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

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

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Abstract

We use exogenous variation in the strength of trade secrets protection to show that a relative weakening of patents (compared to trade secrets) has a disproportionately negative effect on the disclosure of processes – inventions that are not otherwise visible to society. We develop a structural model of initial and follow-on innovation to determine the effects of such a shift in disclosure on overall welfare in industries characterized by cumulative innovation. We find that while stronger trade secrets encourage investment in R&D, they may have negative effects on overall welfare – the result of a significant decline in follow-on innovation.

Keywords: cumulative innovation; disclosure; self-disclosing inventions; Uniform Trade Secrets Act.

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. With relatively stronger protection of such trade secrets (or with relatively weaker patent protection), fewer of the proverbial shoulders become visible and therefore available for others to stand on. This effect is particularly prevalent 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. We study how differences in the visibility of technologies affect disclosure decisions and cumulative innovation.

Secrecy is an important tool in a firm's intellectual property management toolbox. 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). There is ample survey-based evidence that trade secrets are 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. Trade secrets laws offer protection against *misappropriation* of secrets – that is, the acquisition of a trade secret by *improper means* (for instance, theft, bribery, misrepresentation, breach of contract, or espionage) or the disclosure of a trade secret without consent. However, unlike patents, trade secrets laws generally do not grant exclusivity.[2] This means, a trade secret is not protected if it accidentally leaks or is uncovered through independent discovery or reverse

[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.

[2] Codified trade secrets laws in the U.S. go back to the Restatement (First) of Torts (1939). The Uniform Trade Secrets Act (1979, amended 1985) was recommended for state-level adoption to clarify and harmonize trade secrets protection at the state level. With the passing of the Economic Espionage Act of 1996 (criminal) and the Defend Trade Secrets Act of 2016 (civil), the U.S. now has two federal law bodies governing trade secrets.

engineering (Friedman et al., 1991).[3]

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 relative to patents affects the diffusion of knowledge through the decision to invest in innovation, the disclosure of inventions, and the ability to build on these inventions. We use exogenous variation of trade secrets protection across states and time from the staggered adoption of the Uniform Trade Secrets Act (UTSA) of 1979/1985 to study the trade-off between secrecy and disclosure through patenting for different technology types.[4] Using new data on the type of a patented invention – product or process – to capture how visible or self-disclosing an invention is, we show that stronger trade secrets protection results in a disproportionate decrease of process patents.

The welfare implications of such changes in intellectual property protection depend on the ex-ante incentives to innovate as well as the facilitation of follow-on innovation. To make inferences about these incentives, one needs to estimate not only the distribution of *realized* but also of *potential* inventions. We estimate both distributions in a structural model of sequential innovation. We find that total welfare may in fact decline as trade secrets protection grows stronger when the costs of R&D are relatively small. This negative welfare effect is mainly due to the reduced patenting of process inventions, which are less visible and for which disclosure is essential for follow-on innovation. In contrast, stronger trade secrets protection could increase welfare when R&D projects are more costly, because it can lead to increased investment in initial R&D.

The paper proceeds in four steps. In Section 2, we develop a simple model of an inventor's decision to disclose a new technology through a patent. The value of the invention from a patent increases with the underlying invention's visibility: visibility (*of use*) allows for easier enforcement of the patent – guaranteeing exclusive access to the technology. The value of the invention that is kept secret, however, decreases in visibility (*of invention*), because secrecy (and therefore exclusive access) is more difficult to maintain.[5] We assume that *processes* are on average less visible than *products*. The assumption implies that, on average, inventors of processes value secrecy more than those of products – consistent with survey evidence (Levin et al., 1987; Cohen et al., 2000; Arundel, 2001; Hall et al., 2013). For a given baseline share of process *inventions*, our model predicts that, as trade secrets protection improves, the share of process *patents* decreases. This theoretical prediction serves as the basis for the empirical analysis in the rest of the paper.

[3]The Uniform Trade Secrets Act, for instance, lists as such *proper means*: "discovery by independent invention; discovery by reverse engineering [...]; discovery under a license from the owner of the trade secret; observation of the item in public use or on public display; obtaining the trade secret from published literature."

[4]Although we do not explicitly study trade secrets, the strength of trade secrets protection should affect the decision to keep an invention secret. We do not consider the joint use of patents and secrecy (Arora, 1997) or disclosure without patenting (for instance, through academic publishing (Gans et al., 2017) or corporate technical journals, such as the IBM Technical Disclosure Bulletin or the Xerox Disclosure Journal). Our assumption of the choice between secrecy and patents comes without loss of generality as long as there is *some* degree of substitutability between these two options.

[5]We consider these two notions of visibility closely linked and for our theoretical framework will assume them to be the same.

In Section 3, we discuss our two main datasets that we merge with basic bibliographic patent information. First, we use an index constructed by Png (2017a) that measures the strength of legal protection of trade secrets before and after a state's adoption of the UTSA. It reflects the trade secrets protection to which an inventor in a given state was exposed at the time of her disclosure decision. Second, we use patent-claim-level data compiled by Ganglmair et al. (2019) to construct process and product patent indicators.

In Section 4, we use these data to test the model implications. We use exogenous variation across locations and time in the level of trade secrets protection due to the staggered adoption of the UTSA by various U.S. states to estimate the effect of stronger trade secrets protection on the likelihood that a patent covers a process in a difference-in-differences estimation. Consistent with results from our theoretical model, we find that better 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, for whom a single state's adoption likely implies a change in a larger fraction of their overall market. We confirm the identifying assumptions in our baseline results using an instrumental variables strategy that uses state-specific adoption of other, unrelated policies to estimate a state's UTSA adoption (Png, 2017b). We further provide evidence from placebo tests and a number of robustness checks that confirm our main findings.

In Section 5, we estimate the parameters of a dynamic model of sequential innovation. We use these estimates to make inferences about the socially optimal strength of patents and trade secrets protection to encourage investment in initial innovation as well as to facilitate follow-on innovation. We model follow-on innovation consistent with stylized facts: more disclosure of technical information boosts follow-on innovation (Williams, 2013; Gross, 2019), patents on early ideas raise the costs of creating future ideas (Scotchmer, 1991; Heller and Eisenberg, 1998; Galasso and Schankerman, 2015), and the information disclosed in patents is useful and of sufficient quality (Furman et al., 2018; Hegde et al., 2019).

Our structural model provides estimates for the ex ante distributions of each invention type as well as their visibilities, conditional on the costs of R&D. These allow us to calculate the R&D intensity and the share and characteristics of trade secrets (over all realized inventions). Counterfactual analyses show that the optimal level of trade secrets protection is increasing in the costs of R&D, or conversely decreasing in its profitability. Stronger trade secrets protection has a negative overall welfare effect in industries with relatively profitable R&D. When the benefits of trade secrets protection are inframarginal to an inventor, stronger legal protection of trade secrets has 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. In this case, stronger legal protection improves welfare by encouraging initial R&D.

Beyond a number of studies based on survey data, there is limited empirical work on trade secrets – because of obvious data limitations. 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 (implying more rapid knowledge diffusion) had a mitigating effect on licensing delays.

A related strand of literature studies the effect of changes in legal trade secrets protection on innovation and patenting behavior. Png (2017a) finds that stronger trade secrets protection has a positive effect on firms' investment in R&D, at least in the high-tech industry and for large companies. Similarly, Png (2017b) finds that strengthening trade secrets protection 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. Angenendt (2018) finds that patent applicants respond to stronger trade secrets protection through the UTSA by reducing the number patent claims and decreasing the amount of information disclosed. We add to this body of literature by analyzing the role of an invention's visibility in measuring the effect of an increase in trade secrets protection on patenting and innovation decisions.

We explicitly model and estimate an inventor's behavioral response to stronger trade secrets (or weaker patents) and the subsequent decline in disclosure of inventions. Such a general equilibrium approach is critical to assessing the full welfare consequences of recent U.S. Supreme Court rulings that have narrowed the scope of what is and what is not patentable (see Sampat and Williams, 2018). Our welfare results provide new insights for the evaluation of these rulings. Moreover, to our knowledge, this is the first paper presenting welfare results explicitly for changes in trade secrets laws. This is particularly interesting in light of the EU Trade Secrets Directive 2016/943 adopted in June 2016, for which impact evaluations are not yet available. Results from the U.S. can thus inform an ongoing policy debate in Europe.

2 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.[6] 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 in Section 5 when we present our welfare

[6] 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 it 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). Patentability of the invention in our context implies that the inventor is given a true choice between disclosure (through a patent) and secrecy.

results.

2.1 An Inventor's Decision to Disclose

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

An inventor is given the choice to disclose an invention in a patent ($\tilde{\pi} = D$) or keep the invention secret ($\tilde{\pi} = S$). We set the inventor's private returns $V_{\tilde{\pi}}$ equal to the *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 thus means the inventor reaps a smaller fraction of these rents. In both disclosure states $\tilde{\pi} = D, S$, the probability of exclusive use depends on the *visibility* of the invention.[7]

Once the inventor has disclosed the invention in a patent, she can accumulate profits only if that patent is enforceable and other firms can be excluded from its use. In order to enforce a patent, the patent holder must be able to detect the use of an invention by a potential infringer. A more visible invention with higher observability of its use is therefore easier to enforce (and exclusivity prevails). Patents for non-visible inventions, on the other hand, are not enforceable and of zero value because rents dissipate once the invention is freely available. The expected commercial value the inventor is able to materialize is therefore $\phi \cdot v$. In addition, the inventor receives a patent premium λ.[8] It captures the benefits from patenting over trade secrets.[9] We define the inventor's private value of disclosing the invention as

$$V_D(\phi) = \phi\,(1 + \lambda)\,v. \tag{1}$$

While visibility of use is important to determine the value of a patent, the value from trade secrecy is determined by the visibility of the invention *per se*. To keep the model tractable, we do not distinguish between these two notions of visibility. 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 against misappropriation of trade secrets but not against simple copying. This means that, even with perfect trade secrets protection ($\tau = 1$), keeping the invention

[7] 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).

[8] 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. Webster and Jensen (2011) further provide evidence for a premium from commercialization, showing that being refused a patent has a significant negative effect on a firm's decision to launch and mass produce a product.

[9] For simplification, the patent premium λ captures these benefits in excess of what the inventor, if anything, could earn, for instance, from licensing the invention as a trade secret.

secret is of little value to the inventor if it is visible.[10] 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.[11] We define the private value from secrecy as

$$V_S(\phi, \tau) = \tau\,(1 - \phi)\,v. \tag{2}$$

The inventor of (ϕ, Θ, v) chooses disclosure if, and only if, $V_D(\phi) \geq V_S(\phi, \tau)$. This condition can be rearranged to read

$$\phi \geq \frac{\tau}{1 + \lambda + \tau}. \tag{3}$$

The inventor chooses disclosure through patenting if, and only if, visibility of the invention is sufficiently high (or trade secrets protection and the patent premium are sufficiently low). For a given ϕ, we can summarize the decision to disclose and patent, $\tilde{\pi} \in \{D, S\}$, as

$$\tilde{\pi} = \begin{cases} D & \text{if } \phi \geq \dfrac{\tau}{1 + \lambda + \tau} \\ S & \text{if otherwise.} \end{cases} \tag{4}$$

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 the invention's visibility).[12] The following lemma summarizes basic comparative statics of the inventor's decision to disclose. The proofs of this and all other results are relegated to Appendix A.

Lemma 1. *An inventor is more likely to disclose her invention by filing for a patent as the degree of visibility ϕ and the patent premium λ increase; she is less likely to patent as the degree of trade secrets protection τ increases.*

External sources provide corroborating evidence for our prediction. 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.

[10] Note that in our model we do not allow for independent discovery (that is independent of visibility ϕ). We also assume that if a competitor has rightfully acquired the invention, she cannot seek patent protection for that invention.

[11] This is not as strong an assumption as it appears to be. Generally, the threat of legal sanctions will deter (at least some) misappropriation, and the lack of such a threat will encourage it. Friedman et al. (1991) and also Lemley (2008) have argued that if trade secrets protection is weak, firms erect often inefficient safeguards. The costs of these is expected to increase in v and decrease in τ. Without trade secrets protection, the effective commercial value may in fact fully dissipate.

[12] 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).

2.2 Value of Trade Secrecy by Invention Type

We assume that an invention's visibility ϕ is unobservable but distributed on the unit support with cdf G_Θ. What is observable is an invention's *type* Θ that is correlated with its visibility. More specifically, an invention is either a process (or method), $\Theta = M$, or a product, $\Theta = P$. Invention types are Bernoulli distributed where $\theta = \Pr(\Theta = M)$ is the probability that the realized invention is a process. We denote this distribution by $\mathcal{G}$. Note that these distributions (G_Θ for $\Theta = M, P$ and $\mathcal{G}$) are *conditional* distributions given a realized invention.

We assume that processes are on average less visible than products. We formally capture this by assuming first-order stochastic dominance: G_P first-order stochastically dominates G_M so that $G_M \geq G_P$ for all ϕ. One implication of this assumption is a higher value of secrecy for processes than for products, given v. Conversely, the value of disclosure is lower for processes than for products. The (expected) value of secrecy of an invention of type Θ is

$$EV_{S|\Theta}(\tau) = \int_0^1 \tau\,(1-\phi)\,v dG_\Theta(\phi); \tag{5}$$

the expected value of disclosure is

$$EV_{D|\Theta}(\tau) = \int_0^1 \phi\,(1+\lambda)\,v dG_\Theta(\phi). \tag{6}$$

We show the claim in

Proposition 1. *Let $G_P(\phi) \leq G_M(\phi)$ for all ϕ. For a given level of trade secrets protection τ, the value of secrecy is higher for processes than for products, $EV_{S|M}(\tau) > EV_{S|P}(\tau)$. Conversely, the value of disclosure is lower for processes than for products, $EV_{D|M}(\tau) < EV_{D|P}(\tau)$.*

Empirical evidence comports with this theoretical finding. Using survey data, Levin et al. (1987), Cohen et al. (2000), Arundel (2001), or Hall et al. (2013) find that the propensity to patent is higher for products than processes, suggesting a higher value of secrecy for processes. In Appendix A, we present empirical evidence for the same. We exploit a change of the publication policy of pending U.S. utility patent applications through the *American Inventors Protection Act of 1999* (AIPA). Eligible patent applicants were given the option to delay the disclosure of their inventions (i.e., publication of their applications) and thus to extend the period of temporary secrecy. While the baseline probability of opting out of disclosure is somewhat low (Graham and Hegde, 2015), we find strong evidence that applicants are more eager to extend the temporary secrecy of processes than of products.

2.3 Probability of Disclosure for Different Invention Types

For our main theoretical result and prediction, we derive the probability ρ that a given patent covers a process invention. We first establish three auxiliary results. In Lemma 2, we show that the probability that a process is patented is weakly smaller than the probability that a product is patented. For this, let $\pi(\phi, \tau) = 1$ if $\tilde{\pi} = D$ and $\pi(\phi, \tau) = 0$ if $\tilde{\pi} = S$. The probability that an invention of type Θ is patented and disclosed is

$$\pi_{\Theta}(\tau) = \int_0^1 \pi(\phi, \tau) dG_{\Theta}(\phi). \tag{7}$$

Lemma 2. *For a given level of trade secrets protection τ, $\pi_M(\tau) \leq \pi_P(\tau)$.*

In Lemmas 3 and 4, we show that patenting probabilities are decreasing in trade secrets protection for both invention types, and that the patenting probability for products is decreasing at a lower rate than that for processes.

Lemma 3. *The patenting probabilities for products $\pi_P(\tau)$ and processes $\pi_M(\tau)$ are decreasing in τ.*

Lemma 4. *The difference between the patenting probabilities for products $\pi_P(\tau)$ and processes $\pi_M(\tau)$ is increasing in trade secrets protection τ.*

The patenting probability $\pi_{\Theta}(\tau)$ captures the probability that an invention of type Θ is disclosed through patenting. We do not observe, however, the characteristics of the underlying invention. Instead, we assume distributions G_{Θ}. Given the distribution $\mathcal{G}$ of invention types with $\theta = \Pr(\Theta = M)$, the probability that a given patent covers a process is

$$\rho(\tau) = \frac{\theta \pi_M(\tau)}{\theta \pi_M(\tau) + (1 - \theta) \pi_P(\tau)}. \tag{8}$$

The expression in (8) can be interpreted as the share of process patents in a sample of patents (where patents are either process or product patents). It is decreasing as trade secrets protection increases. We show this in

Proposition 2. *The share of process patents (patents covering a process or method invention) is decreasing as trade secrets protection increases.*

In other words, 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 Section 4, we take this prediction to the data.

