Regulatory Transparency and Innovation

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Abstract

What is the effect of regulatory transparency on innovation? The information environment deeply affects innovation, as firms rely heavily on secrecy. Yet the impact of government-mandated transparency outside the patent system remains largely unstudied. Drawing on a dataset of the universe of wireless-enabled devices in the U.S. and difference-in-differences and regression discontinuity designs, this paper finds that increased regulatory transparency increases follow-on innovation by 78–166 percent. The increase affected both products in the same category and in new categories, suggesting novelty. The effect wanes over several years, potentially due to an increase in innovation appropriation measures: secrecy and patenting. The results show that the information environment, shaped by government regulations, has significant effects on innovation.

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1 Introduction

Since before the industrial revolution, governments regulated the information environment over innovation—the invention and diffusion of new products or services. Venetian medieval laws constrained the movement of glass workers to maintain a technological lead (Amato, 1997). 18th century British parliamentary rewards system actively encouraged innovation disclosure, paying the inventor Thomas Lombe for exhibiting silk working machines in the Tower of London (Burrell and Kelly, 2015). The U.S. 1999 American Inventor's Protection Act accelerated the disclosure of patent applications, and likely increased technology diffusion (Hegde et al., 2023). Today, government support for open access innovation, proposals such for AI algorithmic transparency, as well as recent closures of U.S. government websites, may likewise impact innovation by changing the information environment.

The effects of regulatory transparency on innovation may be large, given how heavily firms rely on secrecy in innovation. Surveys consistently find that firms rely on secrecy and lead time more than patenting in almost all industries across countries (Levin et al., 1987; Arundel, 2001; Cohen et al., 2000; Hall et al., 2014). In a 1994 U.S. survey—closest to the focus of this paper—Cohen et al. (2000, p. 33) finds that R&D laboratories in communication equipment industry report patents effective as an appropriation mechanism for 26 percent of their products (midpoints mean, N = 34), compared to 47 and 66 percent for secrecy and lead times. They find somewhat stronger role of patents in computers and electronic equipment industries, but all relevant industries report secrecy as more effective than patents in product innovation. Disclosure requirements mandated by governments may thus have an effect on follow-on innovation.

In this paper, we use a unique dataset of wireless-capable products to study the effects of regulatory transparency on follow-on innovation. The empirical setup has two advantages: it covers the universe of all wireless-capable products introduced to the U.S. market, including a majority that are not protected by a patent; and it includes detailed technical description of each product, making it possible to track the use of a specific technologies. Wireless-enabled products represent most of high-tech electronic products today, and the U.S. market is globally representative to the frontier of technology in wireless-enabled devices, making our results broadly relevant.

We study the effects of a 1998 government transparency shock that made this documentation available on the internet, and its effect on follow-on innovation by competitors. We primary rely on a difference-in-differences design for identification, which differentiates between follow-on innovation by the firms firm and by its competitors. The setup includes product-level random effects, which control for otherwise unobserved product characteristics, and explains most of the variation. We supplement this approach with regression-discontinuity design for robustness and extensions.

Our results find a sizable positive effect of the transparency shock on follow-on innovation. Perhaps surprisingly, this increase affected both products in the same category and in new categories, suggesting novelty. Governments nowadays typically do not aim at boosting innovation with policies that affect information availability such as algorithmic transparency, AI regulations, medical device databases, or restrictions on non-compete agreements. Our findings suggest that this may be a missed opportunity.

2 Prior literature

The proliferation of secrecy obscures empirical research on innovation, as undisclosed innovation is difficult to observe. Most prior work relies on innovation observable in patents, in which firms voluntarily disclose their inventions in exchange for legal protection (Hall and Harhoff, 2012). Ingenious study designs leveraged variation in the costs of information access and the timing of disclosure to estimate the effects of patent disclosure on innovation. Cox (2019) estimate an increase in patenting after 1734 U.K. patent disclosure requirement (restricted to London, where patent descriptions were stored), and Furman et al. (2021) find a similar increase in U.S. locations where a patenting library had opened between 1995 and 1997. Gross (2023) find a significant decrease in follow-on innovation due to delayed grant and publication of a patents due to a Second World War patent secrecy program, and (Rassenfosse et al., 2024) find a similar decrease in patents subject to an analogical Cold War-era program. Multiple studies analyze the effects of the 1999 U.S. American Inventors Protection Act (AIPA), which accelerated patent application disclosure, and find positive effects on follow-on innovation and patent licensing (Hegde and Luo, 2018; Kim and Valentine, 2021; Baruffaldi and Simeth, 2020; Hegde et al., 2023).

These findings show consistent evidence of positive effect of patent disclosure on follow-

on innovation. However, they are limited to the minority of inventions that are (eventually) patented, which skews towards large firms in some industries. Disclosure in patent documents is also a selective strategic choice of firms and is complicated due the willful infringement doctrine, which discourages inventors from reading patents (Sandrik, 2021).

A fruitful approach to overcoming the limitations of patent data relies on firms having to disclose their products when entering a market. Moser (2005) relies on product data from 19th century World's Fairs, which arguably covered most of high-tech inventions globally, (Argente et al., 2021) relies on barcode readers in stores to measure innovation in retail products. These studies confirm that most inventions were not patented, but did not evaluate the effects of disclosure on innovation. The open access movement provided some variation in science and innovation disclosure. Recent studies on open access mandates find positive effect on follow-on innovation, relying mostly on patent and academic publications data (Bryan and Ozcan, 2021; Staudt, 2020), although its broader impact is disputed (Probst et al., 2023). Closer to product market effects, Murray et al. (2016) find a positive effect of lower costs of access to genetically modified mice on entry of new researchers and exploration of more diverse research paths. Finally, in a simultaneous study, (Kim et al., 2024) use a subset of the dataset used here to study the effects of open-source drivers on downstream Wifi router supply chains.

This paper expands this literature by estimating the causal effects of government-mandated transparency on follow-on innovation outside of the patent system, inclusive of all products irrespective on intellectual property protections, and in a large high-tech industry. Broadly, it contributes to literature on follow-on innovation and innovation spillovers (which mostly relies on patent data (Bloom et al., 2013; Sampat and Williams, 2019)) and to literature on the effects of government transparency (which mostly focused on governments rather than firms (Porumbescu et al., 2022; Corduneanu-Huci and Trlifaj, 2024)).

3 Wireless products regulation

Well-established regulations govern safety and reliability of the thousands of devices in our everyday life that emit electromagnetic signal. In the U.S., the Federal Communication Commission is responsible for this regulation since the 1934 adoption of the Section 302 of the Communications Act, following an increase in incidents of interference of unrelated

devices such as cash machines and TV receivers (Knapp and Wall, 1997).

The FCC's equipment authorization program is a major regulatory instrument in this effort. It requires any firm marketing a product that could interfere in electromagnetic spectra to comply with strict technical rules and document the compliance in an application to the FCC, which then grants authorization for the product marketing. In late 1990s, the period of focus of this paper, these products included hearing aids, domestic and industrial remote controllers, pagers, mobile phones, microwaves, or alarm systems. Today, many digital products of daily use are under the regulation, including smartphones and personal computers, wireless headphones, home appliances, cars and even some light bulbs. In 2022 alone, about 32 thousand of new products were authorized.

The documents submitted to the FCC in this regulatory process contain detailed information about the product and its producer. The purpose of this disclosure is for consumers, engineers, and regulatory agencies to be able verify that marketed devices meet established standards. Today, the documents are publicly accessible on FCC's website (this was not always the case, as we elaborate later).[1] The website is a valuable resource for reporting on product introductions (Weatherbed and Lawler, 2024, e.g.), and the user manuals from this database are widely circulated on the internet. They represent a detailed overview of the universe of all wireless-capable products introduced to the U.S. market, which is representative of the frontier of technological wireless development globally. To our knowledge, the dataset is presented here for the first time in an academic study, apart from (Kim et al., 2024) who contemporaneously use it to analyze the effects of open-source drivers on Wifi router supply chains.

4 Dataset construction

We begin by web-scraping the universe of all product applications submitted to the FCC from 1981 to 2021 from FCC's website. We start with a unique *Firm* identification based on a cleaned name and country of the firm that applied for the application. Our unit of analysis is based a unique identifier of products or their components (*Product*).[2] We also

[1] `https://www.fcc.gov/oet/ea/fccid`.

[2] We use Application ID instead of the more known FCC ID. About 20 percent of products contain more than one regulated wireless-capable device under different class or technology. To simplify the data structure, we perform all analysis on the Application ID level.

code application dates, and applicant country.

