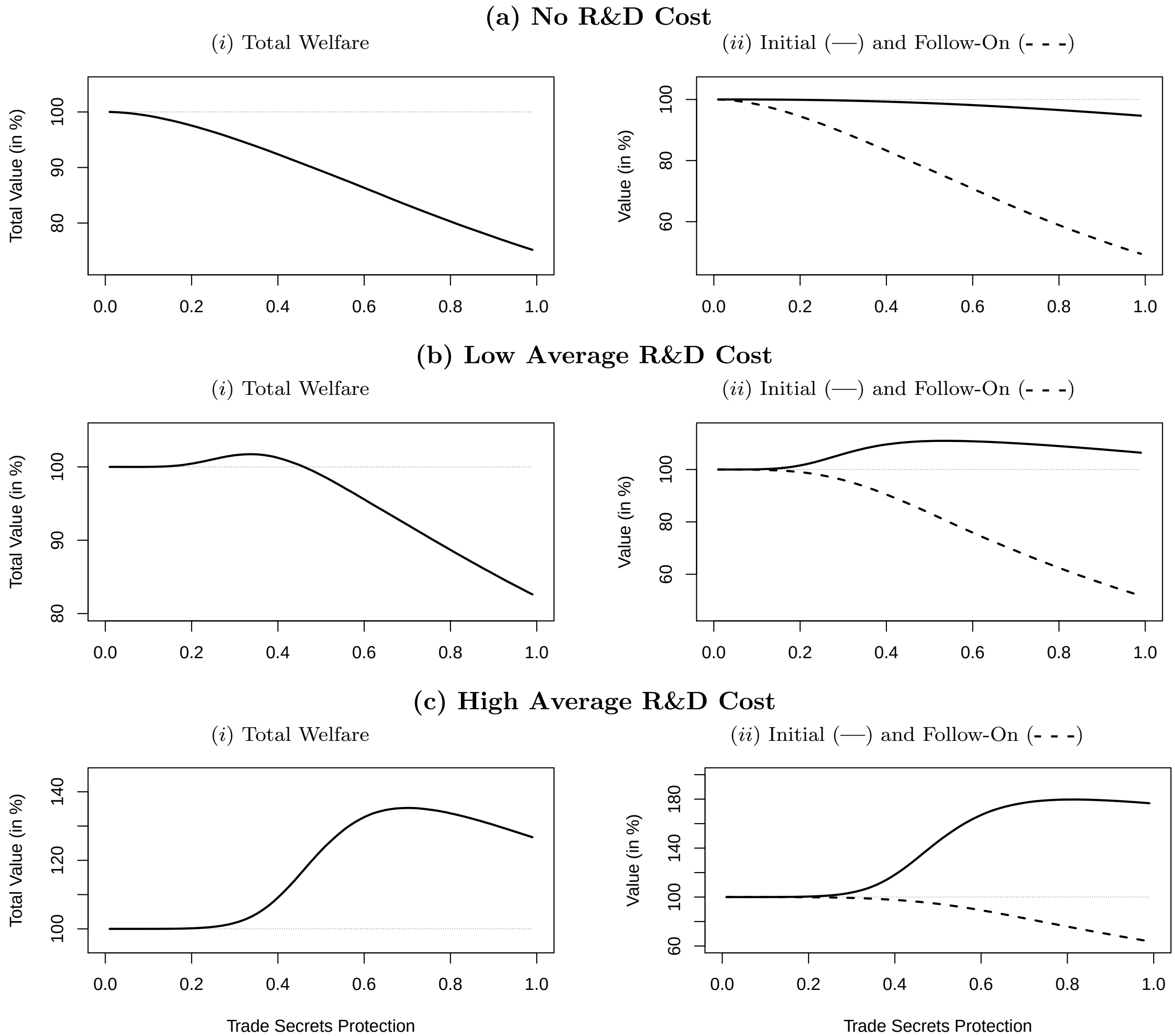
### 6.3.2 Varying the Level of Trade Secrets Protection

Figure 4 illustrates the welfare results under varying levels of trade secrets protection for no R&D costs, low average R&D costs (40% of the expected R&D value), and high average costs (80%). The graphs on the left depict the value of $\overline{W}(\tau)$ (in % of $\overline{W}(0)$). For no R&D costs (Panel (a)), stronger trade secrets protection has an unambiguously negative effect on total welfare. But as R&D costs increase, stronger trade secrets protection can increase welfare. The right side of Figure 4 separately depicts the surplus associated with initial R&D and with follow-on innovation to illustrate the channels that affect welfare.

**Deadweight Loss from Monopoly Power:** Stronger legal protection for trade secrets increases barriers to access to a technology, which increases the deadweight loss (captured by $W_S(\phi,\tau)$ in Equation (10)). We can see this effect in the solid-line graph (for initial innovation) in Figure (*ii*) of Panel (a), which isolates this deadweight loss because, without R&D costs, all R&D projects are realized.

**Decision to Innovate:** When costs are nonzero, trade secrets protection has a positive effect on initial R&D by increasing the expected value of realized R&D projects. This in turn has a positive effect on $W(\tau)$. We observe this effect in the solid-line graphs in Figures (*ii*) of Panels (b) and (c).

**Figure 4:** Effect of Trade Secrets Protection on Welfare




*Notes:* This figure plots welfare changes (in % of the value when $\tau = 0$) for values of $\tau \in [0, 1]$, when there are no R&D costs (Panel (a)), with low average R&D costs (40% of the expected R&D project value, Panel (b)), and with high average R&D costs (80%, Panel (c)). In each scenario, we simulate a sample of $N$ = 1,000,000 inventions, using the estimates for unconditional distributions from Step 2 and assuming baseline success probabilities of $\psi_S = 1$ and $\psi_D = 2/3$. In all figures we show average effects for the entire sample period, where a proportional number of simulated inventions have $\theta_t$ from each of three time periods. In the left Panel ($i$), we show the aggregate value of both initial and follow-on innovation ($\overline{W}(\tau)$). In the figures on the right ($ii$), we separately plot the social value of initial R&D (solid) and follow-on innovation (dashed).

**Follow-on Innovation (1):** Stronger trade secrets protection affects welfare by lowering the share of inventions that are disclosed. This has a negative effect on overall welfare $W(\tau)$ in Equation (8) through $\tilde{\psi}_{i_F,\tilde{d}}$: effective visibility decreases, which in return reduces the success probability of follow-on innovation. We observe this negative effect of trade secrets protection in the dashed graphs on the right-side figures.

**Follow-on Innovation (2):** Stronger trade secrets protection has a secondary effect on follow-on innovation. The increased ex-ante R&D activity implies there is more initial R&D to build on. This counteracts the negative effect of trade secrets on follow-on innovation from reduced disclosure, especially when R&D costs are high. To observe this, compare the dashed graphs in Figures (*ii*) for the value of follow-on innovation for Panels (b) and (c). For higher costs (Panel (c)), trade secrets protection has a stronger incentivizing effect on initial R&D. As a consequence, the decrease in the value of follow-on innovation is smaller here (decrease of 30% for $\tau = 1$) than for low costs (decrease of 50% for $\tau = 1$).