3 Institutional Background and Data

We exploit the staggered, state-specific adoption of the Uniform Trade Secrets Act (UTSA) to examine the effect of trade secrets protection on patenting behavior. For our identification strategy, it is essential to determine to which level of trade secrets protection a patent applicant was exposed at the time of the disclosure decision. In this section, we link our information on trade secrets protection to the location and timing of the inventor's disclosure decision. We then introduce a dataset to identify process and product patents and discuss additional control variables.

3.1 Uniform Trade Secrets Act (1979/1985)

The UTSA is a body of laws relating to the protection of trade secrets. It 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).[13]

The objective of the UTSA was to clarify and harmonize across U.S. states the protection of trade secrets. Among other things, it attempted to standardize the definition of a trade secret, the meaning of misappropriation, and remedies (including damages) for trade secret holders in case of a violation. Using information on the level of trade secrets protection before and after a state's adoption of the UTSA, Png (2017a) constructs an index that measures the level of legal protection of trade secrets (up to 2008). We observe a strengthening of trade secrets protection if, for instance, the UTSA introduces a broader definition of what is a trade secret or a wider list of circumstances under which trade secrets law has been violated.[14]

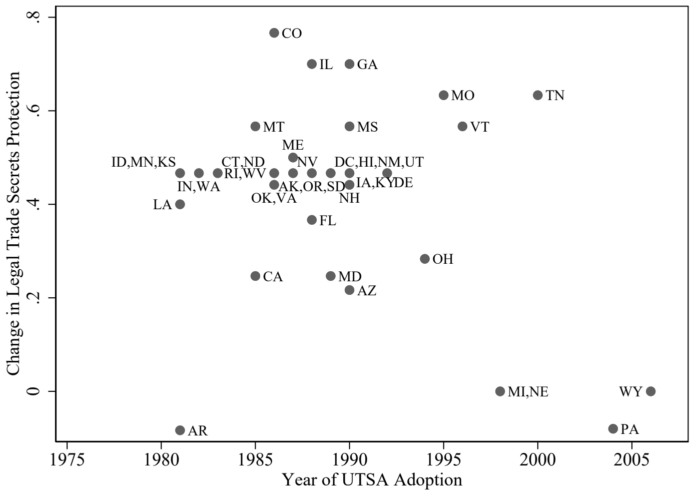
Figure 1 illustrates the *change* in this index in individual states as they adopted the UTSA in a given year, with higher values implying larger increases in protection. In most states, the UTSA resulted in a strengthening of trade secrets protection, with the exception of Michigan, Nebraska, and Wyoming, 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.

We use annual data of Png's trade secrets protection index for all 50 states (plus the District of Columbia) for the years 1976 through 2008. This index serves as exogoneous variation in the level of trade secrets protection τ across states and time.

[13] The list of adopting states includes all states except New York, Massachusetts, and North Carolina (Sandeen and Rowe, 2013).

[14] The index summarizes the inclusion of six different factors: continuous use requirement, requirement to take reasonable effort to protect trade secrets, mere acquisition as misappropriation, limitations on when a trade secret owner can take legal action, limitations of injunctions, and availability of a punitive damages multiplier.

Figure 1: Change in Legal Protection of Trade Secrets (Png, 2017a)



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.

3.2 Timing of the Disclosure Decision and Patent Location

We use the earliest priority date of the respective granted patent to determine the timing of the disclosure decision. 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.[15] We believe that the relevant disclosure decision was made at the time of the parent application, and we use that application's priority date as the disclosure date for all related patents.[16]

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.[17] While many patents list multiple inventors and assignees, oftentimes located in different states, our approach allows us to unambiguously identify a patent's location. It also ensures that the patent applicant's decision was driven by only that state's level of trade secrets protection, and not contaminated by laws in other states.[18]

For our final sample, we drop all business method patents.[19] With our assumption of single-state patents, we limit our overall sample to 1,473,878 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.[20]

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

[16] Our results are robust to using the more commonly used definition of the patent's application date. We present results in Appendix B.

[17] We disregard foreign inventors and assignees for this patent-state identification.

[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. In that case, the Court finds that "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] We loosely follow Lerner (2006) who identifies business methods patents as patents with a United States Patent Classification (USPC) main class 705. Our results are robust to this sample restriction (results upon request). Strandburg (2004) argues that business methods are "self-disclosing processes" and thus highly visible.

[20] We describe how our subsample differs from the broader sample in Appendix B. For alternative specifications, we use

Table 1: Summary Statistics

	N	Mean	Median	SD	Min	Max
Process patent	1461240	0.472	0	0.499	0	1
Number of process claims	1473486	0.863	0	1.402	0	60
Number of product claims	1473486	1.903	2	1.884	0	104
Indep. claims	1463686	2.873	2	2.283	1	116
Length of first claim (words)	1463682	168.969	148	106.535	1	7078
Length of description (chars.)	1473876	26031.370	15628	39648.204	4	3608036
Generality	1114531	0.639	0.719	0.244	0	1
Originality	1295568	0.626	0.694	0.244	0	1
4th year renewal	1379555	0.825	1	0.380	0	1
Observations	1473878					

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.

3.3 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.[21] 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.[22]

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 a process is disclosed at all.[23]

Table 1 provides summary statistics for our patent 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.

as patent location the location of the first assignee or the location of the first inventor listed on the patent. As reported in the Appendix, results are very similar.

[21] 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.

[22] These data come from Ganglmair et al. (2019), who employ a two-stage approach. They rely on a carefully crafted list of keywords to classify the preamble of the claim and use syntax analysis to determine if the body of the claim lists steps of a process or the components of a product. The claim category is then a combination of the preamble and the body type. For more detailed information on data creation (including more descriptive statistics and information on validation), see the Online Appendix.

[23] Our results are robust to less aggressive definitions of process patents, as we show in Appendix B. We further treat product-by-process claims as process claims, because what they disclose is a process more than a product.

3.4 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 (in characters) of the patent's detailed description text.

To capture the external value (or technological impact) of a patent, we construct measures 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.[24] As a measure of internal or private value of a patent, we use information on whether the patent holder paid the patent maintenance fee during the 4th year of the patent term (see, e.g., Pakes, 1986; Schankerman and Pakes, 1986).[25]

4 Empirical Estimation and Results

We take advantage of the staggered adoption of the UTSA across U.S. states over the course of more than 20 years to estimate the likelihood that a patent includes a process (Proposition 2) in a difference-in-differences setting. We then provide evidence that the state-specific timing of the adoption was random for the purposes of this study.

4.1 The Impact of the Protection of Trade Secrets

In our main specification, we estimate the probability that a patent covers a process invention as a function of the patent's characteristics as well as the state's trade secrets protection index. Formally, we estimate:

$$process_{jst} = \beta_1\, protection_{st} + \beta_2 X_{jst} + \nu_s + \mu_t + \eta_j + \epsilon_{jst}, \tag{9}$$

[24] There are about 450 main classes and about 150,000 subclasses in the United States Patent Classification (USPC) system. For more information, see `http://www.uspto.gov/patents/resources/classification/overview.pdf`.

[25] For more information on patent maintenance, including the fee schedule, see `https://www.uspto.gov/patents-maintaining-patent/maintain-your-patent`.

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- and USPC class-specific characteristics that do not vary over time, we include priority-year (μ_t) and location-state (ν_s) fixed effects, respectively, as well as dummy variables for patent j's first USPC main class (η_j).[26] Further, X_{jst} includes patent-specific measures of complexity and value, as described in Section 3.[27] Thus, our coefficient of interest β_1 captures the effect of the change of protection. Finally, we cluster standard errors by the patent's state and first USPC main class to allow for common trends within these states and classes.

Table 2 shows the coefficients from the baseline specification, including different sets of control variables.[28] All specifications estimate a negative impact of a UTSA-related strengthening of trade secrets protection on the probability that a patent is a process patent. The specification including control variables on measures of patent complexity *and* value (Column (4)) finds that a patent is 2.6 percentage points less likely to be a process patent if the trade secrets protection index rises by a full point. At a baseline of 42.3% of process patents before UTSA adoption, and with a mean increase in trade secrets protection of 0.36 points across all patents, this corresponds to a mean decrease of 2.2% in the probability that a patent is a process patent when a state adopts the UTSA. This impact corresponds to economically significant changes in patenting decisions and is statistically significant.

4.2 Identification and Instrumental Variables

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. Second, the adoption of the UTSA is not affected by an expectation that certain types of innovation 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 expand on this. First, we explain that our results are inconsistent with changes in innovation behavior due to the strengthening of trade secrets protection. We then implement an instrumental variables estimation similar to Png (2017b) to address concerns about the causal relationship between trade secrets protection and patenting. We further provide evidence from a set of placebo tests to examine whether the adoption of the UTSA was motivated by changes in innovation and patenting behavior.

[26] 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).

[27] While some of these variables are likely endogenous, we control for 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.

[28] We report results of a linear probability model for ease of interpretation.

Table 2: Baseline Results – Impact of Trade Secrets Protection

	(1)	(2)	(3)	(4)
Trade secrets protection	-0.018*	-0.021**	-0.026***	-0.026***
	(0.009)	(0.009)	(0.009)	(0.008)
Log(indep. claims)		0.233***		0.231***
		(0.003)		(0.003)
Log(length of first claim)		-0.044***		-0.051***
		(0.004)		(0.003)
Log(length of description)		-0.002		0.001
		(0.002)		(0.002)
Originality			0.025***	0.010**
			(0.005)	(0.005)
Generality			0.061***	0.038***
			(0.004)	(0.004)
4th year renewal			0.044***	0.025***
			(0.002)	(0.002)
Observations	1475058	1465095	907867	899932
$\overline{R}^2$	0.300	0.345	0.289	0.337

Notes: Linear probability model with 1[process patent] as the dependent variable, and the index of trade secrets protection (Png, 2017a) as the independent variable of interest. Robust standard errors, clustered by USPC main class and state, in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Additional controls include indicator variables for the patent's first listed USPC main class, the location state, and the priority year.

4.2.1 Innovation of Products and Processes

It is possible that overall innovative output increases at the margin as trade secrets protection increases. If this is the case, creators of process inventions are likely affected disproportionately because they benefit the most from secrecy. Such an increase could be due to a rise in innovative activity.[29] 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] However, we observe a relative *decrease*. Our results can therefore be interpreted as a lower bound of the effect of trade secrets protection.

4.2.2 Instrumental Variables

Despite anecdotal evidence that the UTSA was introduced in individual states for "whimsical" reasons, one might still 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 (2017b) and instrument for a state's adoption decision using four other state-level uniform laws as

[29] An alternative mechanism is firms and inventors moving 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 (or probability) of process patents in Equation (8). Assume for a moment that π_M and π_P do not change with τ; but let $\theta = \theta(\tau)$ be a function of τ. Then $\rho'(\tau) = \frac{\pi_M \pi_P \theta'(\tau)}{(\pi_P + (\pi_M - \pi_P)\theta(\tau))^2}$. If $\theta'(\tau) > 0$, then the share of process patents increases.

Table 3: Impact of Trade Secrets Protection – Instrumental Variables Regressions

	(1)	(2)	(3)	(4)
Trade secrets protection	-0.087**	-0.080*	-0.105**	-0.113***
	(0.037)	(0.042)	(0.041)	(0.040)
Log(indep. claims)		0.233***		0.232***
		(0.004)		(0.005)
Log(length of first claim)		-0.042***		-0.054***
		(0.005)		(0.007)
Log(length of description)		-0.002		0.003
		(0.002)		(0.003)
Originality			0.026***	0.011**
			(0.005)	(0.005)
Generality			0.058***	0.039***
			(0.011)	(0.007)
4th year renewal			0.037***	0.029***
			(0.003)	(0.005)
Observations	1461196	1451265	902874	894959

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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Additional controls include indicator variables for the patent's first listed USPC main class, the location state, and the priority year.

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. The identifying assumption is that states which adopted one uniform law early may have also been more likely to adopt other uniform laws early. Png (2017b) provides evidence that this assumption holds.

We create four sets of instruments for a state's level of trade secrets protection. For each law, we introduce a dummy variable that is 1 in state s if the state has implemented the law by the time of a patent's priority date. The first-stage results are strong: the coefficients on all four acts are highly statistically significant, for a first-stage F-statistic of 456.1.[31]

The second-stage results in this instrumental variables regression are shown in Table 3. The coefficients on the trade secrets protection variable are negative and statistically significant in all four specifications, supporting our findings from the baseline estimation although the coefficients appear larger in this specification. We continue in the following analyses without instruments to provide more conservative and more precise estimates, noting that all qualitative results hold if we include the instruments.

[31] We present the first-stage results in Appendix B.

Table 4: Placebo Test: Effect of (Placebo) UTSA Adoption

	(1) 1 year	(2) 2 years	(3) 3 years	(4) 4 years
After placebo UTSA adoption	-0.003 (0.005)	-0.007 (0.004)	0.000 (0.004)	0.004 (0.004)
Complexity controls	Y	Y	Y	Y
Value controls	Y	Y	Y	Y
Observations	137446	137446	137446	137446
$\overline{R}^2$	0.318	0.318	0.318	0.318

Notes: Linear probability model with 1[process patent] as the dependent variable and a binary variable that is equal to 1 in the one, two, three, and four years before the state adopted the UTSA as the independent variable of interest. All observations after the state's actual adoption are dropped. Robust standard errors, clustered by USPC main class and state, in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Additional controls are identical to the main analysis (specification (4) in Table 2).

4.2.3 Placebo Tests

One might still 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. In that case, we might see a significant change in the likelihood that a patent covers a process invention *before* a state adopts the UTSA. We examine this possibility in a placebo test. 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.[32] We then estimate the effect of the placebo UTSA adoption on the probability that a patent is a process patent.

In Table 4, we show the coefficients of interest (for the full specification – Column (4) – from Table 2), assigning placebo UTSA adoption dates of one, two, three, and four years prior to the true date. In all specifications, the coefficient on the placebo UTSA adoption is small and statistically insignificant. These results suggest that states adopted the UTSA exogenously with respect to changes in the distribution of product and process patents. Still, to be sure, we account for potential state-specific pre-trends in Appendix B, finding robust negative effects on the share of process patents.

4.3 Heterogeneous Effects

Trade secrets have been found to be more important as a means to protect intellectual property for small firms than large firms. A similar degree of heterogeneity is reported with respect to technology.[33] Here, we examine whether the effect of trade secrets protection on the share of process patents exhibits similar patterns. Specifically, we repeat the estimations from Table 2, adding indicators for the size of the patent applicant and for the patent's NBER technology category, respectively, and interacting these with the trade secrets protection variable.

[32] 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.

[33] Hall et al. (2014) provide a comprehensive survey of the literature.

Table 5: Heterogeneous Effects of Trade Secrets Protection

Panel (a): Patent Applicant Size

	(1)	(2)	(3)	(4)
Individual × Trade secrets protection	-0.041***	-0.043***	-0.052***	-0.047***
	(0.009)	(0.008)	(0.009)	(0.008)
Small firm × Trade secrets protection	-0.023**	-0.021**	-0.025**	-0.021**
	(0.009)	(0.009)	(0.010)	(0.009)
Large firm × Trade secrets protection	-0.002	-0.008	-0.008	-0.013
	(0.012)	(0.011)	(0.011)	(0.011)
Complexity controls	N	Y	N	Y
Value controls	N	N	Y	Y
Observations	1475058	1465095	907867	899932
$\overline{R^2}$	0.299	0.343	0.289	0.336

Panel (b): NBER Categories

	(1)	(2)	(3)	(4)
Chemicals × Trade secrets protection	-0.063***	-0.060***	-0.059***	-0.053***
	(0.014)	(0.013)	(0.015)	(0.014)
Computers × Trade secrets protection	0.069***	0.062***	0.054***	0.046***
	(0.015)	(0.013)	(0.015)	(0.014)
Drugs × Trade secrets protection	-0.026	-0.020	-0.019	-0.017
	(0.021)	(0.020)	(0.020)	(0.019)
Electronics × Trade secrets protection	-0.010	-0.016	-0.033**	-0.036**
	(0.015)	(0.014)	(0.015)	(0.014)
Mechanics × Trade secrets protection	-0.030**	-0.035**	-0.040***	-0.038***
	(0.015)	(0.014)	(0.014)	(0.014)
Other × Trade secrets protection	-0.033***	-0.039***	-0.038***	-0.037***
	(0.010)	(0.010)	(0.010)	(0.010)
Complexity controls	N	Y	N	Y
Value controls	N	N	Y	Y
Observations	1475058	1465095	907867	899932
$\overline{R^2}$	0.297	0.342	0.287	0.335

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 NBER technology categories (Hall et al., 2001): Chemical; Computers & Communications; Drugs & Medical; Electrical & Electronic, Mechanical, and Others. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Additional controls include indicator variables for the patent's first listed USPC main class, the location state, and the priority year.