For each product, we code its *Class* and the vector of frequencies that it operates on. We code *NewFrequency* as a binary variable equal to 1 if the product uses a combination of frequencies not used by any prior product.

As the primary outcome variable of interest, we count the products that used the same combination of frequencies within 5 years after the introduction of the focal product, *ForwardUse*. Frequency combinations approximate the follow-on use of a narrowly defined technology after its introduction in the new product. It is akin to identifying innovative products based on new product characteristics (Argente and Yeh, 2022) or tracking future patent applications in a patent class (Bell et al., 2018; Rigby, 2015; Hall et al., 2001). Compared to FCC product classes, which are broad and of which there are only about a hundred in the dataset, this approach provides us with thousands of narrow technologies in the period of interest. Based on a manual review of the data, products using the same set of frequencies are often closely related: for example, they may be two phones with identical wireless connectivity but different design (see examples below).

We count separately the future frequency use by the same firm as applied for the first product (*ForwardUse, Self*) and by other firms (*ForwardUse, Competition*). There are about five time as many future uses of by competition as by the original firm. Among competition future use, we further split between products by domestic and foreign firms (*Domestic*, *Foreign*), products by incumbents and new entrants (*Incumbent*, *Entrant*), and products in the same class as the original product and in a different class (*InClass*, *OutClass*). Table 3 provides an overview of these variables.

The FCC requires the applicant to submit documentation including external and internal photos, block diagram, schematics, parts list, technical description, list of operation frequencies, and a form listing product classification, applicant details, and product description. The applicant can claim confidentiality on some of the documents if they contain a trade secret or confidential information.[3] As the treatment variable, we code *Transparency* equal to 1 if these documents are available online. We also code *Secrecy* as a binary variable

[3]These include schematics, block diagrams, operational description, parts list, tune-up info; and in rare cases internal photos and user manual. The applicant need to justify the request in a letter and pay a fee that in 1998 amounted to 130 dollars (Federal Communications Commission, 1998b). Applications classified for national security purposes are under stricter regime, and are not analyzed here.

equal to 1 if the applicant claimed confidentiality.[4]

As a control, we also code *Internet* as a binary variable equal to 1 if the product uses frequency that is associated with 3G, 4G or wifi internet connectivity. We code products that were subject to deregulation by mapping the deregulated FCC rules. We exclude these products from the analysis for reasons discussed later. For an overview of the internet frequencies and FCC rules, and other details on data construction, see Appendix A.1 and A.2.

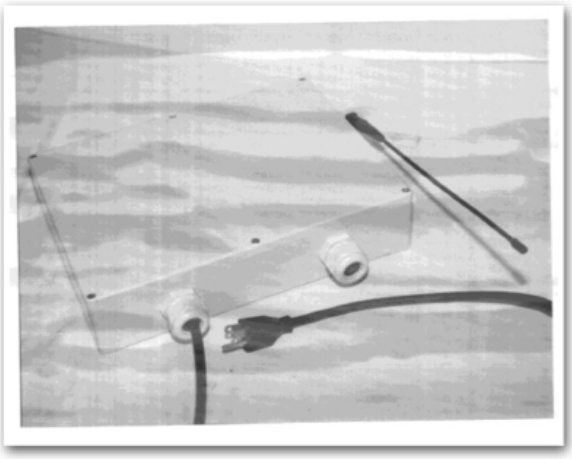
We further match the dataset to USPTO / PatentsView data by firm cleaned name and country. We code *RecentPatent* as a binary variable equal to 1 if the firm applied for at least one patent within three years prior to the FCC application. We only consider U.S. patents even for foreign applicants, because U.S. is the place of marketing of products under FCC regulation.

4.1 Product examples

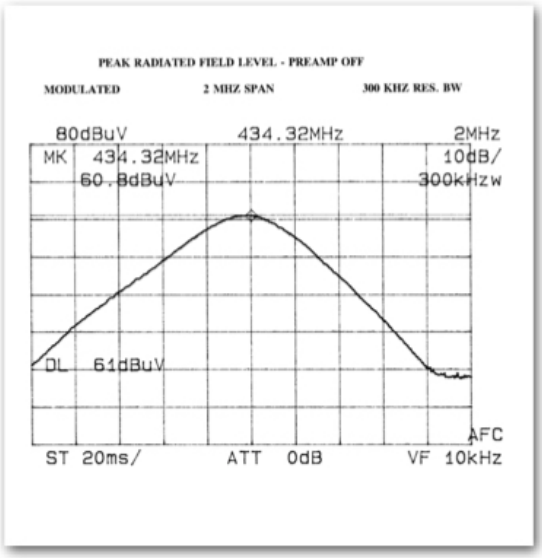
Two product examples illustrate the dataset. The product with FCC ID CBFCRANET1 is a crane control transmitter applied for by Control Chief Corporation, U.S., on October 5, 1998. It operates on one frequency, 433–434 MHZ, a previously unused range. Four other products used this frequency within the next five years, one receiver by the same company, and another three products by different companies for similar use (an 'industrial remote control' transceivers and receivers, for example). Seven exhibits of this application are available online (see Figure 1 for excerpts). The firm did not claim secrecy on the exhibits, nor did it apply for a patent in the three years prior.

The product with FCC ID A3LSCH855 is a flip phone applied for by Samsung Electronics, U.S., on July 18, 2000. It uses three frequencies, two at 824–849 MHZ and one at 825–848 MHZ. The combination of frequencies is not new, as Sony Electronics, Germany, used it a phone year earlier. 32 exhibits from this application are available online (see Figure 2 for excerpts) three additional exhibits are claimed confidential by Samsung Electronics: the block diagram, schematics, and circuit description. The firm did patent in three years prior.

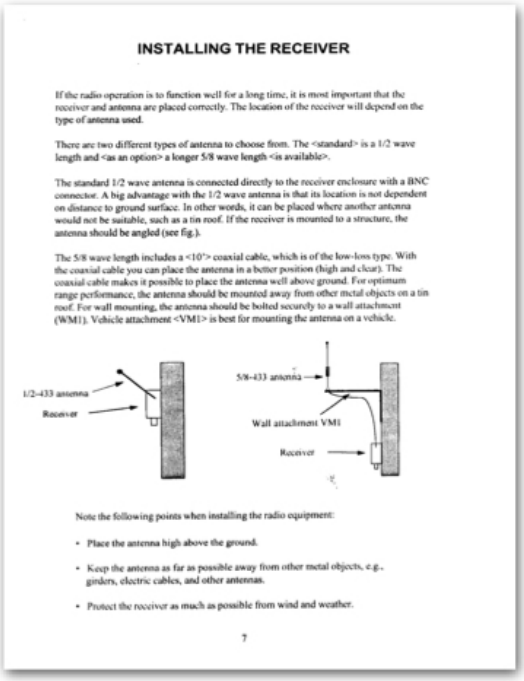
[4]We disregard short confidentiality as it is highly correlated with long confidentiality and its effect is time bound in time.



A



B



INSTALLING THE RECEIVER

If the radio operation is to function well for a long time, it is most important that the receiver and antenna are placed correctly. The location of the receiver will depend on the type of antenna used.

There are two different types of antenna to choose from. The <standard> is a 1/2 wave length and <as an option> a longer 5/8 wave length <is available>.

The standard 1/2 wave antenna is connected directly to the receiver enclosure with a BNC connector. A big advantage with the 1/2 wave antenna is that its location is not dependent on distance to ground surface. In other words, it can be placed where another antenna would not be suitable, such as a tin roof. If the receiver is mounted to a structure, the antenna should be angled (see fig.).

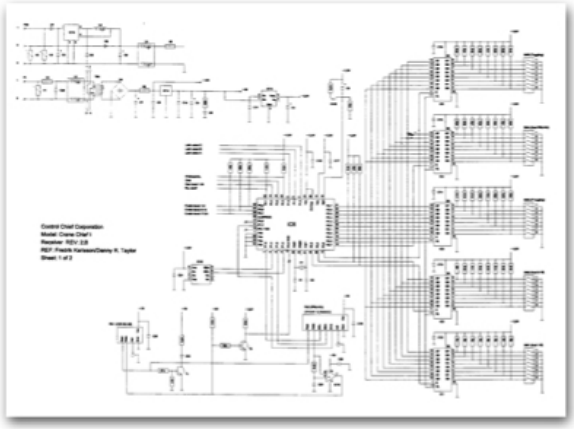
The 5/8 wave length includes a <10'> coaxial cable, which is of the low-loss type. With the coaxial cable you can place the antenna in a better position (high and clear). The coaxial cable makes it possible to place the antenna well above ground. For optimum range performance, the antenna should be mounted away from other metal objects on a tin roof. For wall mounting, the antenna should be bolted securely to a wall attachment (WM1). Vehicle attachment <VM1> is best for mounting the antenna on a vehicle.