Finally, observe from the locations of the maxima in the left graphs of Figure 4 that the optimal level of trade secrets protection increases in R&D costs. This rationalizes existing law and practice, which tends to provide stronger protection for higher-cost projects. In the State of New York (that has not adopted the UTSA but follows common law principles) one factor to determine whether something is a trade secret explicitly lists the costs of developing the information.[44] Moreover, under the UTSA, trade secrets holders must also show significant costs of duplication of the secret information to establish the validity of their case, for example by referring to their own costs of R&D (Sandeen and Rowe, 2013:34).

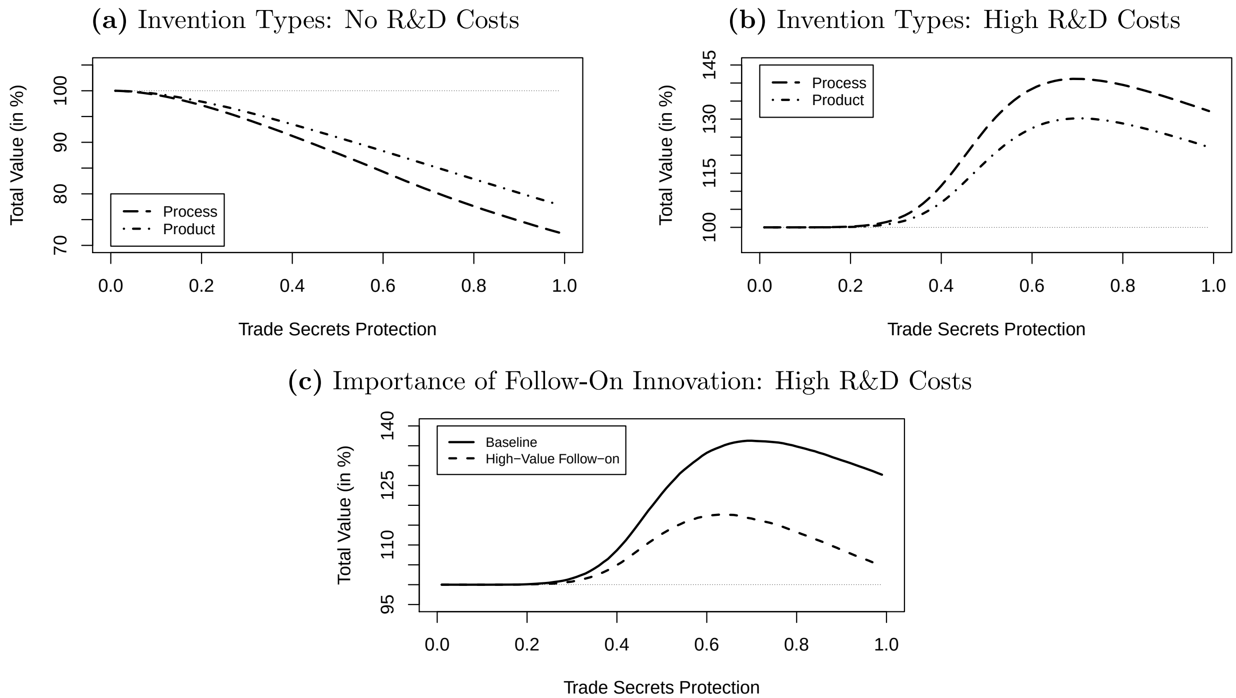
## 6.4 Mechanisms

### 6.4.1 Separate Effects for Processes and Products

Both positive and negative effects of trade secrets protection are amplified for less visible inventions (processes). The positive incentive effect of trade secrets protection is stronger for processes, because they are less likely patented, and stronger trade secrets protection increases appropriability. As we formalize in Section 3 and show in Section 5, the negative disclosure effect is also stronger for processes. Processes become relatively less likely disclosed in patents, which jeopardizes their follow-on innovation disproportionately.

[44] Restatement (First) of Torts, §757 cmt. b (1939). Despite the adoption of the UTSA and the publication of the Restatement (Third) of Unfair Competition (also governing aspects of trade secrets protection), courts and commentators in many states continue to cite this Restatement of Torts (Sandeen and Rowe, 2013:19).

**Figure 5:** Mechanisms of Welfare Effects




*Notes:* This figure plots the welfare function $W(\tau)$ (in % of $W(0)$) for $\tau \in [0,1]$. We simulate a sample of $N$ = 1,000,000 inventions, using the estimates for unconditional distributions from Step 2 and assuming baseline success probabilities of $\psi_S = 1$ and $\psi_D = 2/3$. In Panels (a) and (b), we plot the welfare functions separately for processes (dashed line) and for products (dash-dotted line). In Panel (a), we use the estimates for no R&D costs; in Panel (b), we use the estimates for high average R&D costs (such that costs are 80% of the expected R&D project value). In Panel (c), for the high-cost environment, we plot the welfare function for two different values of follow-on innovation. The solid line describes the baseline from Figure 4 (where $v_{i_F} \sim \exp(1/10)$), the dashed line describes the scenario in which the value of follow-on innovation is drawn from $\exp(1/20)$.

The top of Figure 5 illustrates these findings. We isolate the negative disclosure effect in the no-cost environment in Panel (a), in which ex-ante incentive effects do not play a role. As R&D costs increase, the positive effects on ex-ante incentives become more important. In the high-cost environment in Panel (b), they more than offset the negative disclosure effect.

### 6.4.2 Impact on Follow-on Innovation

In Panel (c) of Figure 5, we illustrate how the welfare effects change when the value of follow-on innovation increases and the incentives to create initial innovations are fixed. To do so, we compare, in a high-cost environment, the results from the baseline model (where initial and follow-on innovation follow the same distributions) with a scenario in which follow-on innovation is on average twice as valuable. That is, we only change the value of follow-on innovation. We find that when follow-on innovation is more valuable, the positive effect of trade secrets protection on total value $\overline{W}$ is weaker, implying that the negative disclosure effect on follow-on innovation outweighs the positive effect from the increased potential for follow-on innovation due to more initial innovation. That is, even in this high-cost environment, where the positive effects on follow-on innovation are most pronounced, the net effects of trade secrets on follow-on innovation remain negative. Consequently, the optimal value of trade secrets protection for the initial invention is lower in industries that are characterized by a relatively larger value of follow-on innovation. This is seen by the shift to the left of the peak of the welfare function when the value of follow-on innovation is doubled.