Table 5 presents the results. Panel (a) shows the effect of trade secrets protection by applicant size. We consider three different sizes of patent applicants: individuals, small firms, and large firms.[34] The estimated decrease in the probability that a patent is a process patent is largest for individuals, 4.7 percentage points if the trade secrets protection index increases by 1 full point in Column (4). At the means of the change in trade secrets protection and the initial share of process patents for individuals, the effect corresponds to an average decrease in the probability of a process patent of 6.0% (compared to an estimated average effect of 2.2% from Table 2). The (negative) impact is smaller for small firms, and statistically insignificant for large firms. This result is in line with expectations, for two reasons. First, each individual state is only a small part of a large firm's overall market. The adoption of the UTSA in just one of these states is then unlikely to have a strong impact on its patenting behavior – in contrast to individuals and small firms. Second, the 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, as we show in the data.

In Panel (b), we present results for the effect of trade secrets protection by NBER technology categories (Hall et al., 2001).[35] Much of the average effect reported in Table 2 seems to be driven by innovation in the "chemical", "electrical and electronic", "mechanical", and "other" technology categories. In contrast, we find a *positive* effect in the "computers and communications" technology category. This category consists in large part (89%) of software patents, which are often filed as process patents even if the invention does not include any processes. Dropping software patents from the sample results in a much smaller and statistically insignificant effect.[36]

4.4 Robustness Analysis

Our data construction and empirical approach rely on a number of assumptions. In Appendix B, we present a set of sensitivity analyses to these assumptions. In short, we find that our main findings are robust. First, instead of assigning a patent's priority date as the time of the disclosure decision 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 consider both a broader definition of patent location (based on the first U.S.-based assignee, or first U.S.-based inventor if an assignee is not listed) and a narrower definition (using only single-assignee patents), showing that restricting our main sample to single-state patents does not drive our results. Third, we examine our definition of a process patent by considering two less stringent definitions and by dropping software patents.[37] Fourth, we include state-specific linear time

[34]For more details on how we construct our size index, see the Online Appendix.

[35]The six broad technology categories are based on USPC main classes. These categories are Chemical (1), Computers & Communications (2), Drugs & Medical (3), Electrical & Electronic (4), Mechanical (5), and Others (6). For more details, and for results by NBER sub-categories, see the Online Appendix.

[36]Results available upon request. As we show in Appendix B, the overall negative effect of trade secrets protection on the share of process patents remains robust to dropping them.

[37]After the U.S. Supreme Court decision Diamond v. Diehr (450 U.S. 175, 101 Supreme Court 1048 [1981]) that allowed patents for software, the share of software patents has been steadily increasing, going hand-in-hand with the diffusion of

trends before UTSA adoption to account for possible time-varying differences across states.[38]

5 Welfare Implications

In the previous section, we showed a negative effect of trade secrets protection on the ratio of process patents relative to products. Strengthening trade secrets protection can incentivize investment in initial *R&D*, but it may also retard knowledge diffusion because of a reduction of disclosure of less visible inventions. In what follows, we evaluate the total welfare effects of this trade-off.

5.1 An Augmented Model of Cumulative Innovation

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).

5.1.1 Stage 1 (Initial R&D)

An inventor observes a *potential* invention (idea) i with characteristics (ϕ, Θ), where ϕ denotes the invention's visibility and Θ its type (product or process). Visibility ϕ is drawn from an invention-type specific distribution with cdf F_Θ. The invention type Θ is drawn from a (Bernoulli) distribution $\mathcal{F}$ where $\theta^{\mathcal{F}} = \Pr(\Theta = M)$. We assume the inventor forms expectations of the invention's commercial value v_i based on the known distribution.[39] The inventor further observes costs C_i and undertakes the R&D project if the expected payoffs from the invention (a function of the disclosure decision at Stage 2) outweigh its cost. We refer to both F_Θ and $\mathcal{F}$ as *unconditional* distributions, that means, those of potential inventions *before* the R&D decision is taken.

5.1.2 Stage 2 (Disclosure or Trade Secret)

The second stage of our augmented model is the model in Section 2 in which the inventor takes her disclosure decision given the realized invention (conditional on a positive R&D decision). This disclosure decision depends on τ and ϕ_i, where ϕ_i is drawn from the invention type specific conditional distribution with cdf G_Θ. We further refer to the conditional distribution of invention types as $\mathcal{G}$.

5.1.3 Stage 3 (Follow-on Innovation)

For any potential initial invention i, there is a potential follow-on invention i_F with random value v_{i_F} and cost C_{i_F}, to be realized by another inventor. The realization depends on how much of the initial

software in a broad range of industries (Branstetter et al., 2019). When dropping software patents, the share of process patents (following our main specification) drops from 47.2% to 39.9% in our overall sample.

[38] 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.

[39] We do not estimate this distribution and therefore, for brevity, refrain from introducing more notation.

invention i is visible after the inventor's disclosure decision. We denote the *effective visibility* of initial invention i by $\tilde{\phi}_i$. It is equal to

$$\tilde{\phi}_i = \begin{cases} 0 & \text{if no R\&D in Stage 1;} \\ \phi_i & \text{if R\&D in Stage 1 and trade secret in Stage 2;} \\ 1 & \text{if R\&D in Stage 1 and patent in Stage 2.} \end{cases} \tag{10}$$

Effective visibility is equal to zero if the invention has not been realized and equal to the invention's visibility ϕ_i if the invention is realized but kept as a trade secret. We assume the disclosure function of patents is perfect, that means, the invention is fully disclosed through patenting. This implies that if the inventor decides to patent her invention in Stage 2, then effective visibility is equal to 1.

Given the effective visibility, the success probability of follow-on innovation is $\tilde{\beta}_{i_F,\tilde{\pi}} = \beta_{\tilde{\pi}}\tilde{\phi}_i$ where $\beta_{\tilde{\pi}}$ is the baseline success probability of follow-on innovation following a realized initial invention with disclosure state $\tilde{\pi}$. For the remainder of our analysis, we assume $\beta_S = 1$ and $\beta_D < 1$.

5.1.4 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 four main assumptions. First, follow-on innovation is by other firms rather than the inventor of the initial innovation. Consistent with this assumption, 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.[40] Second, disclosure has a positive effect on follow-on innovation. In line with this, Williams (2013) documents that a *restriction* of access to human genome data leads to a 20–40% *reduction* in follow-on research. Similarly, Gross (2019) finds that a policy during World War II to keep certain patent applications secret resulted in fewer citations.

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 (Heller and Eisenberg, 1998) 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; Boldrin and Levine, 2004; Green and Scotchmer, 1995; Bessen and Maskin, 2009; Galasso and Schankerman, 2010). For our welfare analysis, we set $\beta_D = 2/3$, a number consistent with empirical findings in Galasso and Schankerman (2015).[41]

Fourth, we assume that disclosure through patenting is perfect. By law, patent applicants are required

[40]Note that the patent premium λ in our model is equipped to capture the inventor's ability to engage in follow-on innovation. Suppose patenting of invention i increases a rival's probability $\tilde{\beta}_{i_F D}$ of follow-on innovation. Then trade secrecy becomes more attractive for the initial inventor, so that λ decreases.

[41]Using data for U.S. patents, Galasso and Schankerman (2015) find an average increase in forward citations of 50% in response to the invalidation of the cited patent. Gaessler et al. (2018) find an increase of 20% using data for European patents. Related results on the effect of patents rights on follow-on innovation from historical episodes of compulsory licensing can be found in Moser and Voena (2012) and Watzinger et al. (2019).

to provide a written description of the invention in sufficient detail to allow any person of skill in the field to make and use the invention (35 U.S.C. §112(a)). This requirement is called *enablement*. While the quality of such disclosures has been called into question by legal scholars (Roin, 2005; Fromer, 2009), Furman et al. (2018), for instance, document that the opening of patent libraries (during the pre-internet era) had a positive effect on patenting by local firms, and Hegde et al. (2019) find that accelerated disclosure of patent applications (due to the AIPA) increased the rate and magnitude of knowledge diffusion.

5.2 Structural Estimation and Results

We use the state- and year-specific trade secrets protection index along with the annual distributions of U.S. process and product patents to estimate the *unconditional* distributions F_Θ (of visibility ϕ) and $\mathcal{F}$ (of invention type Θ) for potential inventions (ϕ, Θ) given R&D costs C_i. We present a short summary of our estimation procedure below and provide further details in Appendix C.

We proceed in two steps. In Step 1, we estimate the *conditional* distributions $\mathcal{G}$ of invention type Θ and G_Θ of their type-specific visibilities ϕ by maximizing the log-likelihood of observing the empirical distributions of process and product patents at Stage 2. The log-likelihood is a function of G_Θ, $\mathcal{G}$, and the patent premium λ (from the disclosure decision in Equation (3)). For our estimation, we make a number of assumptions. First, for our preferred model we set $\lambda = 0.1$, a value in line with the estimates reported by Schankerman (1998).[42] Second, visibility ϕ follows a triangular distribution. We hold the mode for the distribution for products constant at 0.5 and estimate the distribution for processes without imposing first-order stochastic dominance. Third, we assume a time-variant distribution of invention types and estimate three values for θ_t (i.e., the probability that a realized invention in time t is a process).[43] We then proceed to Step 2, in which we estimate the unconditional distributions through simulated method of moments, matching simulated moments of the distributions of visibility and the shares of process inventions with those estimated in Step 1.

We report estimation results from Step 1 in Table A.5 in Appendix C. For our preferred model with $\lambda = 0.1$, our estimated visibility distributions satisfy the assumption of first-order stochastic dominance, with the modes of the triangular distributions differing in the expected direction. The estimated parameters comport with our theoretical predictions. Patenting probabilities for processes are lower than products (Lemma 2), decreasing in τ (Lemma 3), decreasing at different rates so that $\pi_P(\tau) - \pi_M(\tau)$ is increasing (Lemma 4) and the share of process patents decreases as trade secrets protection increases (Proposition 2). Together with the empirical distribution of the trade secrets protection index, the estimates of the time-variant innovation type distributions with parameters θ_t (increasing over time) imply

[42] We provide model estimates for different values of λ in Appendix C. Our results are consistent.

[43] Our results hold with more estimated values of θ_t (see the Online Appendix). For computational reasons, we choose a parsimonious version with three estimated parameters as our preferred model.

that the share of process patents, $\rho_t \equiv \rho(\hat{\tau}|\theta_t)$, is increasing over time from 0.33 to 0.58. This is in line with the positive time trend we observe for the share of process patents.[44]

The results for Step 2 of our procedure are shown in Table A.6. We report results for no R&D costs, low costs, and high costs. For all three scenarios, the results continue to satisfy first-order stochastic dominance. Moreover, for both invention types, we observe a selection of higher-visibility inventions into development at Stage 2. Our estimates further imply relatively large R&D intensities – ranging from 0.59 for high R&D costs to 1 without any costs – in Stage 1. In Stage 2, over 79% of realized inventions are indeed patented, and the fraction is larger for lower R&D costs. These results are in line with survey evidence reported by Mansfield (1986) who finds that in industries in which patenting is relatively important, 84% of patentable inventions are patented.[45] Finally, at Stage 3, up to one half of all realized initial inventions lead to follow-on innovation (with the share decreasing in R&D costs).

5.3 Welfare Results

With our estimates of the *unconditional* visibility and invention distributions, we conduct a number of counterfactual exercises to assess the welfare effects of trade secrets protection. We simulate a sample of initial ideas i and respective follow-on inventions i_F for each set of parameters to calculate total welfare. We begin by defining our welfare measure.

5.3.1 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, and the aggregate surplus from realized follow-on innovation, W_{i_F}. The expected total value added of a given idea is equal to

$$W(\tau) = E_{(\Theta_i,\phi_i,\tilde{\pi}_i,v_i,v_{i_F})}\left[\mathbf{R}_i(\tau)\left(W_i + \tilde{\beta}_{i_F,\tilde{\pi}_i}\mathbf{R}_{i_F}W_{i_F}\right)\right] \tag{11}$$

where expectations $E[\cdot]$ are over the invention type Θ, visibility ϕ, disclosure state $\tilde{\pi}$, and commercial values v_i for initial and v_{i_F} for follow-on innovation.

The inventor decides to undertake the initial R&D project and W_i if $EV_i \geq C_i$. We denote by EV_i the expected gross value of the invention to the inventor: the maximum of expected value of secrecy, $EV_{S|\Theta}(\tau)$, and of disclosure through patenting, $EV_{D|\Theta}(\tau)$. If the initial R&D project is undertaken, the indicator variable $\mathbf{R}_i(\tau) = 1$, and equal to 0 if otherwise. Moreover, 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,

[44] Figure A.3 in Appendix C illustrates the described patterns.

[45] The share is 66% in other industries. Mansfield's results suggest that patenting is relatively more important in pharmaceuticals, chemicals, petroleum, machinery, and fabricated metal products, whereas it is of less importance in primary metals, electrical equipment, office equipment, instruments, motor vehicles, rubber, and textiles.

$v_{i_F} \geq C_{i_F}$ and successful with probability $\tilde{\beta}_{i_F,\tilde{\pi}}$.

For the measures of aggregate surplus W_i and W_{i_F}, we assume that $2v_i$ is the *potential* aggregate surplus that materializes when there are no barriers to access to the invention. We first consider W_i. 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, with a maximum deadweight loss (from a scenario with full barriers to access) of $v_i/2$.[46]

For patented inventions, barriers to access increase in visibility ϕ, and the aggregate surplus, W_D, as a function of visibility is equal to

$$W_D(\phi) = 2v_i - \frac{\phi v_i}{2} - C_i, \tag{12}$$

where C_i is the cost of R&D of the potential idea. For inventions kept as trade secrets, barriers to access decrease in ϕ and increase in trade secrets protection τ. As discussed in Section 2, the probability that the inventor has exclusive access, implying full monopolistic deadweight loss, is equal to $\tau(1-\phi)$. Aggregate surplus, W_S, as a function of visibility and trade secrets protection is equal to

$$W_S(\phi,\tau) = 2v_i - \frac{\tau(1-\phi)\, v_i}{2} - C_i. \tag{13}$$

To summarize, using the disclosure condition in Equation (3), we use

$$W_i = \begin{cases} W_D(\phi) & \text{if } \phi \geq \dfrac{\tau}{1+\lambda+\tau}, \\ W_S(\phi,\tau) & \text{if otherwise.} \end{cases} \tag{14}$$

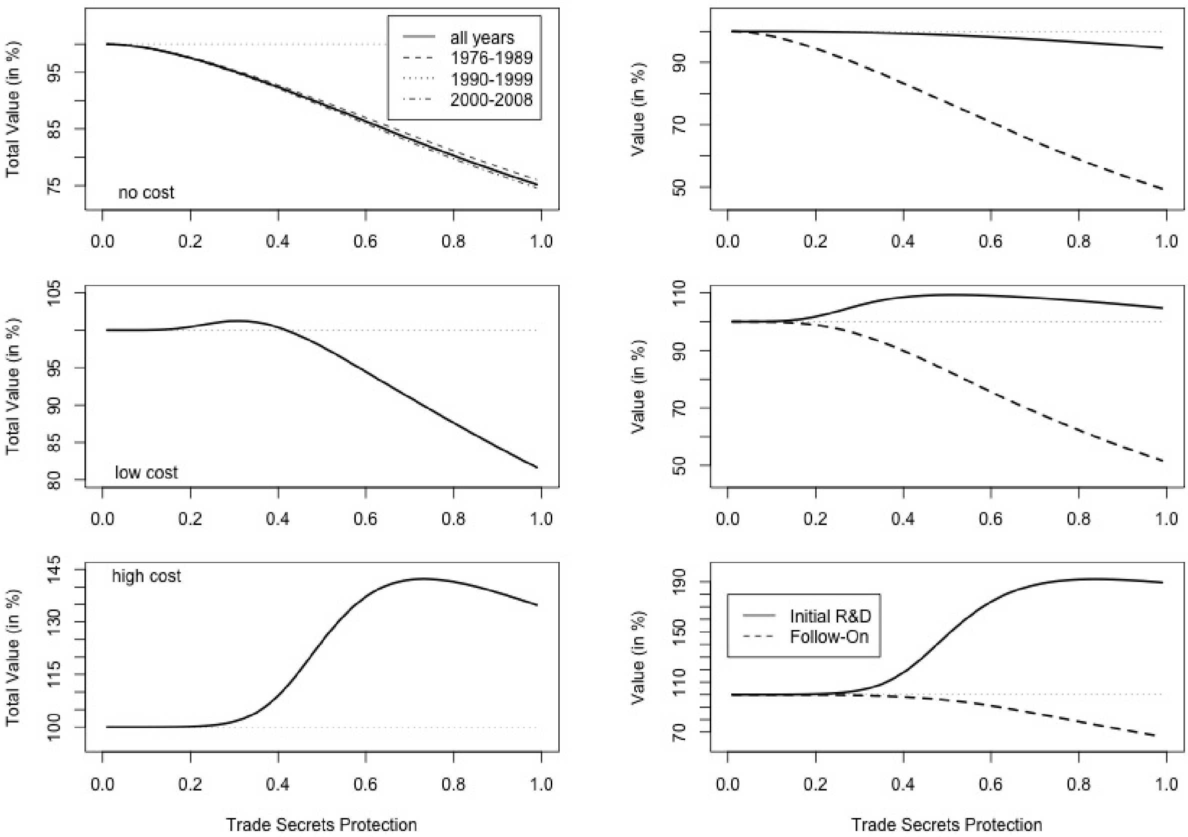
for the aggregate surplus of the initial invention. For the aggregate surplus of follow-on innovation, conditional on initial invention i being realized, we assume free access, so that $W_{i_F} = 2v_{i_F} - C_{i_F}$.