Note the following points when installing the radio equipment:

- Place the antenna high above the ground.
- Keep the antenna as far as possible away from other metal objects, e.g., girders, electric cables, and other antennas.
- Protect the receiver as much as possible from wind and weather.

7

C

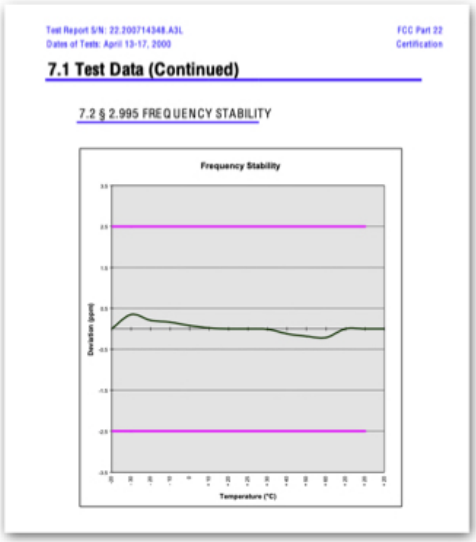


D

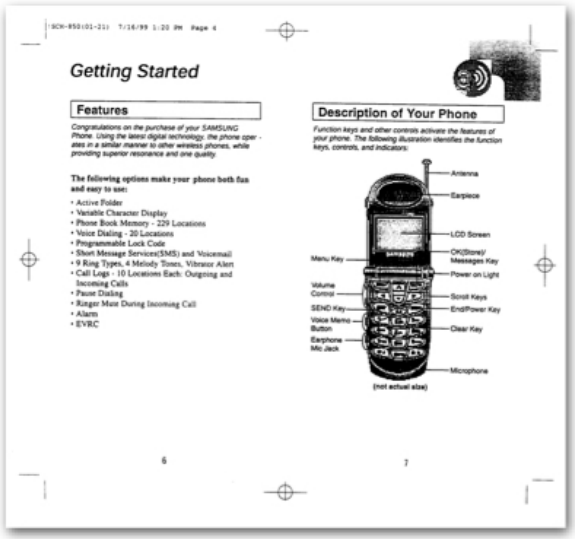
Figure 1: Authorization exhibits example, FCC ID CBFCRANET1.
Excerpts from documentation submitted to the FCC as part of the equipment authorization process, and available online: A) external photos, B) test results, C) user manual excerpt, D) schematics.



A



B



C

Figure 2: Authorization exhibits, FCC ID A3LSCH855.
Excerpts from documentation submitted to the FCC as part of the equipment authorization process, and available online: A) external photos, B) test results, C) user manual excerpt. Schematics were claimed confidential by the applicant.

5 Transparency shock

In 1998, the FCC implemented several changes intended to streamline the authorization process. These changes were presented at a 1997 IEEE conference (Knapp and Wall, 1997), shown for public consultation (Federal Communications Commission, 1997a,b) and enacted in two orders (Federal Communications Commission, 1998a,b). As the main change of interest, FCC digitalized the application process, and launched a public available website that details all products authorized by the FCC—the very website that we web-scraped in the data construction process.

Conveniently for our purposes, the FCC made available all prior product authorizations going back to 1981. In a key difference, products in the database authorized in the digitalized process include all exhibits in a pdf format (except documents claimed confidential by the applicant), whereas only basic technical information is available for products authorized prior to digitization. In short, basic information became available on all products, but significantly more details on products submitted in the new digitalized process. The digitalization was voluntary in the first year of the announcement, but compliance built fast: just eight months after, virtually all applications were submitted digitally.[5]

The policy shock did not change the public access regime of the authorizations or the technical requirements. The information available online since the digitization had been available before through individual requests, as FCC stated in response to concerns about confidentiality raised during the public consultation (Federal Communications Commission, 1998b). The option to claim secrecy on some documents had also been available since before the policy change, but few applicants used it. In 1993, five years prior to the changes, only nine percent of applications claimed secrecy. This increased dramatically around the time of the policy change, and in 2003, 71 percent of applicants claimed secrecy (see Figure 8 in appendix).

It was the availability of data on secrecy and the increase in its use that initially sparked out interest in FCC transparency policies in this time period. We conceptualize the transparency policy change as a lowering of the costs of information about devices regulated by

[5]An alternative explanation of the fast uptake is that FCC staff was scanning remaining paper applications to PDFs, as they indicated in their decision (Federal Communications Commission, 1998a, p. 11,333). In either case, the effect was that from November 1998, exhibits of virtually all applications were available on the website.

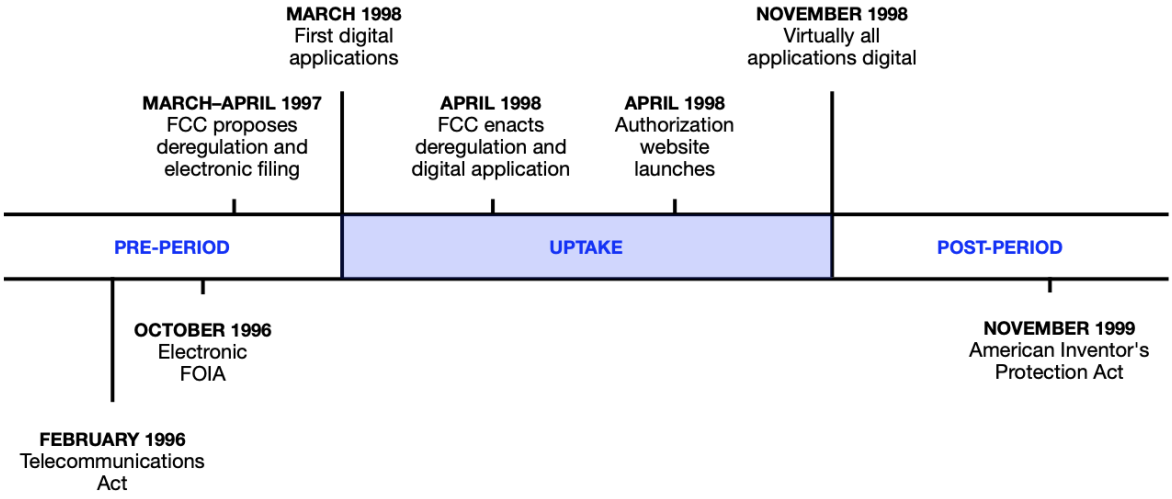


Figure 3: Timeline of relevant events.

the FCC. Detailed information on most recent wireless-capable products became instantly available for anyone with internet connectivity, right from the moment of marketing. The strategic use of secrecy (and potentially patenting and other appropriation mechanisms, Hall et al., 2014), could have moderated the effect of the policy over time. We estimate the causal effect of the transparency shock on follow-on innovation, and provide some evidence on the strategic responses. Figure 3 presents the timeline of events, including several related changes happened during this period that we outline in the next section.

5.1 Empirical context

Several other changes occurred during the relevant time period that contextualize the FCC policy shock, and may conflate the estimates of its effects. The Electronic Freedom of Information Act of 1996 mandated government agencies to publish specific records electronically by the end of 1999 (U.S.C., 1996a). We did not find any effect this would have beyond the transparency changes enacted detailed above.

The Telecomunications Act of 1996 significantly revised the original 1934 law, focusing on enabling market entry in internet telecommunications services markets and increasing interoperability and standardization. It did not directly change the technical requirements

in the product authorization process, but an amendment to section 302 enabled the delegation of equipment testing and certification to private laboratories (U.S.C., 1996b; Emeritz, 1996). This meant that the mandatory testing documentation firms submit in their authorization applications became more often provided by an external testing provider. We believe that the causal identification strategies outlined below are robust to the effects of these changes, as products applied for in the pre- and post-periods and in the treatment and control groups would be affected equally by this change.

The American Inventor's Protection Act (AIPA) of 1999 accelerated disclosure of patent applications. Prior literature found a positive effect on follow-on innovation which may have spilled-over to products that use patented technologies in our dataset (Hegde and Luo, 2018; Kim and Valentine, 2021; Baruffaldi and Simeth, 2020; Hegde et al., 2023). We control for this effect with a binary variable *AIPA* equal to 1 for applications submitted by applicants with prior patents on or after its effective date of November 29, 2000.