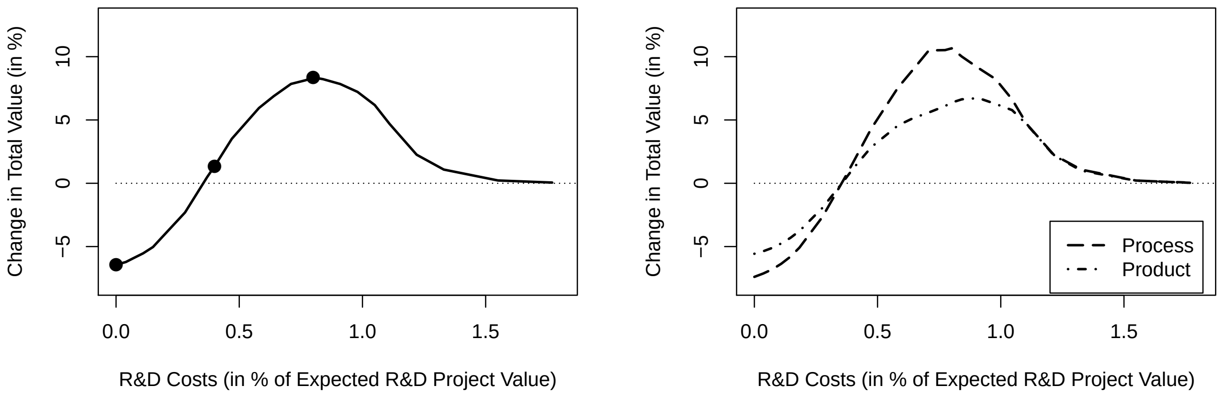
### 6.5 Average Effect of the UTSA

To evaluate the effect of the UTSA as a whole, we simulate data from our augmented model for the average value of trade secrets protection before UTSA adoption, $\tau^{\text{pre}} = 0.071$, and after adoption, $\tau^{\text{post}} = 0.394$. Figure 6 plots the percentage change of welfare for varying values of average R&D costs. Panel (a) of the figure depicts the effect across all potential inventions, whereas Panel (b) shows the average effect by invention type. The dots mark the scenarios of no costs, low costs, and high costs from Figure 4.

We find a negative effect of the UTSA for no R&D costs, a near-zero effect for low costs, and a positive effect for higher costs. Our results suggest that in industries with relatively profitable R&D (where benefits from stronger trade secrets protection are inframarginal), the adoption of the UTSA had the unintended consequence of lowering total welfare by impeding follow-on innovation. This pattern is reversed for R&D projects that are relatively less profitable (when the benefits of trade secrets protection are marginal for the decision to invest in R&D). In this case, the UTSA improved welfare by encouraging initial R&D.[45]

[45]Note that as R&D costs increase further, the average welfare effect converges to zero because very few

**Figure 6:** Average Welfare Effect of the UTSA




**(a)** All Ideas

**(b)** By Invention Type

*Notes:* In this figure, we show the average welfare effect of the introduction of the Uniform Trade Secrets Act. We plot the difference between total welfare (as a fraction of pre-UTSA total welfare) evaluated at the average post-UTSA value of the trade secrecy index, $\tau^{\text{post}} = 0.394$, and the total welfare evaluated at the average pre-UTSA value, $\tau^{\text{pre}} = 0.071$. On the horizontal axis, we use R&D costs as a fraction of the expected R&D project value. Panel (a) depicts the effect across all ideas; Panel (b) shows the effect by invention type.

Panel (b) shows that these effects are more pronounced for processes, consistent with Panels (a) and (b) in Figure 5.

# 7 Conclusion

While the effects of intellectual property rights on incentives to innovate are relatively well-understood, we know less about the differences between the effects on initial and follow-on innovation. We add to recent discussions by arguing that the effects on follow-on innovation also depend on the visibility of the original idea. For highly visible inventions, patents limit the ability of others to build on said innovation. For inventions whose technology is less visible, however, trade secrets limit access entirely. In this case, patents can disclose information, which boosts follow-on innovation. Therefore, an intellectual property policy that particularly encourages patenting of less visible inventions could increase innovative activity as a whole.

The tradeoff between the incentives to innovate and the ability of others to build on

ideas are realized regardless of trade secrets protection.

existing inventions also depends on the profitability of R&D investment. When R&D is relatively profitable (with low R&D costs), strengthening protection of a trade secret does little to incentivize additional investment in initial innovation, but it might discourage the disclosure of existing inventions. This hurts follow-on work, especially when the invention is not otherwise visible. On the other hand, when R&D is costly enough to prevent some innovation, a stronger trade secrets law could lead to more investment in initial R&D. If the increases in initial innovation are large, they could offset the losses from nondisclosure of some existing inventions.

Our results support a body of literature that argues that an optimal policy distinguishes between different types of inventions and industries. Industries with high R&D costs are most likely to benefit from increased trade secrets protection (e.g., pharmaceuticals and chemicals, following survey evidence in Mansfield, 1986). In contrast, industries with relatively low R&D costs likely experience a welfare loss from a strengthening in trade secrets protection.

Because our analysis is constrained by data availability, we are cautious when interpreting the magnitude of the welfare effects. The directional results, however, are strong and depend little on our structural assumptions. Also note that we specifically study secrecy of patentable inventions. A different, and broader, approach to trade secrets relates to the design of the employment relationship (e.g., in the form of covenants not to compete) or broader organizational concerns (such as in non-disclosure agreements). Given the mechanisms in our paper, we view our results as complementary to that literature.

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# A Appendix

## A.1 Formal Proofs of Theoretical Results

**Proof of Proposition 1:** For the proof of this claim, we utilize the stochastic dominance property of our visibility distributions. As stated in the text, our assumption of hazard rate dominance implies first-order stochastic dominance (Krishna, 2010:276). It will be useful to first state the definition and general property of first-order stochastic dominance. We follow the treatment in Mas-Colell et al. (1995:195). Let $u(x)$ be a non-decreasing function in $x \in [0,1]$. Then

$$\int u(x)dG_P(x) \geq \int u(x)dG_M(x) \iff G_P(x) \overset{FOSD}{\succ} G_M(x). \tag{A.1}$$

Integrating by parts, we obtain

$$\int u(x)dG_\Theta(x) = [u(x)G_\Theta(x)]_0^1 - \int u'(x)G_\Theta(x)dx$$

Because $G_\Theta(0) = 0$ and $G_\Theta(1) = 1$ for $\Theta = M, P$, we can rewrite the condition in the claim as

$$\int u(x)dG_P(x) - \int u(x)dG_M(x) = \int u'(x)\left[G_M(x) - G_P(x)\right]dx \geq 0.$$

Because $G_P(x) \leq G_M(x)$ by first-order stochastic dominance, the condition holds for any non-decreasing function so that $u'(x) \geq 0$. Note that if $u(x)$ is strictly increasing and $G_P(x) < G_M(x)$ for some $x$, then the inequality is strict.