We will for the remainder of the paper assume that the patent premium $\lambda \leq 1/2$, so that the private returns do not exceed the social returns from R&D. With this assumption, the implications from our model are in line with results shown by Bloom et al. (2013).[47]

[46] 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 $(=v_i/2)$. In the Online Appendix, we provide a simple competition model to derive the reduced-form aggregate surplus from invention i.

[47] Higher social returns to R&D are typically linked to knowledge spillovers and the public goods aspect of research (Nelson, 1959; Arrow, 1962). The inventor's disclosure decision is socially optimal (with aggregate surplus $W_{\tilde{\pi}}$ as benchmark) only for intermediate values of visibility. The inventor discloses for $\phi \geq \frac{\tau}{1+\lambda+\tau}$. Disclosure is socially optimal and $W_D(\phi) \geq W_S(\phi,\tau)$ if $\phi \leq \frac{\tau}{1+\tau}$. For intermediate values of ϕ, the inventor's decision to disclose is socially optimal. For high values of ϕ, the inventor discloses when it is socially optimal to keep the invention a secret; for low values of ϕ, the inventor keeps the invention a secret when it is socially optimal to disclose.

Figure 2: Effect of Trade Secrets Protection on Welfare



(a) Total Welfare

(b) Initial and Follow-On

Notes: This figure presents our welfare results. In Panel (a), we plot the welfare function $W(\tau)$ (in % of $W(0)$). For values of $\tau \in [0, 1]$, 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 $\beta_S = 1$ and $\beta_D = 2/3$. We show the total value for our entire sample period (where a proportional number of simulated inventions have θ_t) as well as for the three subsample periods (for no cost). In Panel (b), we plot the social value of initial R&D (solid) and follow-on innovation (dashed), again in % of the value for $\tau = 0$. For the top panels, we use the estimates for $C = 0$ (no cost); for the center panels, we use the estimates for $C = 2$ (low cost); and for the bottom panels, we use the estimates for $C = 4$ (high cost).

5.3.2 Effect of Trade Secrets Protection

Figure 2 illustrates the welfare results under varying levels of trade secrets protection. Panel (a) plots the value of $W(\tau)$ in percent of the value under no trade secrets protection, $W(0)$, for three different levels of R&D costs (no costs, low costs, high costs). We see that, for no R&D costs, stronger trade secrets protection has an unambiguously negative effect on total welfare.[48] For positive R&D costs, trade secrets protection can lead to a welfare improvement – with larger benefits as costs increase. This effect comes through various channels. To illustrate these channels, Panel (b) of Figure 2 separately depicts the surplus from initial R&D and from follow-on innovation.

1. Trade secrets protection affects welfare conditional on the disclosure decision. For trade secrets, stronger legal protection increases barriers to access to a technology, which increases the deadweight

[48] We show in Appendix C that the effects of trade secrets protection are more pronounced as the difference of visibility distributions increases.

loss (captured by $W_S(\phi, \tau)$ in Equation (13)). We can see this effect in the solid-line graph in the top picture of Panel (b), where we isolate this deadweight loss because, without R&D costs, all R&D projects are realized regardless of the level of trade secrets protection.

2. Stronger trade secrets protection affects welfare by lowering the share of inventions disclosed, conditional on innovation. This has a negative effect on overall welfare $W(\tau)$ in Equation (11) through $\tilde{\beta}_{i_F,\tilde{\pi}}$: 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 in Panel (b).

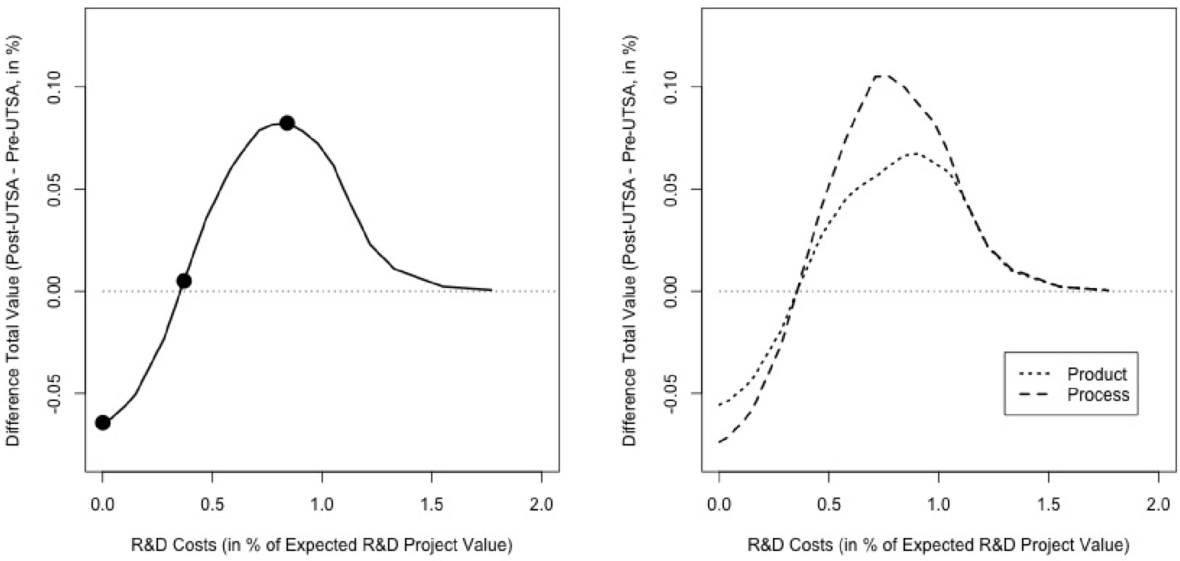
3. Trade secrets protection also affects the decision to innovate (ex ante). It has a positive effect on initial R&D by increasing the expected value of realized R&D projects. This in turn has a positive effect on $W(\tau)$. We observe this effect in the solid-line graphs in Panel (b) for positive R&D costs. For high R&D costs in particular, the positive effect through higher investment incentives more than offsets the negative effect on W_S (channel 1).

4. Stronger trade secrets has a secondary effect on follow-on innovation. The increased ex-ante R&D activity mentioned (channel 3) 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. We can observe this when we compare the dashed graph in Panel (b) for the value of follow-on innovation for high costs with that for low costs. For higher costs, 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 graphs in Panel (a) of Figure 2 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.[49] Moreover, under the UTSA, trade secrets protection is not extended if the information is "readily ascertainable," for instance, if it can be reverse engineered at insignificant cost. To establish the validity of their case, trade secrets holders must show significant costs of duplication of the secret information which they usually do by referring to their own costs of R&D (Sandeen and Rowe, 2013:34).

[49] 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 to this day continue to cite the more out-dated Restatement of Torts (Sandeen and Rowe, 2013:19).

Figure 3: 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 $\%\Delta W$ in Equation (15), that is, the difference between total welfare (as 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 fraction of the expected R&D project value (given expectations of invention type, visibility, commercial value, and the inventor's patenting decision). We mark the values of no costs, low costs, and high costs used in Figure 2. Panel (a) depicts the effect across all ideas, whereas Panel (b) shows the effect by invention type.

5.3.3 Average Welfare Effect of the UTSA

We use our model results to evaluate the welfare effect of the UTSA as a whole. We simulate data from our augmented model for the average value of trade secrets protection before the adoption of the UTSA, $\tau^{\text{pre}} = 0.071$, and after the adoption, $\tau^{\text{post}} = 0.394$. We then calculate the difference between the post-UTSA and pre-UTSA total welfare as a fraction of pre-UTSA total welfare,

$$\%\Delta W = \frac{W(\tau^{\text{post}}) - W(\tau^{\text{pre}})}{W(\tau^{\text{pre}})}. \tag{15}$$

Negative values of $\%\Delta W$ imply that the UTSA had, on average, a negative effect on welfare. We plot this average effect for varying values of R&D costs (in % of the expected R&D project value) in Figure 3. Panel (a) of the figure depicts the effect across all ideas, whereas Panel (b) shows the average welfare effect by invention type. The dots mark the scenarios of no costs, low costs, and high costs from Figure 2.

We find a negative effect of the UTSA for no R&D costs, a zero effect for low costs, and a positive for higher costs. Depending on R&D costs, the effect varies between a welfare loss of 7% and a welfare improvement of 8%. These results suggest that in industries with relatively profitable R&D (that is, where R&D costs are very low and 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 R&D

costs are higher and 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.[50] We see in Panel (b) that these effects are more pronounced for processes than for products.

6 Conclusion

While the effects of intellectual property rights on incentives to innovate in the first place are relatively well-understood, their role in facilitating follow-on innovation has received less attention until recently. We add to recent discussions by explaining that this role depends on the original idea's visibility. For less visible inventions, a patent implies disclosure of an idea that may have otherwise not been accessible by others. On the other hand, patents for visible inventions limit the ability of others to use said 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 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, although 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 when no proper institutions for protecting one's ideas are in place, 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.

The findings in this paper imply that an optimal patent and trade secrets policy distinguishes between different types of inventions and industries. Industries with high R&D costs are most likely to have benefited from increased trade secrets protection (e.g., pharmaceuticals and chemicals, following survey evidence in Mansfield (1986)). In contrast, industries in which R&D tends to be very profitable likely experienced a welfare loss from a strengthening in trade secrets protection. These patterns are further exacerbated for industries that rely most heavily on process innovation.

We undertake an ambitious analysis and provide novel insights that are constrained by data availability. We are therefore 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 our welfare implications are primarily driven by the effects of trade secrets protection on R&D and disclosure decisions, and respective follow-on innovation in a model of sequential innovation. That is, we study a specific type of secrecy. A different approach to trade secrets relates to the design of the employment relationship (in the form of covenants not to compete or the inevitable disclosure doctrine) or broader

[50] Note that as R&D costs increase further, the average welfare effect converges to zero because very few ideas are realized regardless of trade secrets protection.

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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Appendix

A Theoretical Model: Proofs and Auxiliary Evidence

A.1 Formal Proofs of Theoretical Results

Proof of Lemma 1

Proof. The proof follows from the disclosure decision in Equation (4). □

Proof of Proposition 1

Proof. For the proof of this claim and later results, 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

$$\int u(x)dG_P(x) = [u(x)G_P(x)]_0^1 - \int u'(x)G_P(x)dx$$

and

$$\int u(x)dG_M(x) = [u(x)G_M(x)]_0^1 - \int u'(x)G_M(x)dx$$

Because $G_P(0) = G_M(0) = 0$ and $G_P(1) = G_M(1) = 1$, the two first RHS terms in these expression are equal. We can thus 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 $\tau(1-\phi)v$ is a strictly decreasing function in ϕ. We can simply rewrite the inequality as $-EV_{S|P}(\tau) > -EV_{S|M}(\tau)$:

$$-EV_{S|P}(\tau) = \int_0^1 \underbrace{-\tau(1-\phi)v}_{u(\phi)} dG_P(\phi) > \int_0^1 \underbrace{-\tau(1-\phi)v}_{u(\phi)} dG_M(\phi) = -EV_{S|M}(\tau) \tag{A.2}$$

with $u(\phi)$ increasing in ϕ 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 ϕ. For the second claim, $EV_{D|M}(\tau) < EV_{D|P}(\tau)$, note that $\phi(1+\lambda)v$ is strictly increasing in ϕ, and the above general property applies. □

Proof of Lemma 2

Proof. Because $\pi(\phi, \tau)$ is a non-decreasing function in ϕ, the general property in Equation (A.1) (with $u(\phi) = \pi(\phi, \tau)$) in the proof of Proposition 1 applies. □

Proof of Lemma 3

Proof. Because $\pi(\phi, \tau)$ is (weakly) decreasing in τ for all ϕ, the first derivative of $\pi_\Theta(\tau)$ with respect to τ,

$$\frac{d\pi_\Theta(\tau)}{d\tau} = \int_0^1 \frac{\partial \pi(\phi, \tau)}{\partial \tau} dG_\Theta(\phi), \tag{A.3}$$

is non-positive for $\Theta = M, P$. □

Proof of Lemma 4

Proof. What is to be shown is

$$\frac{d\pi_P(\tau)}{d\tau} - \frac{d\pi_M(\tau)}{d\tau} = \int_0^1 \frac{\partial \pi(\phi, \tau)}{\partial \tau} dG_P(\phi) - \int_0^1 \frac{\partial \pi(\phi, \tau)}{\partial \tau} dG_M(\phi) \geq 0.$$

The cross-derivative of $\pi(\phi, \tau)$ is negative, $\frac{\partial^2 \pi(\phi,\tau)}{\partial \tau \partial \phi} < 0$. As ϕ increases, $\frac{\partial \pi(\phi,\tau)}{\partial \tau}$ is less negative so that $\frac{\partial \pi(\phi,\tau)}{\partial \tau}$ is increasing in ϕ. The general property in Equation (A.1) in the proof of Proposition 1 applies. □

Proof of Proposition 2

Proof. The proof follows from the result in Lemma 4 and the expression for the share of process patents in Equation (8). □

A.2 Auxiliary Evidence from the American Inventors Protection Act

The analysis in the main text relies on the assumption that processes are less visible and patents covering processes are more difficult to enforce. Given this assumption, Proposition 1 implies that inventors of processes should be more likely to keep their inventions a secret. Likewise, when they are given the choice, we expect process inventors to opt for secrecy more often – even if secrecy is only temporary.

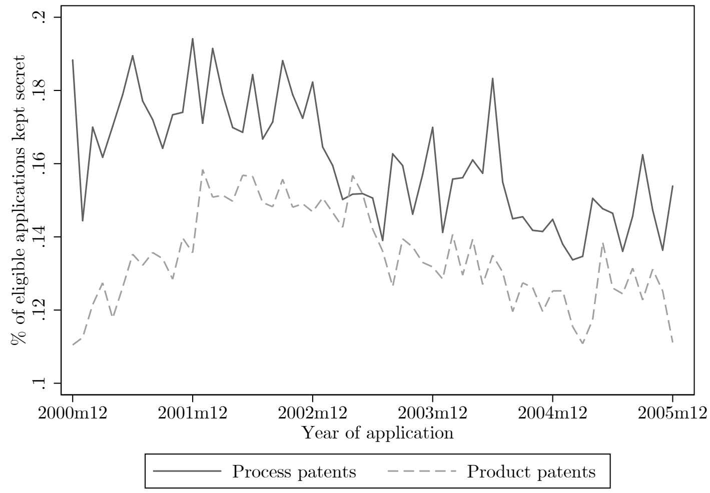
We test this implication of our working assumption by exploiting the enactment of the American Inventors Protection Act of 1999 (AIPA). The AIPA went into effect for all patent applications filed on or after November 29, 2000. It came with two important changes. First, all pending patent applications filed on or after the cutoff date are by default published 18 months after the filing date. This marks a significant change in policy as until then, the USPTO published only granted patents. Second, U.S.-only patents, for which applicants do not seek foreign protection, can opt out of automatic pre-grant publication.