A second set of changes FCC implemented in 1998 changed regulatory regime of several product categories, mainly by deregulating some products that do not actively emit electromagnetic signal (Federal Communications Commission, 1997b, 1998b). The deregulated products no longer had to acquire prior authorization from the FCC unless the firm submitted an application voluntarily. This implies that such products would stop appearing in the dataset. To avoid conflation from a selection bias stemming from the co-occurrence of the two events, we mapped regulatory changes to product categories and excluded all deregulated product from the analysis, including those submitted prior to the policy change. See Appendix A.1 for details and validation of the process.

The period of interest also saw the entry of first wireless internet-connected devices. To control for the effects of this development, we map the frequencies of 3G, 4G and Wifi technologies, and code *Internet* as a binary variable equal to 1 if the product had internet capability. Appendix A.2 lists these frequencies and details the process.

6 Empirical strategy

We evaluate the effect of transparency on follow-on innovation of a subset of products that introduced a previously unused frequency combination ($NewFrequency = 1$). We estimate the causal effect of a product application having exhibits published online, *Transparency*,

on the number of product that use the new frequency combination in the next five years (*ForwardUse*).

Simply regressing *NewFrequency* on *ForwardUse* risks introducing bias to the estimates. Selection into the transparency treatment in the uptake period is voluntary and could bias the estimates. For example, more innovative firms might more likely introduce new frequencies and voluntarily use the digitalized submission process; or they could try to avoid disclosure associated with digitalization. A time-dependent confounder could affect the outcome in the pre- or post-period and bias the results. We include the results of this naive specification based on data from the uptake period in Appendix B.1, which show a positive association consistent with the causal inference results.

To overcome these challenges, we use two causal identification strategies: difference in differences and regression discontinuity designs. The difference-in-differences design allows us to estimate the effect of the change over time and on sub-populations. The regression discontinuity design allows us to estimate the effects on alternative outcomes.

6.1 Difference-in-differences

We leverage the fact that the transparency shock provides new information only to firms other than that which introduced the new frequency product (original firm). The original firm already knows the details of the product's technologies, its competitors may not. The transparency shock therefore only affects the competitors (treatment) and not the original firm (control). We specify:

$$\begin{aligned} Log(ForwardUse_{i,c}) = \alpha &+ \beta_1 \cdot Transparency_i \cdot Competition_c + \beta_2 \cdot Transparency_i \\ &+ \beta_3 \cdot Competition_c + \beta_4 \cdot Internet_i \\ &(+\beta_4 AIPA_i + \beta_5 \cdot Competition_c \cdot AIPA_i) \\ &+ \boldsymbol{\gamma_i} \cdot \boldsymbol{Product_i} + \varepsilon_{i,c} \end{aligned}$$

where $ForwardUse_{i,c}$ notes the count of products that used the frequency combination first used by product i five years post its application date. For each product, we calculate $ForwardUse$ separately for the applicant ($c = 0$, control) and all other firms (treatment,

$c = 1$). $Transparency_i$ indicates if the product was registered in the pre-period (before March 1, 1998) or post-period (after October 31, 1998). $Competition_c$ notes the treatment group. $Competition \cdot RecentPatent_i$ controls for the effects of patenting on competitor applications, and $AIPA_i$ controls for the effects of AIPA whenever we include affected observations.

$\boldsymbol{Product_i}$ notes a vector of product random effects which we add to absorb the effects of product-level characteristic and time-determined policy changes. We use random effects instead of fixed effects because we only have two observations per unit, the outcome variable is highly over-dispersed, and fixed effects models have convergence issues. The random effects partially pools information across products and generates stable conservative coefficient estimates (Clark and Linzer, 2015; Bell et al., 2019).

As our outcome variable is an over-dispersed count, we use a negative-binomial model. We cluster standard errors on the frequency level. [6] As we expect the effect to differ in time, we present results from observations two, four and six years post- the uptake period, with four years in the pre-period. We also estimate dynamic treatment effect, where we interact the treatment group with year-fixed effects. Finally, we include a binary-outcome logistic regression and non-zero observations negative binomial regression with fixed effects in Appendix B.4.

The causal identification rests on the assumption of parallel trends: absent the transparency shock, the future use of newly introduced frequency combinations would evolve similarly for the applicant and competitors. We cannot directly test this assumption, but we include linear pre-trends in Appendix 10 (Wing et al., 2018). Figure 4 plots staggered regression, neither of which shows significant pre-trends.

The presence of spill-overs could be one cause of violation of the parallel trends assumption. An increase in competitors' product market entry could affect the original firms product introduction. This could either induce the firm to introduce further products to keep up with the competition (causing a negative bias in our estimate), or drive the firm out of the technology (causing a positive bias). In Appendix B.3, we substitute the outcome variable in the regression discontinuity design, and show that the transparency shock had no statistically significant effect on future product registration by the original firm.

[6] In a rare case, more than one product is introduced on the same date with the same new frequency combinations. We keep both products and cluster standard errors at the new frequency level.

This suggests that the average spill-over effect is limited, although it does not exclude local spill-over effects. To provide further robustness to our results, we further employ a regression discontinuity design that does not rely on distinguishing between firms.

6.2 Discontinuity

We leverage the sharp discontinuity in availability of information for products registered just before and after the uptake period. Whereas products authorized in January 1998 had no exhibits available online, products authorized in November 1998 did so. When other firms developed their products several years later, they had significantly more information on the second product. We compare products just before (control) and after the transparency shock (treatment). We specify:

$$\begin{aligned} Log(ForwardUse_i + 0.1) = \alpha + \beta_1 \cdot Transparency_i \cdot Distance_i \\ + \beta_2 \cdot Transparency_i + \beta_3 Distance_i + \beta_4 Internet_i + \varepsilon_i \end{aligned}$$

where $Log(ForwardUse_i + 0.1)$ notes the logarithm of count of products that used the frequency combination first used by product i five years after its application date. We only consider product of competition companies, and add a constant to treat zero values. $Transparency_i$ notes the treatment period. $Distance_i$ is the running variable, measuring the number of days until or from the treatment. We exclude observations in the uptake period. We include $Internet_i$ as a control but not $AIPA$ as it took effect more than two years after the shift.

We use the sharp regression discontinuity design developed by Calonico et al. (2015), which fits a non-parametric local regression. We rely on robust estimates and report results from polynomials of degree one, two and three. We let the algorithm choose optimal bandwidth from three years of observations prior and post the uptake period.

One concern arising from this design is the absence of observations during the uptake period (so-called donut model). If the data is noisy and exhibits time trends, changes over the period of eight months could show a discontinuity that is a feature of the data rather than a policy effect. To test this, we calculate boot-strapped p-value by running the model

Dependent Variable:	ForwardUse				
Bandwith (years):	Two	Four		Six	
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Transparency × Competition	0.580***	1.054***	0.977***	0.693***	0.767***
	(0.188)	(0.208)	(0.218)	(0.195)	(0.205)
Random effects					
Product	Yes	Yes	Yes	Yes	Yes
	[2.204]	[0.958]	[0.945]	[0.896]	[0.897]
Fixed effects					
Competition	Yes	Yes	Yes	Yes	Yes
Transparency	Yes	Yes	Yes	Yes	Yes
Internet	Yes	Yes	Yes	Yes	Yes
AIPA			Yes		Yes
AIPA × Competition			Yes		Yes
Fit statistics					
Observations	4,466	7,324	7,324	11,322	11,322
R^2 marginal	0.056	0.207	0.208	0.166	0.168
R^2 conditional	0.781	0.430	0.427	0.374	0.375
AIC	5,056.4	8,945.7	8,944.5	13,558.8	13,561.0
BIC	5,101.2	8,994.0	9,006.6	13,610.2	13,627.0
Over-dispersion	1.03	0.143	0.142	0.127	0.127

Table 1: Difference-in-difference regression results.
Results of the main difference-in-difference specifications, estimated on observations four years prior and two, four and six years post the uptake period, uptake period observations omitted. Follow-on products by the same firm in the pre-treatment period constitute the baseline. Random effects standard deviation in squared brackets, standard errors clustered at the product level.
* p <0.1, ** p <0.05, *** p <0.01

on 10,227 placebo dates outside the true pre- and post-periods, including dropping of eight months of observations in the middle. We show that our estimated effect is higher than 97.2 percent of these placebo runs.

7 Results

We find a statistically significant and meaningful increase in follow-on innovation among products exposed to the transparency treatment using both methods. Overall, the increase amounts to 78–166 percent compared to the control group, and fades over over time.