For the first claim in the proposition, $EV_{S|M}(\tau) > EV_{S|P}(\tau)$, note that $\tau(1-\xi\phi)v$ is a strictly decreasing function in $\phi$ (because $\xi > 0$). We can simply rewrite the inequality as $-EV_{S|P}(\tau) > -EV_{S|M}(\tau)$ or

$$\int_0^1 \underbrace{-\tau(1-\xi\phi)v}_{u(\phi)} dG_P(\phi) \quad > \quad \int_0^1 \underbrace{-\tau(1-\xi\phi)v}_{u(\phi)} dG_M(\phi) \tag{A.2}$$

with $u(\phi)$ increasing in $\phi$ so that the general property above applies. We obtain a strict inequality by the implicit assumption that $G_M(\phi)$ and $G_P(\phi)$ are not identical so that $G_P(\phi) < G_M(\phi)$ for some $\phi$. For the second claim, $EV_{D|M}(\tau) < EV_{D|P}(\tau)$, note that $\phi(1+\lambda)v$ is strictly increasing in $\phi$, and the above general property applies.

**Proof of Lemma 1:** For any given $\tau$, $d_M(\tau) \leq d_P(\tau)$ if, and only if, $G_P(\bar{\phi}(\tau)) \leq G_M(\bar{\phi}(\tau))$. The latter holds by first-order stochastic dominance of $G_P$ over $G_M$.

**Proof of Lemma 2:** Patenting probabilities (weakly) decrease in $\tau$ if $d_\Theta(\tau)$ is (weakly) decreasing in $\tau$. We have $\frac{\partial\bar{\phi}(\tau)}{\partial\tau} = \frac{1+\lambda}{(1+\lambda+\xi\tau)^2} > 0$ so that $G_\Theta(\bar{\phi}(\tau))$ increases in $\tau$ and $d_\Theta(\tau) = 1 - G_\Theta(\bar{\phi}(\tau))$ decreases in $\tau$.

**Proof of Proposition 2:** Using $d_M(\tau) = 1 - G_M(\bar{\phi}(\tau))$ and $d_P(\tau) = 1 - G_P(\bar{\phi}(\tau))$, the first derivative of $\rho(\tau)$ with respect to trade secrets protection $\tau$ is

$$\frac{\partial\rho(\tau)}{\partial\tau} = \frac{-(1-\theta)\,\theta\,[(1-G_P)\,g_M - (1-G_M)\,g_P]\,\bar{\phi}'}{(\theta\,(1-G_M) + (1-\theta)\,(1-G_P))^2}$$

where $\bar{\phi}' > 0$ is the partial derivative of $\bar{\phi}(\tau)$ with respect to $\tau$ and $G_\Theta$ and $g_\Theta$ are evaluated at $\bar{\phi}(\tau)$. The probability $\rho(\tau)$ decreases in $\tau$ if the term in brackets in the numerator is non-negative so that $(1-G_P)\,g_M \geq (1-G_M)\,g_P$ or $\frac{g_M}{1-G_M} \geq \frac{g_P}{1-G_P}$. The latter inequality holds by the assumption of $G_P$ hazard-rate dominating $G_M$.

## A.2 Robustness of the Empirical Results

The main analysis requires that we make several choices about variable definitions and the resulting sample selections. Here, we examine the robustness of our empirical results to these assumptions in additional regressions, replicating the specification from Column (5) of Table 2. In particular, we examine the date and location of the disclosure decision, we examine our definition of a process patent, and we allow for the possibility of pre-trends. All specifications show a robust negative impact of trade secrets protection on the share of process patents. We summarize all results in Table A.1.[46]

**Disclosure Date:** We first assign the application date of each individual patent as the date of the disclosure decision (Column (1) of Panel (a)). The coefficient of interest remains strongly significant and is slightly larger than that in the main specification (-0.030 (se=0.008) instead of -0.026). Next, we circumvent the disclosure date issue altogether by considering only the patent family head – the first patent within its family. Again, the results are almost unchanged (Column (2) in Panel (a)).

**Invention Location:** We test the robustness of our results to the sample selection of single-state patents. In a less conservative approach, we use *all patents* and assign

[46]We also provide details on the representativeness of our sample in the Online Appendix.

**Table A.1:** Robustness Checks

**Panel (a):** Disclosure Date and Invention Location

| | (1) Appl. Date | (2) Family Head | (3) Assignee Loc | (4) U.S. Only | (5) 1 Assignee |
|---|---|---|---|---|---|
| Trade secrets protection | -0.030*** | -0.030*** | -0.028*** | -0.026*** | -0.025*** |
| | (0.007) | (0.007) | (0.006) | (0.008) | (0.007) |
| Observations | 881218 | 799131 | 1438020 | 620100 | 852597 |
| $\overline{R}^2$ | 0.335 | 0.342 | 0.334 | 0.316 | 0.335 |

**Panel (b):** Process Patent Definition and Control Variables

| | (1) Process: 1st | (2) Process: Most | (3) No Software | (4) Pre-Trends |
|---|---|---|---|---|
| Trade secrets protection | -0.022*** | -0.019*** | -0.018*** | -0.054*** |
| | (0.006) | (0.006) | (0.006) | (0.016) |
| Observations | 889102 | 894960 | 654450 | 894956 |
| $\overline{R}^2$ | 0.306 | 0.261 | 0.314 | 0.335 |

*Notes:* Linear probability model with 1[process patent] as the dependent variable. In Panel (a): Column (1) sets the date of the disclosure decision as the patent's application date; Column (2) uses only the first patent in a patent family (the family head); Column (3) uses the location of the first assignee (or the first inventor if no assignee is listed); Column (4) is limited to patents for which all contributors are American and from the same state; and Column (5) drops patents with more than one assignee. In Panel (b), Columns (1)–(3) examine the definition of process patents. Column (1) uses the status of the patent's first claim; Column (2) considers a patent a process patent if at least half of its claims describe a process; Column (3) drops all software patents; Column (4) adds state-specific linear pre-trends. Robust standard errors, clustered at the state and year, in parentheses. All specifications include the same control variables as the full specification in the main text.

the first assignee's state as the location of the disclosure decision, or the location of the first inventor if no U.S. assignee is listed. In a more conservative approach, we drop all patents with non-U.S. contributors, thus guaranteeing that the decision is made in the identified state. Both approaches provide almost identical results to the main specification (Columns (3) and (4) of Panel (a), respectively).

**Decision Maker:** Our focus on single-state patents also helps alleviate concerns about who makes the disclosure decision: if all assignees and inventors are located in the same state, we know where the decision maker is located even if we do not know their identity. In another approach, we focus on patents with only one decision maker: those with just one assignee, or with just one inventor if no assignee is listed. The main result again remains almost unchanged (Column (5) in Panel (a)).