Because all patented inventions are secret until the application is published, opting out of pre-grant publication represents a temporary extension of secrecy. In 2001, the lag between filing a patent application and grant averaged about 38 months (Graham and Hegde, 2015), implying that opting out of pre-grant publication extended temporary secrecy by about 20 months. Graham and Hegde (2015) find that about 15% of all eligible patent applicants filing after the effective date of the AIPA and asserting U.S.-only patent protection opt out of pre-grant publication.[51]

We extend Graham and Hegde's data and analysis by adding our process patent indicator introduced in Section 3 and comparing the applicants' choices of opting out of pre-grant publication across patent types. Our Proposition 1 implies that applicants of process patents will opt out of disclosure via pre-grant publication of their applications more often than those of product patents. Our results provide support

[51] See Graham and Hegde (2012) for an extended version with additional results and details on the AIPA.

Figure A.1: Probability of Extending Temporary Secrecy of Patent Applications



Notes: This figure plots monthly shares of applications (of eligible patents) that opted out of pre-grant publication, by patent type (process or product), for granted patents whose applications were filed within the first five years after the AIPA went into effect. Note that we follow Graham and Hegde (2015) and use the application date (which is the relevant date for the option to opt out of publication).

for our working assumption. Applicants of eligible *process* patents choose to keep their applications secret 16.1 percent of the time, whereas applicants of *product* patents choose secrecy only 13.5 percent of the time. The difference is highly statistically significant with a t-value of 25.8.[52] Figure A.1 plots the monthly shares of process and product patent applications (of granted patents) that were opted out of pre-grant publication. At any time in the five-year period after the AIPA (December 2000 through December 2005), a larger fraction of applicants of process patents (relative to product patents) decided to extend the secrecy of their patent applications.

In more formal regression analyses, we estimate the probability that applicants of eligible patents opt out of pre-grant publication, controlling for the same patent and applicant characteristics as our main analysis. In particular, we estimate the probability that a U.S.-only patent application (after passing of the AIPA) is kept secret until the patent's issuance. We estimate

$$secrecy_{jt} = \beta_1 process_{jt} + \beta_2 X_{jt} + \eta_j + \mu_t + \epsilon_{jat}, \tag{A.4}$$

where the dependent variable is 1 if patent application j in year t is kept secret until the patent is granted. The independent variable of interest, $process_{jt}$, is 1 if the patent is a process patent, X_{jt} includes the same patent-specific measures of complexity and value as the main text. We further include dummy variables for patent j's USPC class (η_j) and the year of application (μ_t). Finally, we cluster standard errors by USPC main class to allow for common trends within these classes.[53]

Table A.1 reports results of a linear probability model. Even after controlling for patent specific characteristics, applicants of process patents are more likely to opt out of application disclosure when given the choice. The estimated decrease of 1.1 percentage points (Column (4)) implies a decrease of 7.1% at the mean of 15.4% of patent applicants choosing secrecy.

[52] The differences in means are similar when using alternative patent type indicators.

[53] Note that our control variables differ from those used in Graham and Hegde (2015) to remain consistent with the remainder of our paper. Our results hold if we use their specification.

Table A.1: Secrecy/Disclosure of Patent Applications After the AIPA

	(1)	(2)	(3)	(4)
Process patent (= 1)	0.015***	0.010***	0.015***	0.011***
	(0.003)	(0.003)	(0.004)	(0.003)
Complexity controls	N	Y	N	Y
Value controls	N	N	Y	Y
Observations	479379	479379	270839	270839
$\overline{R}^2$	0.055	0.058	0.058	0.062

Notes: Linear probability model with 1[application is kept secret] as the dependent variable, and 1[process patent] as the independent variable of interest. Robust standard errors, clustered by USPC main class, in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Additional controls include indicator variables for the patent's first listed USPC main class and the year of application.

Table A.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	0.472	0.499
Log(indep. claims)	1.182	0.450	1.243	0.452	1.239	0.453
Log(length of first claim)	4.984	0.591	4.949	0.603	4.972	0.591
Log(length of description)	9.713	0.969	9.757	0.965	9.698	0.956
Originality	0.602	0.253	0.632	0.241	0.626	0.244
Generality	0.606	0.263	0.634	0.249	0.639	0.244
4th year renewal	0.837	0.370	0.839	0.368	0.825	0.380
Observations	4370594		2433317		1473878	

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.

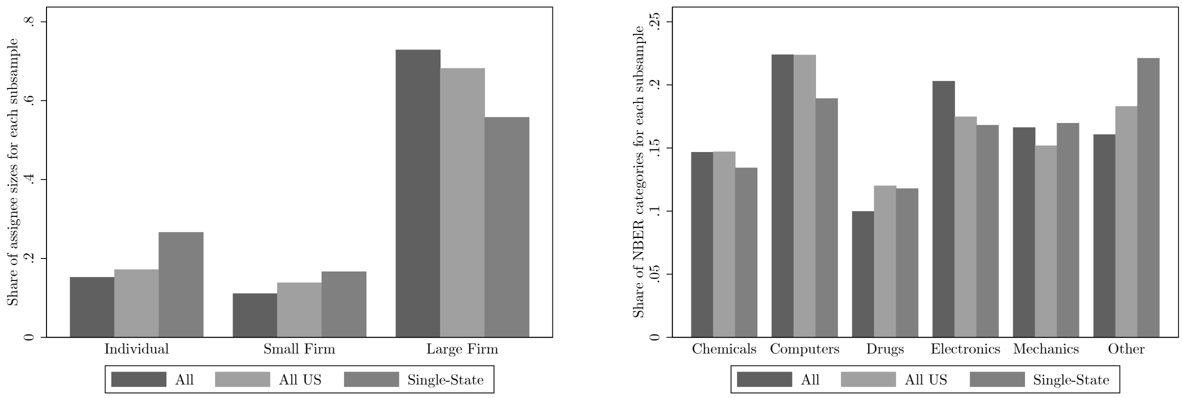
B Additional Empirical Evidence

B.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 (4,370,594 patents); (2) the subset of patents with any U.S. assignee or inventor (2,433,317 patents); and (3) the subset of patents for which all U.S. assignees and inventors are located in the same state (1,473,878 patents). Table A.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. They also seem to have slightly higher degrees of originality and generality. We control for these variables in the main estimation.

Figure A.2 further illustrates the distributions of the sizes of the applicants (left panel) as well as the patents' NBER technology categories (right panel), for the same subsamples as above. The left panel shows that our regression sample slightly over-represents individual applicants and under-represents large firms. Because individual applicants see the largest effect (see Section 4.3), our *average* treatment effects may be slightly over-estimated. The right panel shows the regression sample seems to be made up of

Figure A.2: Applicant and Technology Distributions for Different Subsamples



Notes: This figure presents shares of applicant sizes (left panel) and NBER technology categories (right panel) 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.

fewer computer & communication technologies, and more patents in the 'Other' category.

B.2 First Stage Results (IV Estimation)

Our instrumental variables estimation 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. Here, we provide empirical evidence that this assumption holds. Table A.3 shows the coefficients and partial F-statistic of the first stage. The coefficients on all instruments are strongly statistically significant, and the F-statistic is well beyond any critical value at 456.1.

B.3 Robustness of the Effect of Trade Secrets Protection

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 difference-in-differences regressions, replicating the specification from Column (4) of Table 2. We show the coefficients of interest from these robustness checks in Table A.4, with Panel (a) examining the date and location of the disclosure decision, and Panel (b) examining our definition of a process patent and the possibility of pre-trends.

Disclosure Date: It is possible that an applicant faced a disclosure decision for each new patent within a patent family. Panel (a) of Table A.4 addresses this possibility. Column (1) assigns the application date of the individual patent as the date of the disclosure decision. The coefficient of interest remains strongly significant and is slightly larger than that in the main specification (-0.030 as compared to -0.026). Column (2) circumvents this issue altogether by considering only the patent family head – the first patent within its family. Again, the results are almost unchanged.

Invention Location: In the main analysis, we focus on single-state patents, that means, patents for which all U.S. assignees and inventors are from the same state. We take this conservative approach to

Table A.3: First Stage Results of IV Regression

	(1) DV: UTSA index
UDDA	0.0182***
	(0.0052)
UDPAA	-0.0972***
	(0.0035)
UFTA	0.0741***
	(0.0034)
UFLRA	0.0396***
	(0.0052)
Observations	1,473,832
$\overline{R^2}$	0.7894
F-stat for all instruments	456.08***

Notes: Dependent variable is the effective trade secrets protection index. Robust standard errors, clustered by USPC main class and state, in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Additional controls include the complexity and value variables from the main analysis, as well as indicator variables for the patent's first listed USPC main class, the state, and the priority year.

avoid assigning patents to the "wrong" states. We test the robustness of our results to this selection in Column (3) of Panel (a) in Table A.4, which assigns 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. This definition provides even stronger results than the (more conservative) main specification.

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. Another approach would be to focus on patents with only one decision maker – those with just one assignee, or with just one inventor if no assignee is listed. Column (4) shows the results from a regression with such a subsample. The estimated impact of trade secrets protection on the share of process patents is again almost unchanged.

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 regardless of its role within a patent. 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, and (2) a patent is a process patent if at least 50% of all independent claims are process claims.[54] The results from these specifications are in Columns (1) and (2) of Panel (b), respectively. The impact of increased trade secrets protection remains strongly statistically significant and of similar magnitude to the main regression. Further, we drop all software patents in Column (3), as software patents are often filed as process patents even though they do not inherently include process innovation.[55] The resulting coefficient on the trade secrets protection is similar in magnitude as well, and remains significant at the 5% level.

Accounting for Pre-Trends: Finally, the main text shows Placebo tests that suggest the share of process patents did not change in the years leading up to a state's UTSA adoption. Nevertheless, we

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

[55] 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.

Table A.4: Robustness Checks

Panel (a): Disclosure Date and Invention Location

	(1) Appl. Date	(2) Family Head	(3) Assignee Loc	(4) Single Assignee
Trade secrets protection	-0.030***	-0.030***	-0.028***	-0.025***
	(0.008)	(0.009)	(0.008)	(0.009)
Observations	881197	799099	1438020	852598
$\overline{R^2}$	0.335	0.342	0.334	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***
	(0.007)	(0.007)	(0.008)	(0.017)
Observations	889101	894959	654458	894959
$\overline{R^2}$	0.307	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 and Column (2) considers only the first patent in a patent family (the family head). Columns (3) and (4) examine the location of the invention. Column (3) sets it as the location of the first assignee (or the first inventor if no assignee is listed), and Column (4) considers only patents with single inventors. In Panel (b), Columns (1)–(3) examine the definition of process patents. Column (1) considers the status of the patent's first claim; Column (2) considers a patent a process patent if at least half of all claims describe a process; Column (3) drops all software patents. Finally, Column (4) adds state-specific linear pre-trends. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All specifications include the same control variables as the full specification in the main text: complexity and value controls in addition to indicator variables for the patent's first listed USPC main class, the location state, and the priority year.

account for the possibility of different trends in the share of process patents across U.S. states before UTSA adoption. Specifically, we add state-specific pre-trends to our difference-in-differences regression. The estimated effect of trade secrets protection – after controlling for these pre-trends – is shown in Column (4) of Panel (b). The negative impact is even stronger in this specification, suggesting that states may have adopted the UTSA after a slight increase in the share of process patents. Regardless, all specifications in Table A.4 show a robust negative impact of trade secrets protection on the share of process patents.

C Structural Estimation Approach and Results

In this section, we present a more detailed account of our estimation approach and the main results.

C.1 Estimation Steps

C.1.1 Stage-2 Disclosure Decision (Step 1)

We estimate the conditional distributions G_Θ and $\mathcal{G}$ 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 τ_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 (8). Then, the log-likelihood of the data is given by

$$LL(G_M, G_P, \mathcal{G}, \lambda) = \sum_j \mathbf{M}_j \log \rho(\tau_j) + (1 - \mathbf{M}_j) \log(1 - \rho(\tau_j)) \tag{A.5}$$

It is a function of the (conditional) distributions of visibilities G_Θ, the invention type $\mathcal{G}$, and the patent premium λ. Given data limitations, we estimate our model parameters making a number of assumptions:

1. The patent premium λ is a fixed parameter in our model, and we use values between 0 and 0.5, based on values estimated in previous literature.[56] The discussion of the results in the main text is based on $\lambda = 0.1$.

2. Visibility ϕ follows a triangular distribution with support $[0, 1]$ and mode γ_Θ. We hold the mode for products constant at $\gamma_P = 0.5$ and estimate the mode γ_M for processes. Note that G_P first-order stochastically dominates G_M (as is our working assumption) if $\gamma_M \leq 0.5 = \gamma_P$.

3. We assume a time-variant distribution of invention types with θ_t, $t = 1, \ldots T$. We assume $T = 3$ with θ_1 for all inventions with disclosure decisions from 1976 through 1989, θ_2 for 1990 through 1999, and θ_3 for 2000 through 2008.[57]

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. The value for τ_k is the value of the trade secrets protection index in the patent's state in the year of its priority date.

C.1.2 Estimation of Unconditional Stage-1 Distributions (Step 2)

In the second step of our procedure, we estimate the *unconditional* distributions F_Θ of visibilities and $\mathcal{F}$ of invention types, using as inputs the conditional distributions G_Θ and $\mathcal{G}$ 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 to find F_Θ and $\mathcal{F}$ that yield in simulations of Stage 2 of the augmented model the estimated distributions G_Θ and $\mathcal{G}$. We proceed as follows:

1. For given unconditional distributions $(F_M, F_P, \mathcal{F})$ and some R&D cost C, we simulate a dataset of potential inventions and solve Stage 1 of our augmented model to obtain the *simulated* conditional distributions, $\delta \in \{\hat{G}_M, \hat{G}_P, \hat{\mathcal{G}}\}$.

2. We calculate the simulated conditional moments $\hat{\mu}_m(\delta | F_M, F_P, \mathcal{F})$ for the simulated data and the estimated moments $\mu_m(\delta)$ based on the estimated conditional distributions G_Θ and $\mathcal{G}$.

3. We define the quadratic score function

$$S(F_M, F_P, \mathcal{F}) = \sum_\delta \sum_{m \in \mathcal{M}} \left(\hat{\mu}_m(\delta | F_M, F_P, \mathcal{F}) - \mu_m(\delta)\right)^2 \tag{A.6}$$

   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 $(F_M, F_P, \mathcal{F})$ to obtain the optimal unconditional distributions.

[56] Schankerman (1998) finds that patent rights account for 5–15% of the returns of an invention, depending on technology fields. Arora et al. (2008) further document that for firms with a positive premium, the average patent premium is 50%.
[57] We present results with alternative assumptions about T in the Online Appendix.

Table A.5: Estimates for Conditional Distributions at Stage 2 (Step 1)

		(1)	(2)	(3)
License revenues [fixed]	λ	0.0	0.1	0.5
Mode for processes (G_M)	γ_M	0.572	0.374	0.249
		$[0.539, 0.616]$	$[0.374, 0.374]$	$[0.224, 0.312]$
Share of process inventions (1976–1989)	θ_1	0.327	0.331	0.331
		$[0.325, 0.329]$	$[0.329, 0.333]$	$[0.328, 0.336]$
Share of process inventions (1990–1999)	θ_2	0.475	0.490	0.489
		$[0.473, 0.478]$	$[0.488, 0.491]$	$[0.486, 0.505]$
Share of process inventions (2000–2008)	θ_3	0.575	0.591	0.590
		$[0.573, 0.577]$	$[0.589, 0.593]$	$[0.586, 0.608]$

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 γ_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 ($\mathcal{G}$) with parameter θ_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.

C.2 Results

We report the results for the conditional distributions from Step 1 in Table A.5. 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 assumption of first-order stochastic dominance. For our preferred Model (2) with $\lambda = 0.1$, we find our assumption of 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 (1) for $\lambda = 0$. We show in the Online Appendix that, with a more granular approach for the invention type distributions (with higher value of T), first-order stochastic dominance is satisfied even for the model with $\lambda = 0$.

In Table A.6, we report the parameters of unconditional distributions for no R&D costs ($C = 0$), low costs ($C = 2$), and high costs ($C = 4$). Note that, unlike in Step 1, where we hold G_P constant, in Step 2 we explicitly estimate F_P (i.e., the mode γ_P). Our assumption of first-order stochastic dominance (verified for the conditional distributions) continues to hold. The bottom panel of Table A.6 shows decisions at all three stages that are implied by the estimated parameters. Results are discussed in the main text.