The difference-in-differences design specification, presented in Table 1, show a significant increase in follow-on frequency use among competitors (in comparison to the baseline of the firm that first introduced the frequency combination). Results that rely on observa-

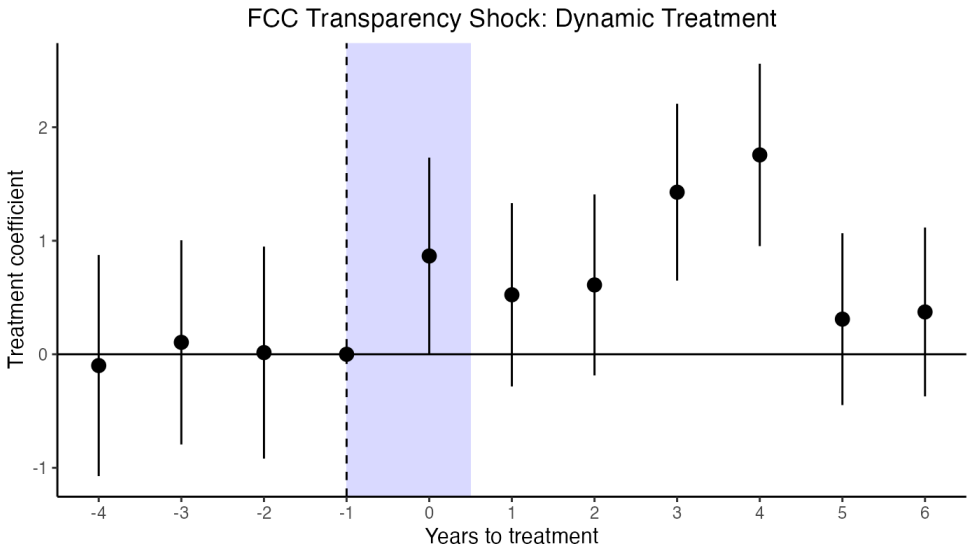


Figure 4: Time-dynamic treatment effect.
Point and 95 percent confidence interval estimates of $TreatmentYear \times Competition$ interaction terms. Standard errors binned at product level. Baseline at year -1, year 0 represents uptake period and is omitted from the main model.

tions from the first two and four years (columns 1 to 3) show a larger effect than six years (4 and 5). Focusing on the four year estimates with all control variables (column 3), the model estimates that transparency treatment increased the number of product that used the same frequency combination by $exp(0.977) = 2.66$, or 166 percent.

The dynamic treatment effect in figure 4 shows that the positive effect is highest in the third and fourth year of the treatment. It peaks in the fourth year with an effect size of 1.76, or an increase of 479 percent. The decrease following that year could be the result of a strategic reaction by firms, as we discuss later.

The discontinuity regression results, presented in Table 2, show a similarly sized increase in follow-on use of a technology introduced just after the policy shift compared to those introduced just before. Considering the robust linear polynomial results (column 1), the transparency treatment increased the number of follow-on products by 83 percent. The results are consistent in magnitude across the degrees of polynomials, although statistical significance decreases with the degree three polynomial. Discontinuity plots in Figure 5 the sudden increase in the follow-on use and a similar pattern across degrees of the polynomial functions.

As a placebo test, we perform an analogical analysis on all 10,227 dates in the pre-

Polynomial degree:	Linear (1)	Quadratic (2)	Cubic (3)
Estimates			
Conventional	0.732***	0.933***	0.845*
	(0.273)	(0.36)	(0.446)
Bias-corrected	0.829***	1.017***	0.776*
	(0.273)	(0.36)	(0.446)
Robust	0.829***	1.017**	0.776
	(0.319)	(0.404)	(0.485)
Effective observations, left	327	382	384
Effective observations, right	524	635	643
Bandwith (days)	357	425	435
Bandwith type	Optimal	Optimal	Optimal
Kernel type	Triangular	Triangular	Triangular

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: Regression discontinuity design results.

period (from January 1, 1984 to December 31, 1994) and post-period (from January 1, 2002 to December 31, 2018). This excludes observations three years prior and post the true treatment to avoid introducing false positive effects. The main result of 0.829 is higher than 97.1 of these placebo runs, which signals that the result is due to noise in the data or omission of the uptake period.

7.1 Extensions

We estimate several variations of our main results for sub-population analysis and alternative outcomes.

Firm survival We test if regulatory transparency had a negative effect on firm survival by substituting the outcome variable in the regression discontinuity design specification in Appendix B.3. The increased use of a frequency by competitors might have put competitive pressure on the firm. Table 7 shows a statistically insignificant negative effect.

Secrecy and patenting The share of authorization applications claiming confidentiality and with recent patent in their inventions increased significantly over our period of interest,

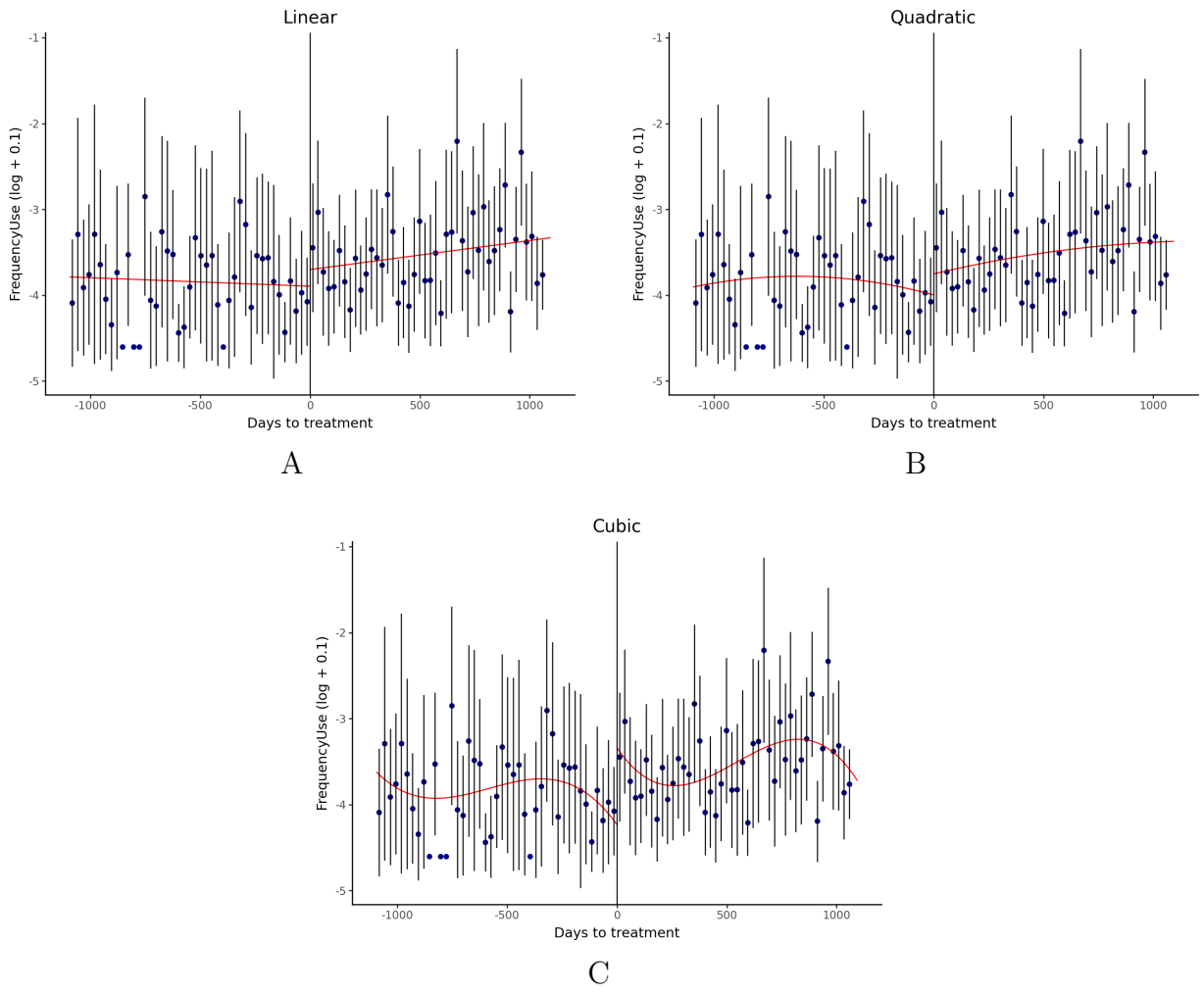


Figure 5: Discontinuity plots.
Regression discontinuity plots before (left) and after (right) the transparency policy shift using linear (A), quadratic (B) and cubic (C) Functions. The points indicate the (log) mean follow-on use of a frequency of products introduced relative to the uptake period (x axis).

as Figure 8 shows. The use of secrecy and patenting started increasing before the transparency shock, but accelerated afterwards. Figure 9b shows this increase coinciding with the transparency shock, and Figure 9a shows a contemporaneous decrease in *ForwardUse*.