**Definition of Process Patents:** The main analysis defines all patents with at least one independent process claim as a process patent because we are interested in disclosure of any process component of the invention. Here, we use two alternative measures of a process patent: (1) a patent is a process patent if the *first* claim is a process claim,[47] and (2) a patent is a process patent if at least 50% of its independent claims are process claims. Our results are of similar magnitude to the main regression (Columns (1) and (2) of Panel (b)). Further, we drop all software patents, because software patents are often filed as process patents even though they do not inherently include process innovation.[48] The resulting coefficient on the trade secrets protection is similar as well (-0.018, se=0.008, Column (3)).

**Accounting for Pre-Trends:** Finally, the placebo tests in the main text suggest the share of process patents did not change in the years leading up to a state's UTSA adoption. Nevertheless, we add state-specific pre-trends to our difference-in-differences regression to account for the possibility that the shares of process patents were changing before UTSA adoption. The negative coefficient on the trade secret protection index is even stronger in this specification (coefficient=-0.054, se=0.017, Column (4) of Panel (b)).

## A.3 Structural Estimation: Details

### A.3.1 Modeling Follow-On Innovation: Discussion

Our model for follow-on innovation at Stage 3 is simple but nonetheless consistent with stylized facts and other models proposed in the literature. We make three main assumptions. First, follow-on innovation as captured by $v_{i_F}$ is by other firms rather than the inventor of the initial innovation. For instance, Sampat and Williams (2018) document that, for their sample of genome patents, most of follow-on research is done by firms other than the patent assignee. Follow-on innovation by the initial inventor does not explicitly enter our model but could be captured by $v_i$ and is not dependent on the effective visibility of any part of the initial invention. Second, disclosure has a positive effect on follow-on innovation. Williams (2013) documents that a *restriction* of access to human genome data leads to a 20–40% *reduction* in follow-on research.

[47] Kuhn and Thompson (2019) argue that under U.S. law the broadest claim is listed first.

[48] We follow Graham and Vishnubhakat (2013) in identifying patents as software patents. In our data, 66% of all software patents include a process claim, as opposed to 40% of non-software patents.

Third, conditional on the effective visibility, the baseline probability of follow-on innovation to a trade secret is higher than that following a patent. This assumption reflects the anticommons effect where technologies are underused because patents on early ideas raise the costs of creating future ideas by introducing frictions in the bargaining process over licenses (Scotchmer, 1991; Galasso and Schankerman, 2010). For our welfare analysis, we set $\psi_D = 2/3$, a number consistent with empirical findings in Galasso and Schankerman (2015).[49]

### A.3.2 Estimation Steps

**Stage-2 Disclosure Decision (Step 1):** We estimate the conditional distributions $G_\Theta$ and values for $\theta$ by maximizing the log-likelihood $LL$ of the observed time-variant patent-type distribution. We observe two types of patents and use $\mathbf{M}_j \equiv \mathbf{M}_j(\Theta = M|\text{patent}) = 1$ to denote if a given patent $j$ is a process patent, and $\mathbf{M}_j = 0$ if it is a product patent. Moreover, for each patent $j$, we observe the level of trade secrets protection $\tau_j$ at the time the decision to disclose the invention was made. Let $\rho(\tau_j)$ be the probability that a patent is a process patent as derived in Equation (5). Then, the log-likelihood of the data is given by

$$LL(G_M, G_P, \theta, \lambda) = \sum_j \mathbf{M}_j \log \rho(\tau_j) + (1 - \mathbf{M}_j) \log(1 - \rho(\tau_j)). \tag{A.3}$$

It is a function of the (conditional) distributions of visibilities $G_\Theta$ and the invention type $\theta$, as well as the patent premium $\lambda$. We estimate the model on the sample of single-state patents with priority dates between 1976 to 2008. For states that have adopted the UTSA, we exclude all patents with priority dates in the year of adoption.

**Estimation of Unconditional Stage-1 Distributions (Step 2):** In the second step of our procedure, we estimate the *unconditional* distributions $F_\Theta$ of visibilities and $\theta^F$ of invention types, using as inputs the conditional distributions $G_\Theta$ and $\theta$ estimated in Step 1. We use the specification and results of our preferred model with $\lambda = 0.1$. For this second step, we follow a simulated-method-of-moments approach. First, for given unconditional distributions $\left(F_M, F_P, \theta^F\right)$ and some R&D cost $C_i$, we simulate a dataset of potential inventions and solve Stage 1 of our augmented model to

[49] They find an average increase in forward citations of 50% in response to the invalidation of the cited patent (U.S. patent data), whereas Gaessler et al. (2018) find an increase of 20% (European patent data).

obtain the *simulated* conditional distributions, $\delta \in \left\{\hat{G}_M, \hat{G}_P, \hat{\theta}\right\}$. Second, we calculate the simulated conditional moments $\hat{\mu}_m(\delta|F_M, F_P, \theta^F)$ for the simulated data and the estimated moments $\mu_m(\delta)$ based on the estimated conditional distributions $G_\Theta$ and $\theta$ from Step 1. Third, we define the quadratic score function

$$S(F_M, F_P, \theta^F) = \sum_{\delta} \sum_{m \in \mathcal{M}} \left(\hat{\mu}_m(\delta|F_M, F_P, \theta^F) - \mu_m(\delta)\right)^2 \tag{A.4}$$

where $\mathcal{M}$ is the set of moments (mean and variance for the visibility distributions and means for the invention-type distributions for $t = 1, 2, 3$). We minimize this score function over $\left(F_M, F_P, \theta^F\right)$ (specifically, the modes of the triangular visibility distributions and the shares of process inventions for the invention-type distributions) to obtain the unconditional distributions.

# Visibility of Technology and Cumulative Innovation: Evidence from Trade Secrets Laws

## Online Appendix*

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# B Online Appendix

## B.1 Instrumental Variables

Despite anecdotal evidence that the UTSA was introduced in individual states for "whimsical" reasons, one might be concerned that states chose to adopt the UTSA when firms were particularly interested in certain types of innovation, compared to other states and years. To address this concern, we follow Png (2017) and instrument for a state's adoption decision using four other state-level uniform laws as instruments. In particular, the Uniform Determination of Death Act (UDDA), the Uniform Federal Lien Registration Act (UFLRA), the Uniform Durable Power of Attorney Act (UDPAA), and the Uniform Fraudulent Transfer Act (UFTA) were introduced in 1978, 1978, 1979, and 1984, respectively, and adopted by individual states over time as well. These four acts are not related to innovation or patenting behavior, but they are related to the UTSA as all were introduced by the Uniform Law Commission to harmonize state regulation around the same time.