In Figure A.3, we illustrate patenting probabilities and process shares as implied by our empirical estimates. As discussed in the main text, these patterns comport with our theoretical predictions.

C.3 Different Distributions of Visibilities

To further 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 illustrate the results of this exercise in Figure A.4. We compare the results from three scenarios to the total value from the estimated distributions from Table A.6. 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 A.6). In scenario 2 (dotted line),

Table A.6: Estimates for Unconditional Distributions at Stage 1 (Step 2)

			(1)	(2)	(3)
			Stage 1: F_Θ, $\mathcal{F}$		
		Stage 2: G_Θ, $\mathcal{G}$	no cost	low cost	high cost
Mode for processes	γ_M	0.374	0.370	0.335	0.103
Mode for products	γ_P	0.5	0.497	0.458	0.191
Share of processes (1976–1989)	θ_1	0.331	0.329	0.339	0.352
Share of processes (1990–1999)	θ_2	0.490	0.489	0.491	0.501
Share of processes (2000–2008)	θ_3	0.591	0.596	0.595	0.596
R&D intensity (Stage 1)			0.998	0.954	0.592
Patents (Stage 2)			0.858	0.850	0.796
R&D intensity (Stage 3)			0.553	0.465	0.357

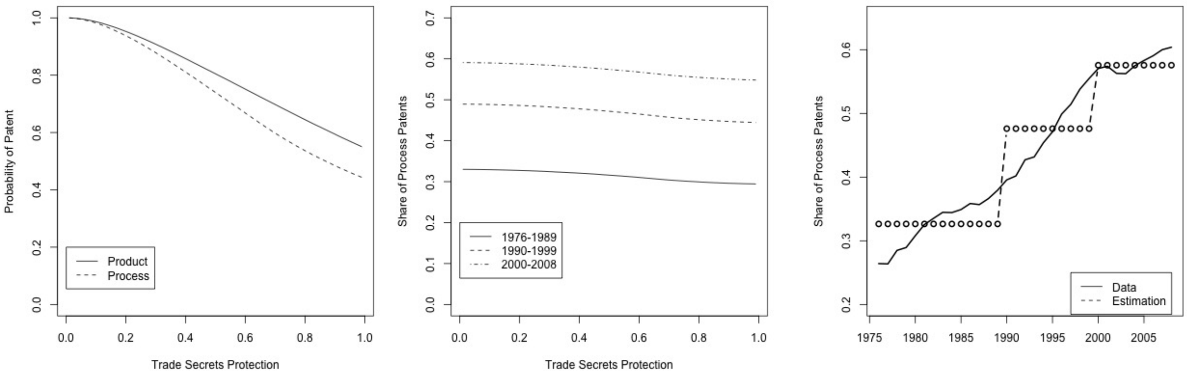
Notes: We report the parameter estimates for the unconditional distribution from Stage 1 of the augmented model. For the simulated-method-of-moments approach, we use the first two moments (mean and variance) for G_M and G_P and the first moment (mean) for $\mathcal{G}_t$. For the costs of the initial 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 ε_i and ε_{i_F} are (independently) logistically distributed with zero mean and scale $1/2$. We set $C = 0 = C_i$ (no cost) in Column (1), $C = 2$ (low cost) in Column (2), and $C = 4$ (high cost) 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.

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 $\gamma_M = 0$ and γ_P 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 welfare. Higher visibilities enter the welfare function in three ways. Higher visibility implies more patenting (Lemma 1), and with higher patenting comes a higher deadweight loss (Equation (12)). At the same time, higher patenting as well as higher visibilities increase effective visibility $\tilde{\phi}_i$ and thus increase follow-on innovation (Equation (10)). Our results in Figure A.4 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.

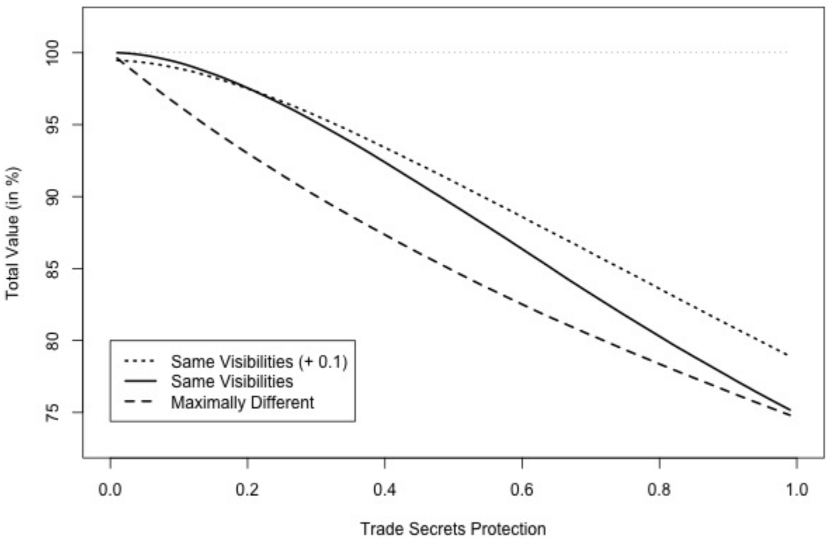
Figure A.3: Results from Structural Model (Conditional Distributions)



(a) Patenting Probability **(b)** Share of Process Patents (by τ) **(c)** Share of Process Patents (by year)

Notes: We depict the estimation results (Step 1) for Model (2) in Table A.5. For Panel (a), we plot the patenting probabilities $\pi_\Theta(\tau)$ (by invention type Θ) as function of trade secrets protection τ. For Panel (b), we plot the share of process patents $\rho(\tau)$ as function of trade secrets protection (τ) for three different estimates of θ_t. For Panel (c), we plot the share of process patents $\rho(\tau)$ over time. The solid line depicts annual process shares from the data, the dash-dotted line depicts the estimated values given θ_t and the empirical distribution of τ for the respective t. Graphs are based on simulated data with N = 1,000,000 potential inventions.

Figure A.4: 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 2. We plot total welfare for equal distributions for the two invention types (solid line) and maximally different distributions (dashed line) while keep 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.

Appendix for Online Publication

Visibility of Technology and Cumulative Innovation:
Evidence from Trade Secrets Law

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Online Appendix

D Further Empirical Evidence

We perform a number of additional robustness checks. First, we estimate – on the state-year level – the effect of trade secrets protection on the number of product and process patents. Second, we estimate heterogeneous effects at the NBER sub-category level. In addition (not reported), we re-run the main specification, dropping each state separately to see whether the results are driven by trends in specific states. We find a robustly negative effect for all dropped states.

The Number of Patents: We create a panel at the state-year level to estimate the effect of trade secrets protection on the number of process and product patents. Formally, we estimate

$$patents_{st} = \beta_1 protection_{st} + \gamma_s + \mu_t + \epsilon_{st}, \tag{B.1}$$

where $patents_{st}$ is the number of (process or product) patents in state s in year t, $protection_{st}$ is the trade secrets protection index, and γ_s and μ_t denote state and priority-year fixed effects, respectively.

Table B.1: Effect of Trade Secrets Protection on the Number of Patents

	(1) Process	(2) Product	(3) All
Trade secrets protection	-465.215***	-142.732**	-599.901***
	(150.127)	(66.427)	(209.485)
Observations	667	667	667
$\overline{R}^2$	0.591	0.371	0.520

Notes: Fixed effects models with the number of patents as the dependent variables, and the trade secrets protection index as the independent variable of interest. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Fixed effects for the location state and priority year included.

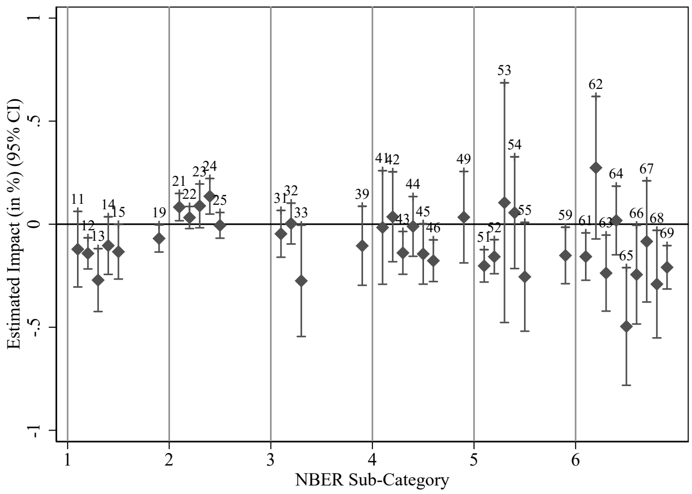
Table B.1 displays the results of this specification, for process patents (Column (1)), product patents (Column (2)), and all patents (Column (3), which is similar to Png (2017b)).[1] We find that an increase in trade secrets protection decreases the number of both process and product patents. We see a UTSA-related decrease of 465 process patents per state and year per point increase in the trade secrets protection index. At an average of 418 process patents per state and year in this sample before UTSA adoption, and with an average trade secrets protection index change of 0.42 points across states, the point estimate suggests a decrease in patenting of process inventions by 47% on average (the 95% confidence interval ranges from 17% to 76%). The number of product patents decreases with a strengthening of trade secrets protection as well, albeit less dramatically. At the mean pre-UTSA number of product patents (521), the mean change in trade secrets protection implies a decrease in patenting of product patents of 11.5% at the point estimate.

Granular Heterogeneity: In the main text, we estimate the heterogeneous effects of trade secrets protection for each NBER technology class. Here, we further divide each technology class into its sub-categories, and we interact each subcategory with the state's trade secrets protection index to estimate

[1] We limit our analysis to the ten years around a state's UTSA adoption to ensure results are not driven by long-run trends in patenting.

more granular effects in the probability that a patent is a process patent. The coefficients on the interaction terms – divided by the average pre-UTSA share of process patents – are illustrated in Figure B.1. Overall, most sub-categories in NBER category 1 (Chemicals) and 6 (Other) are negatively affected, whereas the impact on NBER category 2 (Computers & Communication) appears almost positive.

Figure B.1: Effect of Trade Secrets Protection by NBER Sub-Category



Notes: This figure plots the estimated effect of a one-unit increase in the trade secrets protection index on the probability that a patent is a process patent, by NBER subcategory. The estimated coefficients are divided by the subcategory-specific means to provide relative effects.

E Additional Tables and Figures for Structural Results

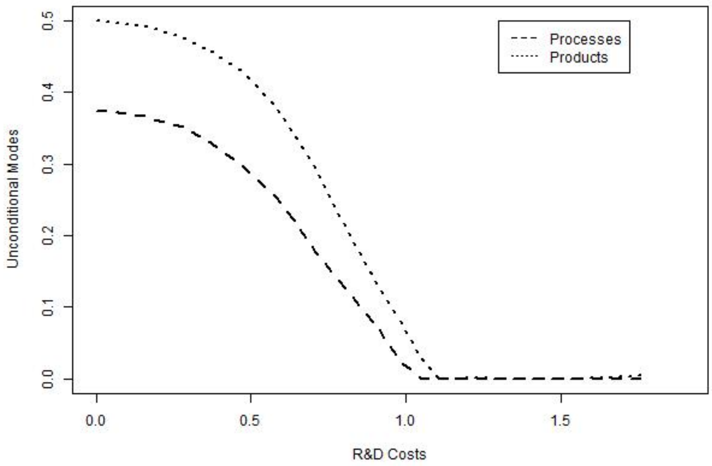
E.1 Estimated Distributions (by R&D Costs)

In Figure B.2, we plot the mode of the estimated unconditional distributions (Step 2) of visibilities for processes (dashed line) and products (dotted line). Analogous to the graph in Figure 3, we vary R&D costs and plot the outcome against R&D in % of Expected R&D Project Value. As R&D costs increase and fewer initial ideas are realized, inventions become on average less visible. For no R&D costs, the conditional and unconditional distributions are the same as all initial inventions (unconditional) are realized (conditional). With higher R&D costs, we observe selection. In order for the conditional distributions to be realized (recall: the conditional distribution is constant, not dependent on the counterfactual value of C), the initial distributions must change with C. For sufficiently high costs, we hit the lower bound of $\gamma_\Theta = 0$.

E.2 Time-Varying Distribution of Invention Types

For the specification of the structural model in the main text, we use a time-varying distribution of invention types with $T = 3$ different values for the share of process inventions, θ_t for $t = 1, 2, 3$. More specifically, in Table B.2, we present estimation results for $T = 7$ with θ_t for $t = 1, \ldots, 7$. Our results are robust. First, our estimates of γ_M satisfy our assumption of first-order stochastic dominance (now also for $\lambda = 0$). Second, our estimates for the distribution of invention types imply an increasing share of realized process inventions. In Figure B.3, we also plot the empirical and implied share of process patents. The solid line depicts annual process shares from the data, the dash-dotted line depicts the estimated values given θ_t and the empirical distribution of τ for the respective t. Third, with θ_t for

Figure B.2: Unconditional Distributions (Modes of Triangular Distribution)



Notes: In this figure, we plot the estimated modes of the triangular distribution for visibilities of processes (dashed line) and products (dotted line). On the horizontal axis, we use R&D costs as fraction of the expected R&D project value (given expectations of invention type, visibility, commercial value, and the inventor's patenting decision).

five-year increments, we are likely to capture effects of the *Uruguay Round Agreements Act* of 1995 and the *American Inventors Protection Act* of 1999.

F A Simple Competition Model

In this section, we derive the reduced-form social surplus functions in Equations (12) and (13) 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 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. This means, 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 ϕ. 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

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

Instead of a patent, let the firm keep the technology a secret. As discussed in the Section 2, 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 equilibrium price (and deadweight loss) is equal to

Table B.2: Estimates for Conditional Distributions ($T = 7$)

		(1)	(2)	(3)
License revenues [fixed]	λ	0.0	0.1	0.5
Mode for processes (G_M)	γ_M	0.436	0.367	0.249
Mode for products (G_P) [fixed]	γ_P	0.5	0.5	0.5
Share of process inventions (1976–1979)	θ_1	0.277	0.276	0.274
Share of process inventions (1980–1984)	θ_2	0.331	0.333	0.333
Share of process inventions (1985–1989)	θ_3	0.368	0.369	0.366
Share of process inventions (1990–1994)	θ_4	0.429	0.434	0.434
Share of process inventions (1995–1999)	θ_5	0.523	0.531	0.530
Share of process inventions (2000–2004)	θ_6	0.574	0.582	0.580
Share of process inventions (2005–2008)	θ_7	0.599	0.607	0.607
Observations N (no. of patents)		1,465,351	1,465,351	1,465,351
Log-likelihood/N		-0.67	-0.669	-0.67

Notes: We report the parameter estimates for the conditional distribution from Stage 2 of the augmented model with seven time periods. 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. We estimate the mode γ_M (of the triangular distribution over support $[0, 1]$) for processes and fix the mode γ_P for products. Invention types are Bernoulli distributed ($\mathcal{G}$) with parameter θ_t, where $t = 1$ for patents with priority dates in 1976–1979 [N = 109,264], $t = 3$ for 1980–1984 [N = 123,186], $t = 3$ for 1985–1989 [N = 127,825], $t = 4$ for 1990–1994 [N = 177,685], $t = 5$ for 1995–1999 [N = 253,815], $t = 6$ for 2000–2004 [N = 261,483], and $t = 7$ for 2005–2008 [N = 166,751]. The reported parameter estimates maximize the log-likelihood in Equation (A.5).

zero. The expected social surplus is

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

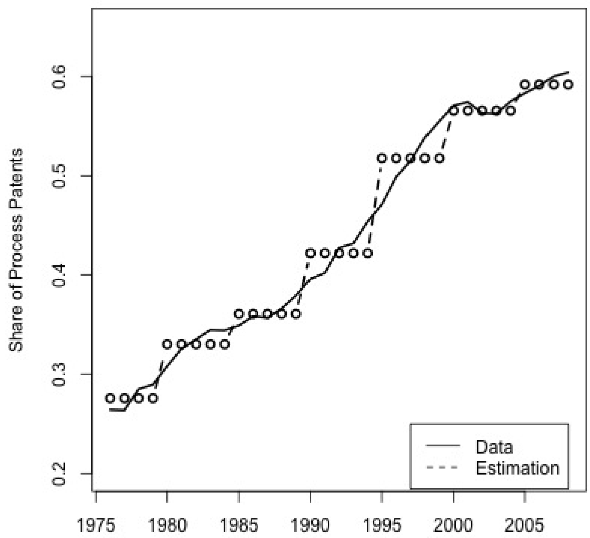
Let v denote the commercial value of the invention if the firm has exclusive access. In other words, let $v = \pi_L^m$, then the expressions for expected aggregate surplus are equal to the expression in Equations (12) and (13).