The presence of a strong pre-trend makes it difficult to design a strong causal identification model and test if the transparency shock caused the increase. We test if firms exposed to the transparency shock were more likely to claim secrecy in their next application using the regression discontinuity design. Similarly, we tested if they were more likely to have registered a patent. These results will be available in the Appendix.

Novelty The follow-on use of a wireless frequency could be a mere copy or involve an innovative step. To test which is the case, we count separately follow-on products by competitors in the same class as the first product (*InClass*), and in other classes *OutClass*. Results in Appendix B.2 show that the increase was both due to products in the same class as in other classes, in support of the novelty hypothesis.

Foreign or domestic The period we analyze also saw a significant increase in global trade and U.S. market entry by foreign firms. We test if the increase in follow-on innovation is driven by firms from the same or from other country than that of the first product. Results in Appendix B.2 show that the increase was primarily due to foreign competitors, both with respect to the U.S. and overall.

New entry The transparency shock could have differentially affected new entrants or incumbents. Results in Appendix B.2 show that the the increase was comparable in both sub-populations of competitors.

8 Conclusion

Government regulations affect the information environment in which firms innovate. To elucidate this dynamic, we test the causal effects of increased regulatory transparency on follow-on innovation. We focus on a late-1990s transparency shock which decreased the costs of accessing detailed technical information about all wireless-enabled devices marketed in the U.S., a globally representative high-tech industry. Results from difference-in-differences and regression discontinuity designs show that transparency increased follow-on innovation by 78–166 percent. These affects waned in the following years, potentially due to the use of appropriation strategies such as secrecy and patenting.

Our results suggest that even regulations with goals other than supporting innovation can have significant unintended effects through affecting information costs. As governments contemplate policies that affect information availability, such as algorithmic transparency, AI regulations, or restrictions on non-compete agreements our results show that these may have significant secondary effects on innovation—even though that may not be the main intention of regulatory transparency.

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A Data coding

Table 3 shows summary statistics.

A.1 Deregulated products

Correctly coding products deregulated around the same time period as the transparency shock is crucial for avoiding selection bias in the analysis. Products falling under different

	Pre-period					Post-period				
	Mean	SD	P.1	Median	P.9	Mean	SD	P.1	Median	P.9
A) Full sample										
NewFrequency	0.23	0.42				0.27	0.44			
B) NewFrequency = 1										
Internet	0.09	0.29				0.33	0.47			
Secrecy	0.22	0.41				0.73	0.44			
RecentPatent	0.27	0.44				0.42	0.49			
ForwardUse, Self	0.15	0.65	0	0	0	0.15	1.08	0	0	0
ForwardUse, Competition	0.69	6.37	0	0	1	0.76	2.89	0	0	2
– Domestic	0.25	1.20	0	0	1	0.27	1.26	0	0	1
– Foreign	0.44	5.97	0	0	0	0.49	2.10	0	0	1
– Incumbent	0.60	5.93	0	0	1	0.67	2.63	0	0	1
– Entrant	0.09	0.54	0	0	0	0.09	0.44	0	0	0
– InClass	0.52	6.21	0	0	1	0.47	1.94	0	0	1
– OutClass	0.17	1.01	0	0	0	0.29	1.77	0	0	0

Table 3: Summary statistics

Summary statistics for main variables. Subsample of non-deregulated products within six years pre- and post- treatment, uptake period excluded. P.1 and P.9 note 10th and 90th percentiles, respectively. Part A) presents the proportion of products with new frequencies among all products, part B) presents other variables within products with new frequencies, a subsample used throughout the analysis.

regulatory regimes are labeled by the applicable *rule parts*, which are noted on the FCC grant document, information from which is available in our data. We match those rule part codes in the data to changes outlined by the FCC.

Products under rule parts 2, 5, 15B, 17, 18, 21, 73, 74, 74E, 78, 87, 78 were deregulated from certification or notification procedure to declaration of conformity or verification, as Federal Communications Commission (1995, 1997b, 1998b) detail. We therefore exclude all products with only these rule parts, including from applications prior to the policy change. Other changes, namely from notification to verification, and fee changes, are minor and mostly administrative in nature, and do not affect data availability. We therefore keep these observations in the dataset.

We verify the accuracy of this approach in two ways. First, the proportion of deregulated products should decrease significantly after 1998, as applicants need to submit these products only voluntarily. Indeed products in deregulated categories decreased from 79 percent in 1995 to 30 percent in 2000, and further of products were in the deregulated categories. Second, a decrease in applications during the time should be explained to these product categories. As Figure 6 shows, this is indeed the case: we see a drop in non-deregulated applications applications, but no drop among those that were not deregulated.

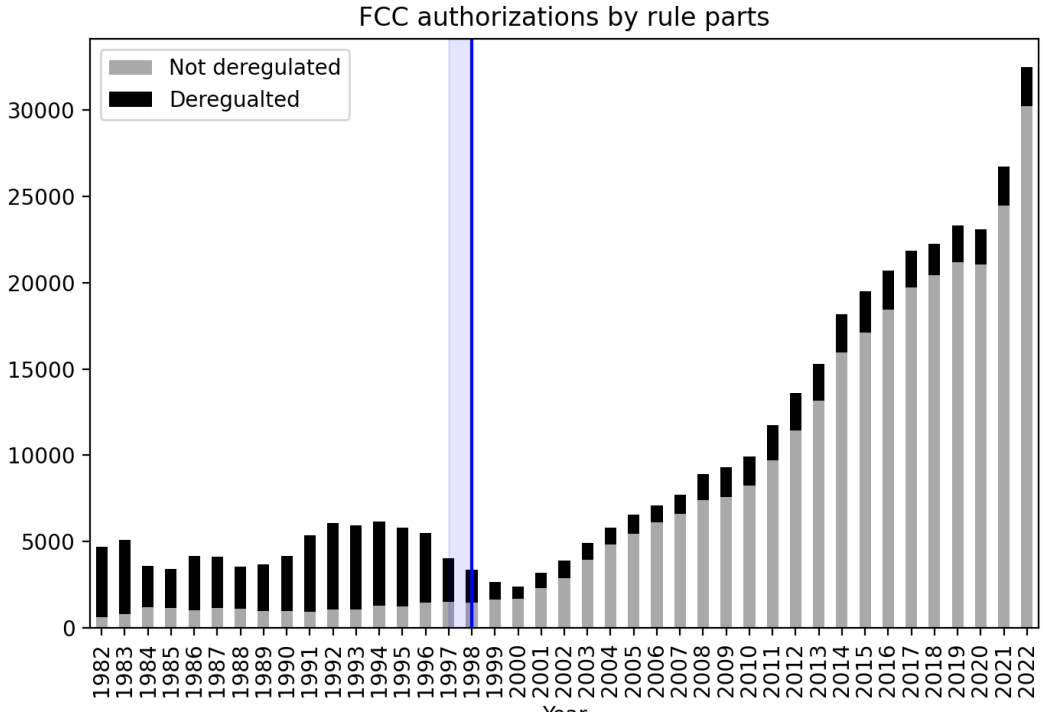


Figure 6: Summary statistics.
[Observations, Q' s meaning etc.]

A.2 Internet-capable products

We code products connected to the internet based on U.S. 3G, 4G, 5G and wifi bands, which we match to applications based on frequencies, output, and year of introduction. Based on Wikipedia overviews and the website `https://www.rfwel.com`, Table 4 summarizes the frequency thresholds we used in this coding. As 5G bands were established after the years of interest, we paid less attention to their encoding, and did not encode 5G wifi for the same reason.

A product that has at least one frequency within the range, output of more than 0.1 MHZ, and year of introduction on or later than the introduction of the wireless band, is counted as having the relevant connectivity. Figure 7 shows the count of non-deregulated products that were coded as internet-connected.