For each of the four laws, we introduce a dummy variable that is 1 if state $s$ has implemented the law by the time of a patent's priority date $t$. We use these to estimate the trade secrets index in the first stage. This instrumental variables strategy relies on two assumptions. First, the instruments are unrelated to the dependent variable in the second stage. Second, they are strongly related to the endogenous variable. The former assumption is likely to hold because the laws we utilize as instruments do not concern innovation and patenting decisions. The latter is also likely to hold: bureaucratic red tape that slows down the state-specific implementation of one law may also affect the implementation of another state-specific law. And we find support for this argument. The coefficients on all instruments are strongly statistically significant, and the F-statistic is well beyond any critical value at 456.1.[1]

The second-stage results of this instrumental variables regression are shown in Table B.1. The coefficients on the trade secrets protection variable are negative and statistically significant in all five specifications, supporting our findings from the baseline estimation, although the coefficients and standard errors are larger in this specification. In the paper, we continue without instruments to provide more conservative and more precise estimates, noting that all qualitative results hold if we include the instruments.

[1] The coefficients for the instruments are: $\beta_{UDDA} = 0.018$ (se=0.005); $\beta_{UDPAA} = -0.097$ (0.004); $\beta_{UFTA} = 0.074$ (0.003); $\beta_{UFLRA} = 0.040$ (0.005).

**Table B.1:** Impact of Trade Secrets Protection – IV Regressions

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Trade secrets protection | -0.144*** | -0.142*** | -0.182*** | -0.155*** | -0.023 |
| | (0.047) | (0.041) | (0.062) | (0.053) | (0.093) |
| Log(indep. claims) | | 0.246*** | | 0.234*** | 0.231*** |
| | | (0.003) | | (0.002) | (0.003) |
| Log(length of first claim) | | -0.092*** | | -0.102*** | -0.054*** |
| | | (0.003) | | (0.002) | (0.004) |
| Log(length of description) | | 0.058*** | | 0.061*** | 0.002** |
| | | (0.001) | | (0.001) | (0.001) |
| Originality | | | 0.133*** | 0.089*** | 0.008*** |
| | | | (0.003) | (0.003) | (0.003) |
| Generality | | | 0.093*** | 0.051*** | 0.037*** |
| | | | (0.005) | (0.005) | (0.006) |
| 4th year renewal | | | 0.128*** | 0.078*** | 0.020*** |
| | | | (0.003) | (0.002) | (0.006) |
| State FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| USPC Mainclass FE | No | No | No | No | Yes |
| N | 1451311 | 1451311 | 894960 | 894960 | 894960 |

*Notes:* Linear probability model with 1[process patent] as the dependent variable, and instrumenting for trade secrets protection with indicators for UDDA, UDPAA, UFTA, and UFLRA adoption. Robust standard errors, clustered by USPC main class and state, in parentheses. Additional controls include indicator variables for the patent's location state and priority year. Column (5) also includes indicators for the patent's first listed USPC main class.

## B.2 Data and Descriptive Evidence

### B.2.1 Representativeness of the Sample

Because our main regression sample is limited to patents whose U.S. assignees and inventors are all from the same state, we introduce the possibility of sample selection. We examine this possibility by comparing our variables of interest across three samples: (1) *all* utility patents with priority dates between 1976 and 2008 and granted between 1976 and 2014 for which we observe the relevant information (4,287,180 patents); (2) the subset of patents with any U.S. assignee or inventor (2,391,486 patents); and (3) the subset of patents for which all U.S. assignees and inventors are located in the same state (our main estimation sample, 1,451,311 patents). Table B.2 shows summary statistics for our process patent indicator as well as the control variables. The regression sample (rightmost column) has a slightly higher share of process patents than the total population of patents, but smaller than the population of U.S. patents. They also seem to have slightly higher degrees of originality and generality.

**Table B.2:** Summary Statistics for Different Subsamples

| | All | | All US | | Single-State | |
|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD |
| Process patent | 0.459 | 0.498 | 0.507 | 0.500 | 0.473 | 0.499 |
| Number of process claims | 0.799 | 1.294 | 0.919 | 1.400 | 0.871 | 1.407 |
| Number of product claims | 1.781 | 1.798 | 1.875 | 1.872 | 1.920 | 1.885 |
| Log(indep. claims) | 1.185 | 0.450 | 1.246 | 0.452 | 1.242 | 0.453 |
| Log(length of first claim) | 4.989 | 0.582 | 4.953 | 0.594 | 4.976 | 0.584 |
| Log(length of description) | 9.716 | 0.965 | 9.759 | 0.959 | 9.699 | 0.951 |
| Originality | 0.602 | 0.253 | 0.632 | 0.240 | 0.626 | 0.244 |
| Generality | 0.606 | 0.263 | 0.634 | 0.249 | 0.638 | 0.244 |
| 4th year renewal | 0.838 | 0.368 | 0.840 | 0.367 | 0.826 | 0.380 |
| Observations | 4287180 | | 2391486 | | 1451311 | |

*Notes:* This table provides summary statistics for all granted utility patents (between 1976 and 2014) with priority dates between 1976 and 2008. Column (1) shows statistics for all patents; Column (2) shows statistics for patents with at least one U.S. assignee or inventor; Column (3) uses single-state patents.

We control for these variables in the main estimation.

Figure B.1 further illustrates the distributions of the sizes of the applicants. It shows that our regression sample slightly over-represents individual applicants and under-represents large firms. Because individual applicants see the largest effect (see Section 5.4 in the main text), our *average* treatment effects may be slightly over-estimated.

### B.2.2 Heterogeneity Results

In the main text, we describe the heterogeneous effects of trade secrets protection for different applicant sizes and technology complexities. We report the regression results in Table B.3.

## B.3 Structural Estimation: Further Results

### B.3.1 Results

We report the results for the conditional distributions from Step 1 in Table B.4. The reported 99% confidence intervals of all estimated parameters are based on 800 bootstrap replications. We obtain the distribution for the visibility of processes relative to the distribution for the visibility of products. A constant value of $\gamma_P = 0.5$ provides for a flexible specification without imposing our theoretical distributional assumptions. For our preferred Model (2) with $\lambda = 0.1$, we find first-order stochastic dominance satisfied. The same is true for Model (3) with $\lambda = 0.5$, the highest value for which the social benefits from R&D outweigh the private benefits (Bloom et al., 2013). First-order stochastic dominance is violated in Model