G Data Appendix

We construct our data sample using a number of sources. We obtain basic bibliographic information from PatentsView at `https://www.patentsview.org/download` for bulk download and `http://www.patentsview.org/api/doc.html` for API queries. We also use data from Ganglmair et al. (2019) for process patent indicators, the USPTO's Patent Maintenance Fee Events database at `https://bulkdata.uspto.gov/data/patent/maintenancefee` to calculate our proxies for patent value as well as applicant size, the USPTO's Patent and Patent Application Claims Research Dataset at `https://bulkdata.uspto.gov/data/patent/claims/economics/2014/` for proxies of patent scope and complexity, and the Google Patents Research Data at `https://console.cloud.google.com/marketplace/partners/patents-public-data` to construct data on the timing of disclosure.[2] In Table B.3, we provide an overview of the steps of our sample construction. For further details, see the descriptions that follow.

[2]We thank Jeffrey Kuhn for his support with Google's Big Query.

Figure B.3: Share of Process Patents ($T = 7$)



Notes: In this figure, we plot the share of process patents $\rho(\tau)$ over time. The solid line depicts annual process shares from the data, the dash-dotted line depicts the estimated values given θ_t and the empirical distribution of τ for the respective t, where $t = 1, \ldots, 7$. The parameter estimates are reported in Table B.2, the estimated values are based on simulated data with $N = 1{,}000{,}000$.

G.1 Main Sample

For our data sample, we start with the census of U.S. utility patents granted between 1976 and 2014. In order to obtain a clean assignment of the level of trade secrets protection to which the patent applicant was exposed at the time of the disclosure decision, we limit our sample to patents with disclosure *timing* between 1976 and 2008 and a *location* within the United States.

Timing: Priority Dates To identify the timing of the disclosure decision, we use the priority date of the head of a simple patent family (i.e., all patents that share the same priority claims). We implement this by using the earliest priority date for all patents from a given simple patent family. Information on simple patent family assignment and priority dates we obtain from the Google Patents Research Data.

Location: U.S.-only Patents To identify the location (i.e., U.S. state) of the disclosure decision, we use information on the location of patent assignees and inventors. PatentsView provides data on disambiguated location, assignee, and inventor names. For each patent, we consider only assignees and inventors within the United States. Out of this subsample of names, we further consider only those patents for which all U.S. assignees and all U.S. inventors are located in the same state. We use this state as the respective state of the disclosure decision (and, by assumption, the relevant U.S. state for the UTSA adoption and trade secrets protection).

For a set of robustness results in the Appendix, we use a more aggressive location definition. There, we define the location of a patent by the location of the first assignee listed on the granted patent. If no assignee is listed, we use the location of the first inventor listed on the granted patent.

G.2 Patent Classification

For basic information on patent classification, we use the current United States Patent Classification (USPC) main classes (applied to all patents retrospectively) obtained from PatentsView. Where multiple

Table B.3: Sample Construction and Sample Size

Sample/Variable	Source	
Patents, granted January 1976 – December 2014	PatentsView	
Priority dates: January 1976 – December 2008	Google Patents	
U.S. only location	*constructed*	
Exclude business method patents	PatentsView	
	Main Estimation Sample:	1,473,878
Process patent indicator	Ganglmair et al. (2019)	
Number of independent claims	USPTO Claims	
Length of first claim	USPTO Claims	
Length of detailed patent description	PatentsView (API)	
Originality	*constructed*	
Generality	*constructed*	
4th year maintenance	USPTO Maintenance	
USPC main classes	PatentsView	
Applicant size	*constructed*	
NBER technology categories	PatentsView	

Notes: Data sources are PatentsView (bulk data download page and API), Google Patents (Google Patents Research Data), USPTO Claims (USPTO's Patent and Patent Application Claims Research Dataset), USPTO Maintenance (USPTO's Patent Maintenance Fee Events database), and Ganglmair et al. (2019). Constructed means that variables are constructed/calculated by authors. For more details, see the descriptions below.

main classes are listed on a patent, we use the first (by sequence).

For our main estimation sample, we exclude all business methods patents. We follow Lerner (2006) and define such patents as those with USPC main class 705 (i.e., the first main class listed on the patent). For a set of robustness results in this Online Appendix, we also rerun our analysis for a subsample that excludes software patents. For the classification of software patents, we follow Graham and Vishnubhakat (2013:fn 7).

Note that for our structural estimates, we use an extended sample that includes all granted patent through 2016. We discuss the reasons for this extension below.

G.3 Construction of Additional Variables

We further collect and construct three sets of variables to proxy a patent's "patent scope and complexity," its "external impact," and its "internal value." For our heterogeneity results, we also collect and construct variables capturing the size of the patent applicant and the broader technology class of the patent.

G.3.1 Patent Scope and Complexity

We follow Lerner (1994) and Lanjouw and Schankerman (2004) and measure patent breadth and scope using the number of independent claims in a patent. Kuhn and Thompson (2019), however, argue that a simple count of (independent) claims may be a poor measure for patent scope.[3] They propose the length of the first patent claim as an alternative measure for patent scope, where shorter claims are broader. They use the first claim for their measure because under U.S. law the broadest claim should be listed first. We adopt their measure (length of the first claim in number of words) alongside the number of independent claims.

We collect the number of independent claims of a paper and the length of the first claim from the USPTO's Patent and Patent Application Claims Research Dataset at `https://bulkdata.uspto.`

[3]Because each claim beyond 20 claims comes at an additional cost, patents with many claims may cover more valuable technologies, but need not be broader than patents with fewer claims.

gov/data/patent/claims/economics/2014. This research dataset provides information on claims from patents granted between January 1976 and December 2014. For more details on the data, see Marco et al. (2016).

We further collect the length (in characters) of the detailed description of each patent from PatentsView through API queries (the data are not available for bulk data download at http://www.patentsview.org/download).

G.3.2 External Impact

We construct measures of patent generality and patent originality as proposed by Trajtenberg et al. (1997). See also Hall et al. (2001).

Patent Originality: Patent originality of a patent j is defined as

$$1 - \sum_{k=1}^{n} \left(\frac{\text{backward citations}_{jk}}{\sum_{m=1}^{n} \text{backward citations}_{jm}} \right)^2 \tag{B.4}$$

where $s_{jk} = \frac{\text{backward citations}_{jk}}{\sum_{m=1}^{n} \text{backward citations}_{jm}}$ is the share of backward citations that patent j makes to patents in patent class $k = 1, \ldots, n$ over all backward citations made by patent j. A higher originality score means patent j draws on prior knowledge from a greater variety of fields. We construct this measure using the first listed USPC main class on a patent j. We have classification information for patents granted in and after 1976. This means that for patents granted early in our sample period that cite patents granted before 1976, we have little information about the classes of their cited patents. Because of this truncation issue, the originality measure is therefore noisier and coarser for earlier patents than for patents granted later in our sample period.

Patent Generality: Patent generality of a patent j is defined as

$$1 - \sum_{k=1}^{n} \left(\frac{\text{forward citations}_{jk}}{\sum_{m=1}^{n} \text{forward citations}_{jm}} \right)^2 \tag{B.5}$$

where $s_{jk} = \frac{\text{forward citations}_{jk}}{\sum_{m=1}^{n} \text{forward citations}_{jm}}$ is the share of forward citations that patent j receives from patents in patent class $k = 1, \ldots, n$ over all forward citations received by patent j. A higher generality score implies a higher widespread impact, influencing subsequent innovation in a broader variety of fields. A large number of patents never receive a patent citation, and our patent generality score is not defined for any patents without forward citations.

G.3.3 Internal Value

We use information on the applicant's renewal behavior as a measure of internal (or private) value of a patent (Pakes, 1986; Schankerman and Pakes, 1986). To this end, we construct a dummy variable equal to 1 if the applicant has paid the 4th-year maintenance fees (to be paid in the fourth year after patent grant).

We use information from the USPTO's Patent Maintenance Fee Events database at https://bulkdata.uspto.gov/data/patent/maintenancefee (January 28, 2019). The database contains all recorded events related to the payment of maintenance fees for patents granted from September 1, 1981 and forward. A patent is said to have been maintained if one of the codes listed in Table B.4 is recorded.

Because we have information on maintenance events through the end of 2018, covering the full four years after our main sample ends, we do not face any truncation issues for an applicant's 4th year maintenance decision. Note, however, that because maintenance information is available only for patents

Table B.4: Codes for Maintenance Fee Events

Code	Description
F170	Payment of Maintenance Fee, 4th Year
F173	Payment of Maintenance Fee, 4th Year, Undiscounted Entity
F273	Payment of Maintenance Fee, 4th Year, Small Entity
M1551	Payment of Maintenance Fee, 4th Year, Large Entity
M170	Payment of Maintenance Fee, 4th Year, PL 96-517
M173	Payment of Maintenance Fee, 4th Year, PL 97-247
M183	Payment of Maintenance Fee, 4th Year, Large Entity
M2551	Payment of Maintenance Fee, 4th Yr, Small Entity
M273	Payment of Maintenance Fee, 4th Yr, Small Entity, PL 97-247
M283	Payment of Maintenance Fee, 4th Yr, Small Entity
M3551	Payment of Maintenance Fee, 4th Year, Micro Entity

Source: Documentation file for Patent Maintenance Fee Events database at `https://bulkdata.uspto.gov/data/patent/maintenancefee`.

granted on or after September 1, 1981, we have 94,323 missing observations for patents granted between January 1976 and August 1981. Further note that we are not restricted by this truncation issue for our structural estimations and therefore use an extended sample with patents granted through December 2016.

G.3.4 Applicant Size

For our variable of applicant size (or entity size), we combine information from the USPTO's Patent Maintenance Fee Events database and bibliographic information on patents from PatentsView. Applicant size takes three values. It is equal to 1 if the applicant is an individual, equal to 2 if the applicant is a small firm (i.e., small entity but not an individual), and equal to 3 if the applicant is a large firm (i.e., large entity but not an individual).

The USPTO's Patent Maintenance Fee Events database provides information on the size of the entity for any recorded maintenance fee event. Entities are either micro or small ("small") or "large." This means, if an applicant's maintenance event for a patent j is recorded in the database, then we know the size of that patent j's applicant. Using assignee information (from PatentsView), we construct an applicant's size history (by year), based on recorded maintenance events. We hold the size of an applicant constant at the value of t until the next recorded event at $t' > t$ where it may or may not change. In addition, we use the size of the first entry for all previous years. With this size history, we can now assign an applicant size for all patents j of an assignee for which no maintenance event is recorded. This gives us size information for all patents by assignees that have at least one recorded maintenance event; patents by assignees without any maintenance events are without applicant size.

An applicant of a given patent j is an individual ($= 1$) if the first assignee listed on the patent is of type "individual" or if no assignee is listed on the patent. If the applicant is not an individual, then its size is equal to 2 if it is a small entity and equal to 3 if it is a large entity (as defined above). For the distribution of applicant size (for different definitions of patent location) see Figure A.2.

G.3.5 Technology Class

We obtain NBER technology classifications from PatentsView. The NBER technology categories are constructed by Hall et al. (2001). Patents are assigned to six categories: Chemical (1), Computers & Communications (2), Drugs & Medical (3), Electrical & Electronic (4), Mechanical (5), and Others (6). We provide a list of the categories with their respective 36 sub-categories in Table B.5. Note that software

Table B.5: NBER Technology Categories and Sub-Categories

NBER Category	NBER Sub-Categories
Chemical (1)	Agriculture, Food, Textiles (11); Coating (12); Gas (13); Organic Compounds (14); Resins (15); Miscellaneous-chemical (19)
Computers & Communications (2)	Communications (21); Computer Hardware & Software (22); Computer Peripherals (23); Information Storage (24); Electronic Business Methods and Software (25)
Drugs & Medical (3)	Drugs (31); Surgery & Medical Instruments (32); Biotechnology (33); Miscellaneous-Drug&Medical (39)
Electrical & Electronic (4)	Electrical Devices (41); Electrical Lighting (42); Measuring & Testing (43); Nuclear & X-rays (44); Power Systems (45); Semiconductor Devices (46); Miscellaneous-Elec. (49)
Mechanical (5)	Materials Processing & Handling (51); Metal Working (52); Motors, Engines & Parts (53); Optics (54); Transportation (55); Miscellaneous-Mechanical (59)
Others (6)	Agriculture, Husbandry, Food (61); Amusement Devices (62); Apparel & Textile (63); Earth Working & Wells (64); Furniture, House Fixtures (65); Heating (66); Pipes & Joints (67); Receptacles (68); Miscellaneous-Others (69)

Source: Hall et al. (2001) and PatentsView. Appendix 1 in Hall et al. (2001) also lists the respective USPC main classes (version 1999) for each sub-category.

patents (see above) predominantly fall into category Computers & Communications and sub-category Computer Hardware & Software.

Filling some gaps in the data, we assign USPC main class 532 to category 1 (Chemical) and sub-category 14 (Organic Compounds); and USPC main classes 901 (robots) and 902 (electronic funds transfers) to category 2 (Computers & Communications) and sub-category 22 (Computer Hardware & Software). For the distribution of NBER technology categories (for different definitions of patent location) see Figure A.2.

G.4 Process Patent Indicator

G.4.1 Summary of Indicator Construction

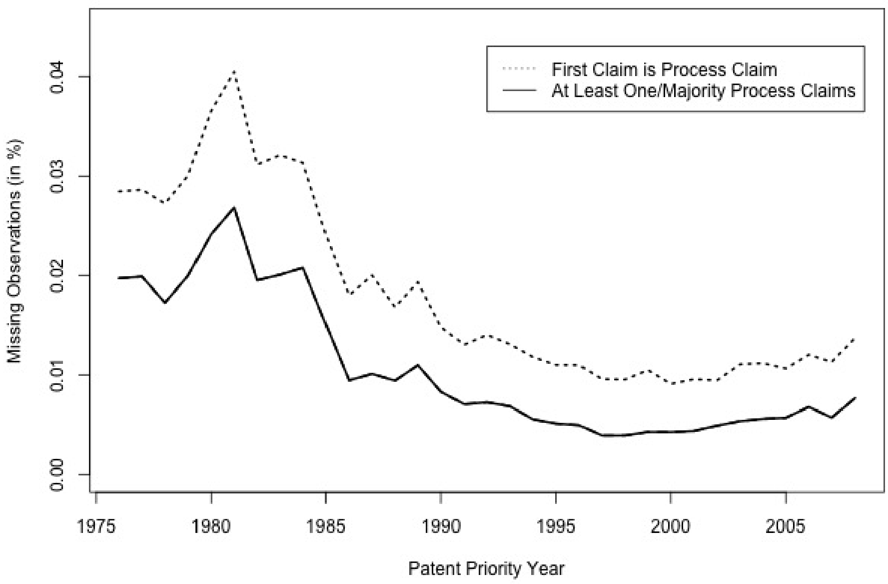
Ganglmair et al. (2019) employ text-analytical methods to identify the invention type of all independent claims in a given patent. We aggregate their claim-level data to obtain data at the patent level. In the sequel, we summarize their approach. Some of the material is also borrowed from Rosenberg (2012). An additional useful source of further background information is WIPO (2007).

The unit of analysis in Ganglmair et al. (2019) is an independent patent claim. A patent claim defines the scope of legal protection provided by a patent. It describes what the applicant claims to be its invention for which the patent grants exclusive 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.

Claims typically consist of two parts: a *preamble* and *body*. The preamble is an introductory phrase or paragraph that identifies the category of the invention of the claim. For example, an invention may be an apparatus or device (as in an *apparatus or device claim*, here referred to as *product claim*) or a method or process (as in a *method claim* or *process claim*). The *body* of a patent claim recites the elements of the claim. In many cases, these elements are *steps* (as in the steps of a process) or *items* (as in the items that define a product).

The approach in Ganglmair et al. (2019) uses information from both the preamble and the body. Both parts of the claim are classified as describing a process or a product. For the preamble, this classification

Figure B.4: Share of Missing Observations (All Three Patent-Level Indicators)



is conducted via a simple keyword search (e.g., "process" or "method" for process-claim preambles; "apparatus" or "device" for product-claim preambles). For the body, the authors take a syntax-analysis approach, analyzing the linguistic structure of each line (or "bullet point") in the body. The steps of a process are listed using the gerund form of a verb, whereas the items of a product (an apparatus, a device) are listed as components. The authors' algorithm accounts for these drafting conventions when classifying a body as process-claim body or product-claim body. In the end, combining the classifications of the preamble and the body, a classification for the entire claim is obtained:

Process claim or method claim: A *process claim* (also called a *method claim*) describes the sequence of *steps* which together complete a task such as making an article of some sort. The preamble of a method claim often uses the terms "process" or "method." The body of a method claim typically consists of a listing of the "steps" of the process.