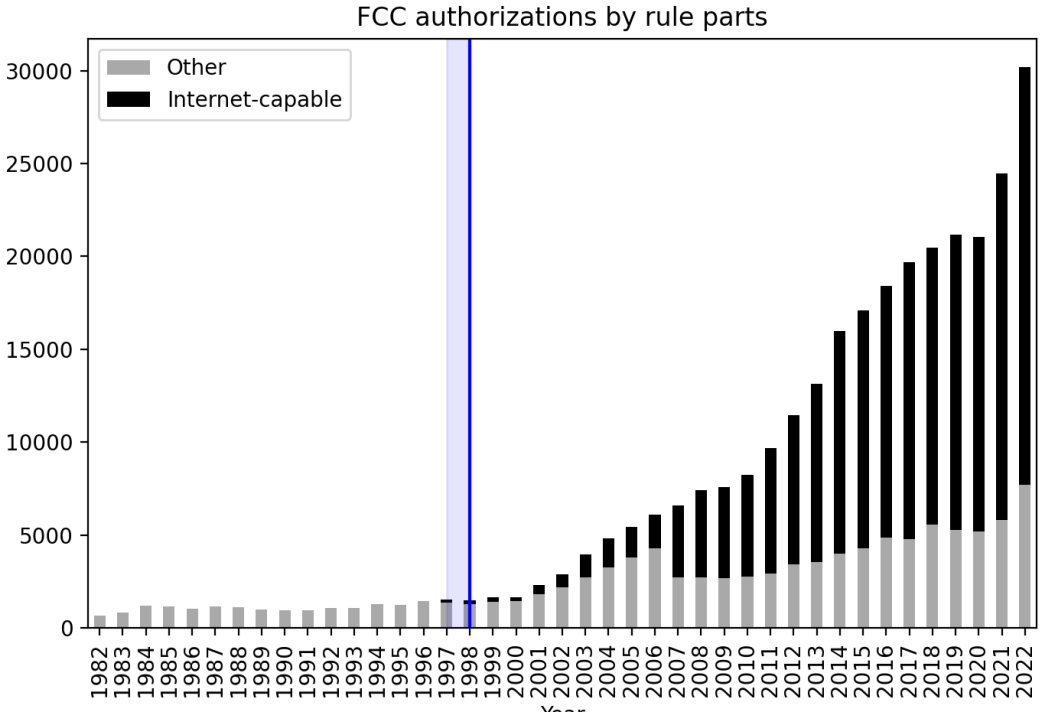


Figure 7: FCC authorization applications by internet connectivity.
Our treatment period also saw an increase in internet-connected devices. A binary variable plotted here controls for the effect this could have on our outcomes of interest. Deregulated products excluded. Blue shading indicates period from announcement to effective date of the FCC policy shock.

A.3 Products with secrecy

B Extensions

B.1 Naive specification

In a naive model, we specify:

$$Log(ForwardUse_i) = \alpha + \beta_1 \cdot Transparency_i + (\beta_2 \cdot Internet_i) + \varepsilon_i$$

where notation is analogical to that in the main specifications. We only estimate this model on products applied for in the uptake period, to complement the results from other specifications which exclude them.

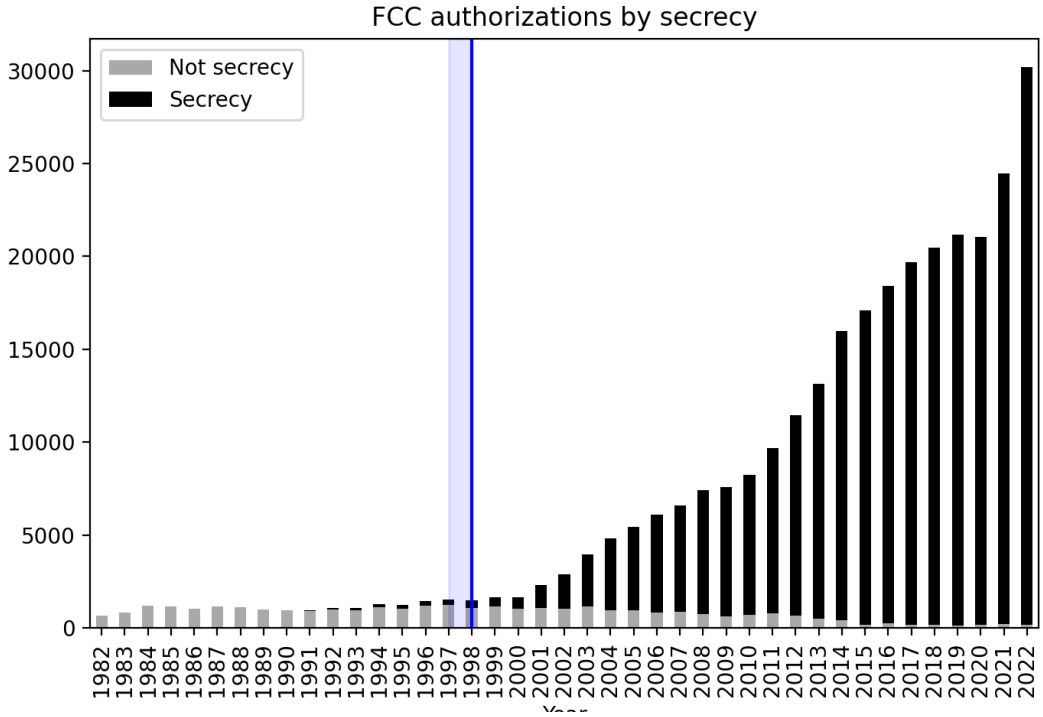


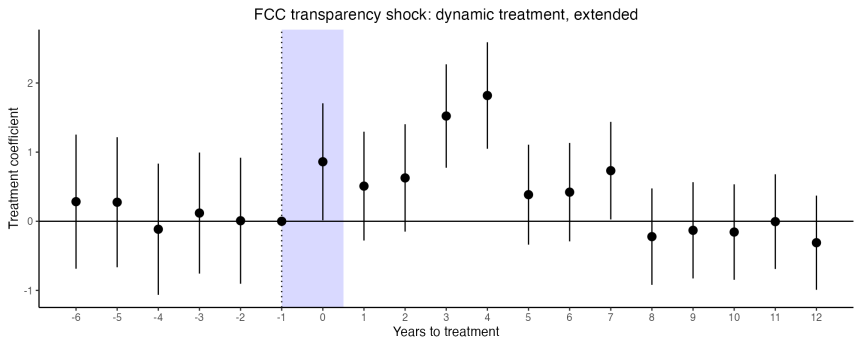
Figure 8: FCC authorization applications by secrecy.
The share of products claiming secrecy on some documentation increased significantly over the period of interest. Deregulated products excluded. Blue shading indicates period from announcement to effective date of the FCC policy shock.

We also include estimation of the main model on the subset of products introduced in the uptake period, excluded from the main model because of self-selection into treatment.

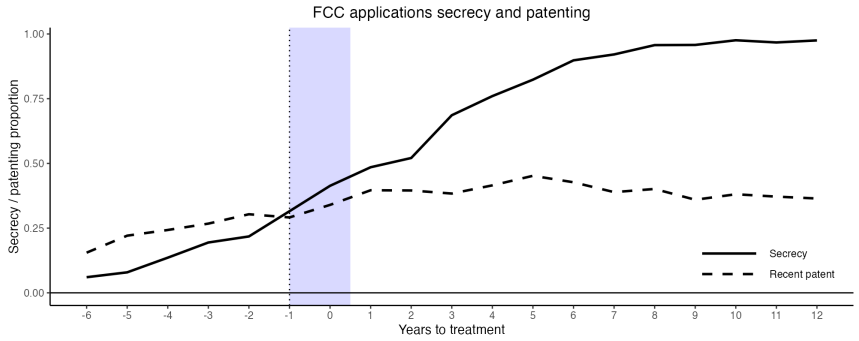
Results of both specifications, presented in Table 5 (1) and (2), respectively, are consistent with the main results, although they do not represent a causal effect estimate.

B.2 Sub-populations

We test if the increase in follow-on innovation is driven by: 1) applications in the same product class (low novelty) or in a different product class (high novelty), 2) applications by new entrants or incumbents, 3) applications from the same or a different country, 4) applications from the U.S. or elsewhere on the subset of U.S. applications. To do so, we count the outcome variable, *ForwardUse*, separately for the same firm (baseline), and competitors split by the sub-populations defined above. The results, presented in Table 6, show that the increase in follow-on innovation is 1) attributable to out-class (more novel)



(a) The dynamic effects of FCC transparency shock, extended plot.



(b) Contemporaneous increase in secrecy and patenting.

Figure 9: Comparison of dynamic treatment and increase in secrecy and patenting.

products as much as in-class products, 2) incumbents as much as new entrants, 3 & 4) foreign competitors more than domestic competitors.

B.3 Survival

We test the survival of the original applicant by substituting the outcome variable in the regression discontinuity design. We specify:

$$Survival_i = \alpha + \beta_1 \cdot Transparency_i \cdot Distance_i + \beta_2 \cdot Transparency_i + \beta_3 Distance_i + \beta_4 Internet_i + \varepsilon_i$$

where *Survival* is a binary variable equal to 1 if the firm applied for the authorization of at least one product five years after the product, or later. Remaining characteristics are the same as in the main specification. The results, shown in Table 7, show no statistically

significant effect.