**Table B.3:** Heterogeneous Effects of Trade Secrets Protection

**Panel (a):** Patent Applicant Size

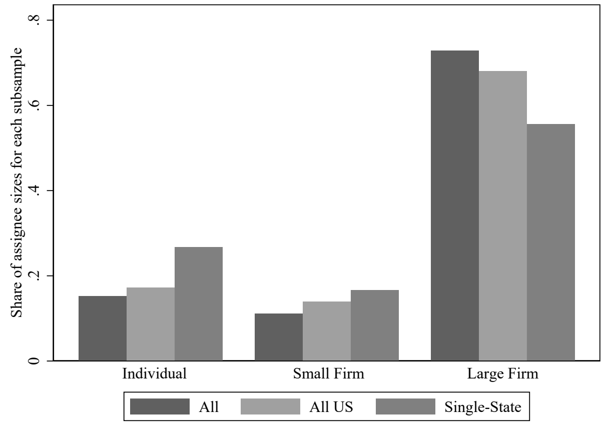
| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Individual × Trade secrets protection | -0.070*** | -0.058*** | -0.082*** | -0.065*** | -0.047*** |
| | (0.011) | (0.010) | (0.012) | (0.011) | (0.008) |
| Small firm × Trade secrets protection | -0.034*** | -0.027*** | -0.044*** | -0.034*** | -0.021** |
| | (0.011) | (0.010) | (0.012) | (0.011) | (0.008) |
| Large firm × Trade secrets protection | 0.014 | 0.000 | -0.007 | -0.016 | -0.013 |
| | (0.011) | (0.011) | (0.012) | (0.011) | (0.008) |
| Complexity Controls | N | Y | N | Y | Y |
| Value Controls | N | N | Y | Y | Y |
| State FE | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| USPC Mainclass FE | N | N | N | N | Y |
| $\overline{R}^2$ | 0.100 | 0.162 | 0.095 | 0.161 | 0.336 |
| N | 1451311 | 1451311 | 894960 | 894960 | 894956 |

**Panel (b):** Discrete vs. Complex Technologies

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| discrete × Trade secrets protection | -0.150*** | -0.145*** | -0.135*** | -0.126*** | -0.064*** |
| | (0.018) | (0.017) | (0.018) | (0.017) | (0.010) |
| complex × Trade secrets protection | 0.029** | 0.025** | -0.011 | -0.007 | -0.008 |
| | (0.012) | (0.011) | (0.013) | (0.012) | (0.008) |
| Complexity Controls | N | Y | N | Y | Y |
| Value Controls | N | N | Y | Y | Y |
| State FE | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| USPC Mainclass FE | N | N | N | N | Y |
| $\overline{R}^2$ | 0.068 | 0.147 | 0.070 | 0.149 | 0.334 |
| N | 1394283 | 1394283 | 855658 | 855658 | 855654 |

*Notes:* Linear probability model with 1[process patent] as the dependent variable. In Panel (a), we report interaction terms of the trade secrets protection index with firm size: individuals, small firms, and large firms. In Panel (b), we report interaction terms of the trade secrets protection index with indicators for discrete and complex technologies. Robust standard errors in parentheses.

**Figure B.1:** Applicant Size Distributions for Different Subsamples




*Notes:* This figure presents shares of applicant sizes of different subsamples of all granted utility patents (between 1976 and 2014) with priority dates between 1976 and 2008. The darkest (leftmost) column shows statistics for all patents; the lightest (middle) column shows statistics for patents with at least one U.S. assignee or inventor; the rightmost column uses single-state patents.

(1) for $\lambda = 0$.

In Table B.5, we report the parameters of unconditional distributions from Step 2, for no R&D costs ($C = 0$), low costs ($C = 2.140$ such that R&D costs are 40% of the expected R&D project value), and high costs ($C = 3.846$ such that R&D costs are 80% of the expected R&D project value). Note that, unlike in Step 1, where we hold $G_P$ constant, in Step 2 we explicitly estimate $F_P$ (i.e., the mode $\gamma_P$). First-order stochastic dominance (verified for the conditional distributions) continues to hold. The bottom panel of Table B.5 shows decisions at all three stages that are implied by the estimated parameters. Results are discussed in the main text.

### B.3.2 Different Distributions of Visibilities

To investigate the role of visibility distributions for our welfare results, we use counterfactual distributions for the visibilities of processes and products. Setting $\theta_t = 0.5$ for all $t$ for convenience, we then illustrate the welfare effects of changes in trade secrets protection in Figure B.2. In scenario 1 (solid line), we assume equal distributions that imply the same mean visibilities as the estimated model (we calculate the mean value of visibilities from the estimated unconditional distribution in Table B.5). In scenario 2 (dotted line), we assume equal distributions but increase the modes of the visibilities $\gamma_M = \gamma_P$ by 0.1. In scenario 3 (dashed line), we assume maximally different distributions, setting $\gamma_M \geq 0$ as low as possible and $\gamma_P \leq 1$ such that the overall mean is equal to the mean in the estimated model.

Comparing scenarios 1 and 2, we find that higher visibilities are associated with higher

**Table B.4:** Estimates for Conditional Distributions at Stage 2 (Step 1)

| | | (1) | (2) | (3) |
|---|---|---|---|---|
| License revenues [fixed] | $\lambda$ | 0.0 | 0.1 | 0.5 |
| Mode for processes ($G_M$) | $\gamma_M$ | 0.572<br>$[0.539, 0.616]$ | 0.374<br>$[0.374, 0.374]$ | 0.249<br>$[0.224, 0.312]$ |
| Share of process inventions (1976–1989) | $\theta_1$ | 0.327<br>$[0.325, 0.329]$ | 0.331<br>$[0.329, 0.333]$ | 0.331<br>$[0.328, 0.336]$ |
| Share of process inventions (1990–1999) | $\theta_2$ | 0.475<br>$[0.473, 0.478]$ | 0.490<br>$[0.488, 0.491]$ | 0.489<br>$[0.486, 0.505]$ |
| Share of process inventions (2000–2008) | $\theta_3$ | 0.575<br>$[0.573, 0.577]$ | 0.591<br>$[0.589, 0.593]$ | 0.590<br>$[0.586, 0.608]$ |

*Notes:* We report the parameter estimates for the conditional distribution from Stage 2 of the augmented model. We estimate our structural model on the sample of single-state patents filed between 1976 and 2008. For states that have adopted the UTSA, we exclude patents from the year the UTSA was adopted. Number of observations is 1,465,351. We estimate the mode $\gamma_M$ (of the triangular distribution over support $[0, 1]$) for processes and fix the mode $\gamma_P = 1/2$ for products. Invention types are Bernoulli distributed with parameter $\theta_t$, where $t = 1$ for patents with priority dates in 1976–1989 [$N$ = 383,020], $t = 2$ for 1990–1999 [$N$ = 523,704], and $t = 3$ for 2000–2008 [$N$ = 558,627]. The log-likelihood over number of observations is $-0.672$ in all three models. We report in brackets the 99% confidence interval from 800 bootstrap replications. The reported point estimates are from one single model using the full sample.

welfare. Higher visibilities enter the welfare function in three ways. Higher visibility implies more patenting and with higher patenting comes a higher deadweight loss (Equation (9) in the main text). At the same time, higher patenting as well as higher visibilities increase effective visibility $\tilde{\phi}_i$ and thus increase follow-on innovation (Equation (7) in the main text). Our results in Figure B.2 show that the latter effect prevails.