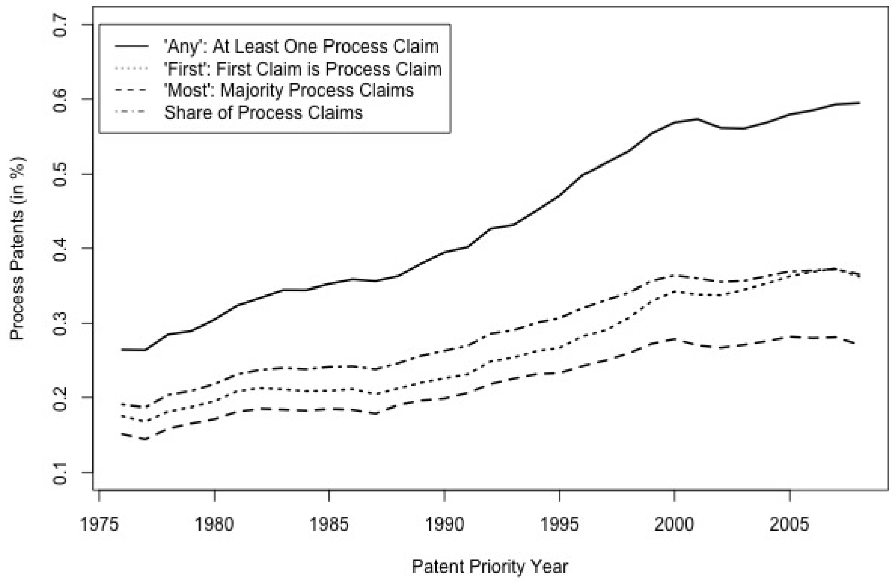
Product claim: A *product claim* (also called a "device claim" or "apparatus claim") describes an invention in the form of a physical apparatus, system, or device. For instance, a claim that covers a tripod for a camera or a window crank is an apparatus claim. In the preamble of a product claim, the patent applicant often recites what the product is and what it does. Then, in the body of the claim, the applicant lists the essential elements (i.e., "items") of the invention.

In addition to process claims and product claims, the special case of product-by-process claim is classified.

Product-by-process claim: A *product-by-process* claim is a claim that defines a product by the process of making it. The product-by-process claim defines a product by several process steps. Though, ultimately, the scope of the claim's coverage is directed toward a physical article (i.e., the "product") rather than the method, the claim includes elements of both product claiming (i.e., elements in the body that describe the items that comprise an article or product) and the sort of steps found in a process claim.

The authors' algorithm deals at great length with a number of issues: badly formatted claims, claims not following the usual drafting conventions, and two-part claims (also called improvement claims or

Figure B.5: Share of Process Patents (Multiple Indicators)



Jepson claims). They have also compiled a dataset of close to 10,000 manually classified claims to test their algorithm and verify the results.

In Figure B.4, we plot the fraction of missing observations for each of our patent-level indicator. For both our main indicator and the process patent indicator with a majority of process claims, at least one patent claim must be classified - the graphs in the figure are therefore the same. The requirement for the indicator of the first process claim is stricter, and the number of missing observations is higher throughout. Notice, however, that the reliability of the approach increases over time as the percentage of missing observations (over all patents in our main sample) drops below 1% around 1985 (with higher numbers for patents with earlier priority dates).

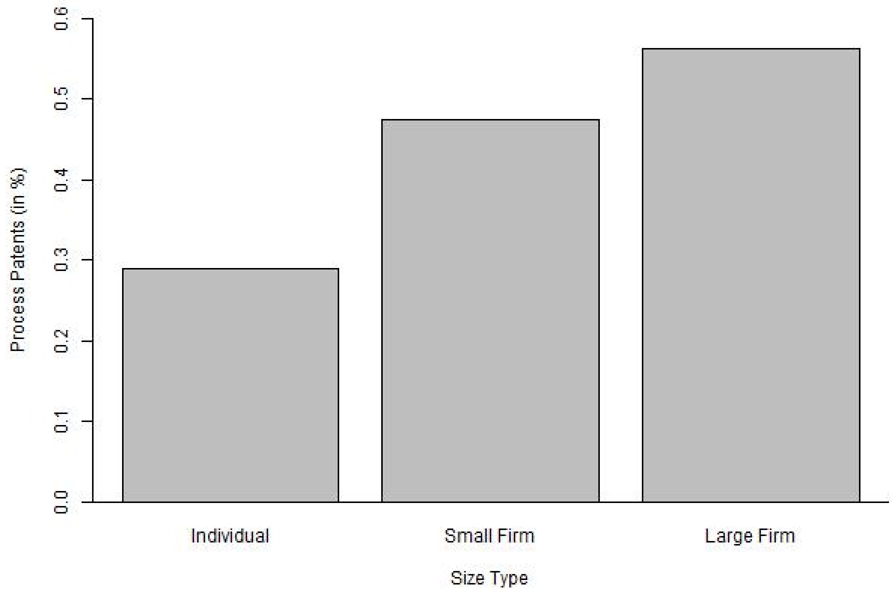
G.4.2 Descriptive Figures

In Figure B.5, we plot the share of process patents by priority year. We show graphs for each of our three process patent indicators. The solid line depicts the share of process patents for our main indicator (at least one patent claim is a process claim, 'Any'). The dotted graph depicts the share of patents with the first patent claim a process claim ('First'); the dashed graph depicts the share of patents with a majority of process claims ('Most'). As we we have discussed in the main text, our main indicator is the most aggressive in terms of identifying patents as process patents. The overall time trends, however, are very similar. We also plot the average share of process claims in a patent (dash-dotted line). The graph follows similar trends.

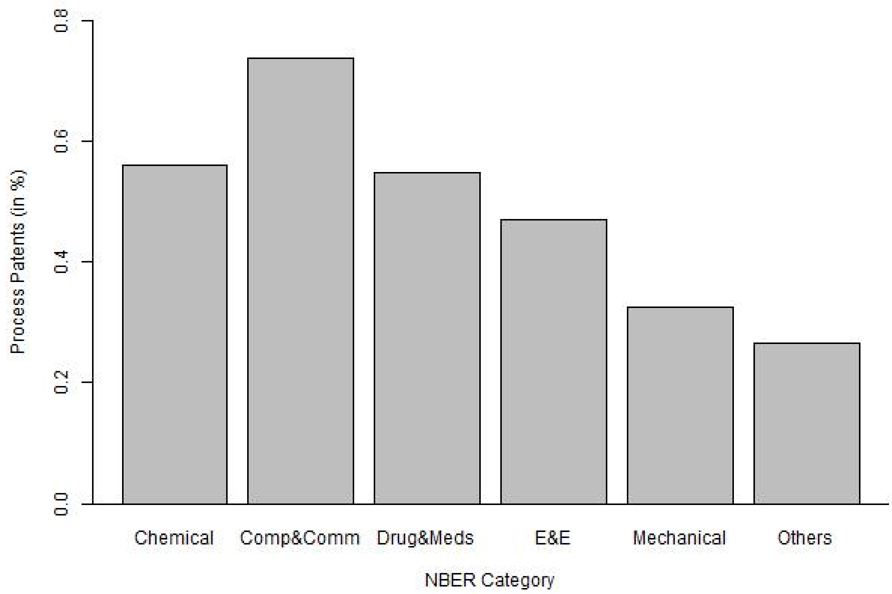
In Figure B.6, we depict the share of process patents by applicant size (Panel (a)) and NBER category (Panel (b)) – the two dimensions we use for our analysis of heterogeneous treatment effects in the main text. The share of process patents is higher in larger firms than in smaller firms, and lowest for individuals. In Panel (a) of Figure B.7 we can further observe this pattern in all NBER categories except "Drugs and Medicals" (Category 3) in which small firms exhibit the highest numbers for process patents, followed by large firms and individuals.

In Panel (b) of Figure B.6, we see that the NBER Category "Computers and Communication" (Category 2) has the highest share of process patents. Within this category, "Computer Hardware & Software" (Sub-Category 22) and "Electronic Business Methods and Software" (Sub-Category 25) stand

Figure B.6: Share of Process Patents

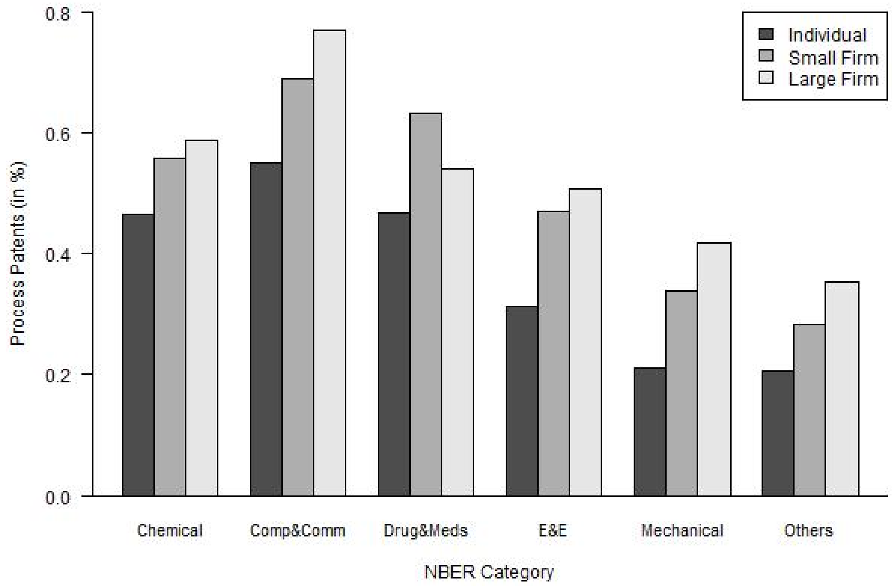


(a) Share of Process Patents by Applicant Size

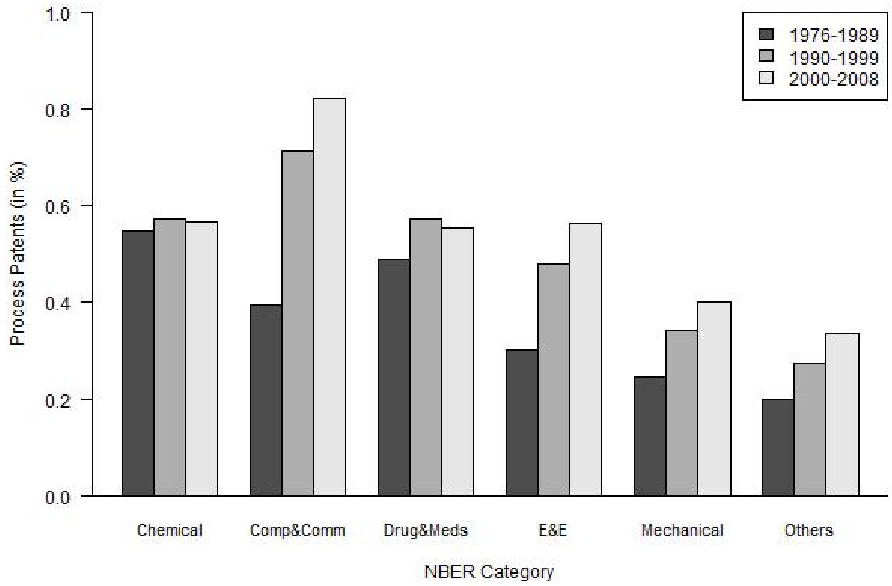


(b) Share of Process Patents by NBER Category

Figure B.7: Share of Process Patents (by NBER Category and Time Period)



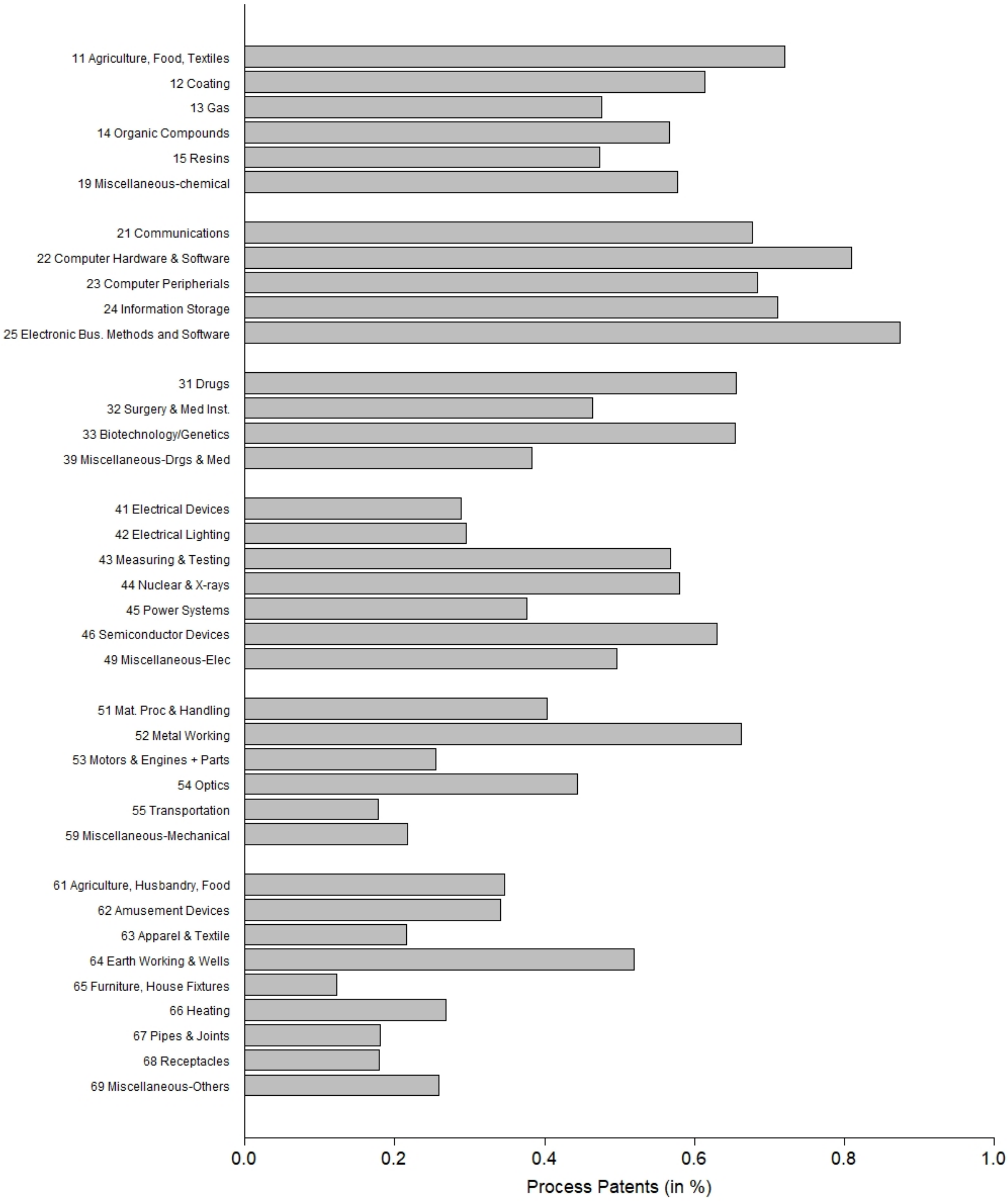
(a) By NBER Category and Applicant Size



(b) By NBER Category and Time Period out. This implies that even without business methods (or: business method patents), category 2 is the a leading category for process patents. On the other end of the spectrum, the catch-all category “Others” (Category 6) exhibits the lowest share. Within this latter category, “Earth Working & Wells” (Sub-Category 64) has the highest share (with more than 50%), whereas “Furniture, House Fixtures” (Sub-Category 65) comes with the lowest share of process patents.

Last, in Panel (b) of Figure B.7 we capture time trends in the share of process patents for different NBER categories. We see strong positive time trends for “Computers and Communication” (Category 2) and weaker trends for “Electrical and Electronic” (Category 4), “Mechanical” (Category 5), and the catch-all category “Others” (Category 6). We see little or no time trends for “Chemical” (Category 1) or “Drugs and Medical” (Category 3).

Figure B.8: Share of Process Patents (by NBER Sub-Category)



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