By comparing scenarios 1 and 3, we can see what happens when the distributions of visibilities become more diverse and products become on average more visible than processes, while overall average visibility remains constant. We find that stronger distributional differences have negative welfare effects. Welfare is consistently lower for the scenario with the maximally different distributions. This is evidence for a central role of visibilities in the welfare calculations.

## B.4 A Simple Competition Model

In this section, we derive the reduced-form social surplus functions in Equations (9) and (10) in the main text from a simple competition model. We derive the expressions for process inventions; the case for product inventions is analogous.

Consider a market with linear demand $D(p) = 1 - p$. A firm with a new technology produces a homogeneous good at marginal production costs of $c_L$. This firm has many

**Table B.5:** Estimates for Unconditional Distributions at Stage 1 (Step 2)

| | | | (1) | (2) | (3) |
|---|---|---|---|---|---|
| | | | Stage 1: $F_\Theta$, $\theta^F$ | | |
| | | Stage 2: $G_\Theta$, $\theta$ | no cost | low cost | high cost |
| Mode for processes | $\gamma_M$ | 0.374 | 0.370 | 0.335 | 0.103 |
| Mode for products | $\gamma_P$ | 0.5 | 0.497 | 0.458 | 0.191 |
| Share of processes (1976–1989) | $\theta_1$ | 0.331 | 0.329 | 0.339 | 0.352 |
| Share of processes (1990–1999) | $\theta_2$ | 0.490 | 0.489 | 0.491 | 0.501 |
| Share of processes (2000–2008) | $\theta_3$ | 0.591 | 0.596 | 0.595 | 0.596 |
| R&D probability (Stage 1) | | | 0.998 | 0.954 | 0.592 |
| Patents (Stage 2) | | | 0.858 | 0.850 | 0.796 |
| R&D probability (Stage 3) | | | 0.553 | 0.465 | 0.357 |

*Notes:* We report the parameter estimates for the unconditional distribution from Stage 1 of the augmented model. For the simulated-method-of-moments approach, we use the first two moments (mean and variance) for $G_M$ and $G_P$ and the first moment (mean) for $\theta_t$. For the costs of the initial invention as well as the follow-on invention, we assume that $C_i = C + \varepsilon_i$ and $C_{i_F} = C + \varepsilon_{i_F}$ where $\varepsilon_i$ and $\varepsilon_{i_F}$ are (independently) logistically distributed with zero mean and scale $1/2$. We set $C = 0 = C_i$ (no cost) in Column (1), $C = 2.140$ (low cost, such that costs are 40% of the expected R&D project value) in Column (2), and $C = 3.846$ (high cost, such that costs are 80% of the expected R&D project value) in Column (3). We further assume that the value of the initial invention and follow-on innovation are (independently) drawn from the same distribution, $v_i, v_{i_F} \sim \text{Exp}(1/10)$. At the bottom of the table, we report R&D intensities at Stage 1 (share of inventions $i$ that are developed) and Stage 3 (share of inventions $i_F$ that are developed, conditional on Stage-1 R&D) and the share of patented inventions $i$ (conditional on Stage-1 R&D) at Stage 2.

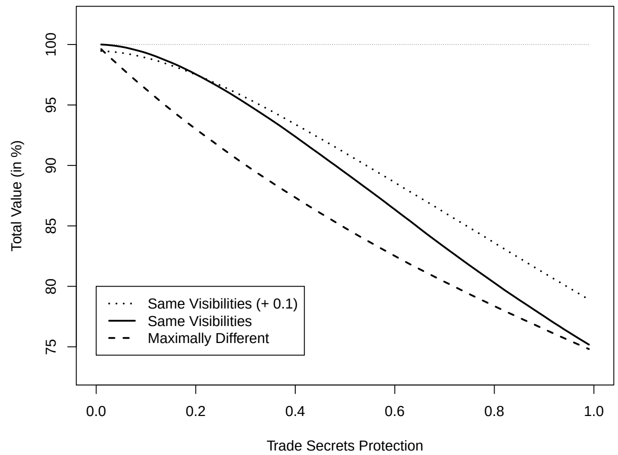
potential competitors that all produce at marginal costs $c_H > c_L$. Competition is in prices. We assume the invention is radical in the sense that the monopoly price (under low costs $c_L$) does not exceed the higher of the marginal costs, $p_L^m \leq c_H$. Moreover, for simplicity let $c_L = 0$. The monopoly profits in this case are $\pi_L^m = \frac{1}{4}$.

Now, suppose the firm has chosen to patent the technology, so that all potential competitors have (restricted) access to the technology. The patent holder is able to detect infringement of its patent and enforce it with probability $\phi$. This means, with probability $1 - \phi$, there is at least one competitor who can freely use the low-cost technology. With at least one competitor producing at zero marginal cost, the equilibrium price (and deadweight loss) is equal to zero. The expected social surplus is

$$\phi \frac{3}{2\pi_L^m} + (1 - \phi) \cdot 0 = 2\pi_L^m - \frac{\phi \pi_L^m}{2}. \tag{B.1}$$

Instead of a patent, let the firm keep the technology a secret. As discussed in Section 3 in the main text, the firm has exclusive access to the techology with probability $\tau\,(1 - \phi)$. This means that with probability $1 - \tau\,(1 - \phi)$ there is at least one competitor who can freely use the low-cost technology. With at least one competitor producing at zero marginal cost, the

**Figure B.2:** Visibility and the Effect of Trade Secrets Protection




*Notes:* In this figure, we illustrate the effect of visibilities of different invention types on total welfare for the no-cost scenario ($C = 0$) from Figure 4 in the main text. We plot total welfare for equal distributions for the two invention types (solid line) and maximally different distributions (dashed line) while keeping the overall mean of visibility constant. More specifically, for *Same Visibilities*, we set $\theta_t = 0.5$ for all $t$ and $\gamma_M = \gamma_P = \hat{\gamma}$ where $\hat{\gamma}$ is such that the mean of the triangular distribution with mode $\hat{\gamma}$ is equal to the mean of the estimated unconditional distribution. For *Maximally Different* we set $\gamma_M \geq 0$ as low as possible and $\gamma_P \leq 1$ as high as possible such that the overall mean is equal to the mean of the estimated unconditional distribution. The estimated values are based on simulated data with $N = 1{,}000{,}000$.

equilibrium price (and deadweight loss) is equal to zero. The expected social surplus is

$$\tau (1 - \phi) \frac{3}{2\pi_L^m} + [1 - \tau (1 - \phi)] \cdot 2\pi_L^m = 2\pi_L^m - \frac{\tau (1 - \phi) \pi_L^m}{2}. \tag{B.2}$$

Let $v$ denote the commercial value of the invention if the firm has exclusive access. In other words, let $v = \pi_L^m$, then the expressions for expected aggregate surplus are equal to the expression in Equations (9) and (10) in the main text.

# References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