B.4 Robustness

As robustness checks to our main difference-in-differences specification, we first estimate two complementary specifications: 1) a logistic regression where the outcome is binary rather than a count, indicating if a at least one further product used the frequency combination, with product random effects, 2) a negative-binomial regression estimated only on products with at least one follow-on innovation, with product fixed effects instead of random effects. The product fixed absorb all the product-level constant variables included in the main model.

Next, we include linear time pre-trends for the treatment group and linear time trend in the main specification.

All results are consistent with the main findings. Treated products have both higher probability of at least one follow-up product in the same frequency (table 8), and among those that have at least one follow-up, the count is higher (table 9). The linear time pre-trend is insignificant and does not significantly change the main coefficient of interest (table 10).

Technology	Band	Uplink (MHz)	Downlink (MHz)	Year
Wifi	2.4 GhZ	2412, 2462		1997
3G	PCS	1850, 1910	1930, 1990	1997
	UMTS	824, 849	869, 894	1997
4G	2	1850 , 1910	1930 , 1990	2007
	4	1710 , 1755	2110 , 2155	2007
	5	824 , 849	869 , 894	2007
	10	1710 , 1770	2110 , 2170	2007
	12	699 , 716	729 , 746	2007
	13	777 , 787	746 , 756	2007
	14	788 , 798	758 , 768	2007
	17	704 , 716	734 , 746	2007
	23	2000 , 2020	2180 , 2200	2007
	24	1626.5 , 1660.5	1525 , 1559	2007
	25	1850 , 1915	1930 , 1995	2007
	26	814 , 849	859 , 894	2007
	27	807 , 824	852 , 869	2007
	30	2305 , 23151	2350 , 2360	2007
	66	1710 , 1780	2110 , 2200	2007
	70	1695 , 1710	1995 , 2020	2007
	71	663 , 698	617 , 652	2007
	74	1427 , 1470	1475 , 1518	2007
	85	698 , 716	728 , 746	2007
4G TDD	35	1850 , 1910		2007
	36	1930 , 1990		2007
	37	1910 , 1930		2007
5G	n2	1850 , 1910	1930 , 1990	2017
	n5	824 , 849	869 , 894	2017
	n12	699 , 716	729 , 746	2017
	n25	1850 , 1915	1930 , 1995	2017
	n66	1710 , 1780	2110 , 2200	2017
	n70	1695 , 1710	1995 , 2020	2017
	n71	663 , 698	617 , 652	2017
	n74	1427 , 1470	1475 , 1518	2017
5G TDD	n41	2496 , 2690		2017
	n48	3550 , 3700		2017
	n77	3300 , 42002		2017
5G mm	n260	37000 , 40000		2017
	n261	27500 , 28350		2017

Table 4: Overview of U.S. internet bands.

Dependent Variable:	ForwardUse	
Model:	(1)	(2)
Variables		
Transparency	1.752***	
	(0.47)	
Competition × Transparency		1.583***
		(0.603)
Fixed effects		
Competition		Yes
Transparency		Yes
Internet	Yes	Yes
Random effects		
Product		Yes
		[2.224]
Observations	312	624
Squared correlation	0.01	
Pseudo R^2	0.015	
R^2 marginal		0.123
R^2 conditional		0.856
AIC	696.17	1632.5
BIC	701.9	1659.0
Over-dispersion	0.132	3.32

Clustered (Product) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Naive regression specifications.

Using observations from the uptake period, we estimate the coefficient on *Transparency* ($Competition = 1$) and $Competition \times Transparency$ (with product random effects). Not controlling for self-selection, the results show an association between transparency and future use of technology even during a period applicants could self-select to treatment. Random effects standard deviation in squared brackets.

Dependent Variable:	ForwardUse			
Model:	(1)	(2)	(3)	(4)
Variables				
Transparency × InClass	0.716***			
	(0.159)			
Transparency × OutClass	0.552***			
	(0.180)			
Transparency × NewEntrant		0.668***		
		(0.134)		
Transparency × Incumbent		0.744***		
		(0.208)		
Transparency × Domestic			0.325**	0.060
			(0.158)	(0.190)
Transparency × Foreign			1.013***	0.968***
			(0.158)	(0.222)
Random effects				
Product	Yes	Yes	Yes	Yes
	[2.59]	[2.652]	[2.67]	[3.07]
Fixed effects				
Internet	Yes	Yes	Yes	Yes
InClass + OutClass	Yes			
RecentPatent × (InClass + OutClass)	Yes			
RecentPatent × AIPA × (InClass + OutClass)	Yes			
NewEntrant + Incumbent		Yes		
RecentPatent × (NewEntrant + Incumbent)		Yes		
RecentPatent × AIPA × (NewEntrant + Incumbent)		Yes		
Domestic + Foreign			Yes	Yes
RecentPatent × (Domestic + Foreign)			Yes	Yes
RecentPatent × AIPA × (Domestic + Foreign)			Yes	Yes
Fit statistics				
Observations	10,986	10,986	10,986	7,356
R^2 marginal	0.035	0.087	0.031	0.015
R^2 conditional	0.837	0.875	0.856	0.902
AIC	10,603.6	10,102.1	10,675.2	6,029.4
BIC	10,683.9	10,182.4	10,762.8	6,105.4
Over-dispersion	0.542	1.03	0.718	0.88

Table 6: Difference-in-differences, sub-populations.

Results of the sub-population difference-in-differences specification of (1) in-class and out-class, (2) new entrants and incumbent, (3) domestic and foreign, (4) domestic and foreign relative to U.S. products. Estimation on observations four years prior and two, four and six years post the uptake period (uptake period observations omitted). Follow-on products by the same firm in the pre-treatment period constitute the baseline.

Polynomial degree:	Linear (1)	Quadratic (2)	Cubic (3)
Estimates			
Conventional	-0.079	-0.097	-0.106
	(0.072)	(0.093)	(0.115)
Bias-corrected	-0.088	-0.105	-0.111
	(0.072)	(0.093)	(0.115)
Robust	-0.088	-0.105	-0.111
	(0.087)	(0.107)	(0.127)
Effective observations, left	298	376	413
Effective observations, right	468	620	713
Bandwith (days)	479	416	481
Bandwith type	Optimal	Optimal	Optimal
Kernel type	Triangular	Triangular	Triangular

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Regression discontinuity design, survival of firms.

Dependent Variable:	ForwardUse > 0		
Bandwith (years):	Two	Four	Six
Model:	(1)	(2)	(3)
Variables			
Transparency × Competition	0.572***	0.820***	0.597***
	(0.204)	(0.178)	(0.162)
Fixed effects			
Internet	Yes	Yes	Yes
Competition	Yes	Yes	Yes
AIPA		Yes	Yes
AIPA × Competition		Yes	Yes
Random effects			
Product	Yes	Yes	Yes
	[1.415]	[1.302]	[1.22]
Fit statistics			
Observations	6,332	9,190	13,188
R^2 marginal	0.039	0.062	0.045
R^2 conditional	0.402	0.381	0.342
AIC	3,313.2	5,476.7	8,415.7
BIC	3,351.6	5,531.9	8,474.3

Table 8: Logistic difference-in-differences regression results.

Results of the logistic difference-in-difference specifications, fit on observations in two, four and six years prior and post the uptake period (uptake period observations omitted). Follow-on products by the same firm in the pre-treatment period constitute the baseline. Random effects standard deviation in squared brackets.

* p <0.1, ** p <0.05, *** p <0.01

Dependent Variable:	ForwardUse		
Bandwith (years):	Two	Four	Six
Model:	(1)	(2)	(3)
Variables			
Transparency × Competition	0.532**	0.849***	0.732***
	(0.269)	(0.247)	(0.212)
Fixed effects			
Competition	Yes	Yes	Yes
Product	Yes	Yes	Yes
AIPA		Yes	Yes
AIPA *times* Competition		Yes	Yes
Fit statistics			
Observations	776	1,740	2,636
Squared Correlation	0.74526	0.87614	0.58172
Pseudo R^2	0.23806	0.27718	0.23781
BIC	4,525.9	11,079.5	17,516.6
Over-dispersion	10.310	13.211	4.1515

Clustered (Frequency) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9: Difference-in-difference regression results, non-zero follow-up products.
Results of the difference-in-difference specifications, estimated on observations four years prior and two, four and six years post the uptake period (uptake period observations omitted). Estimated only on products with at least one follow-on innovation. Follow-on products by the same firm in the pre-treatment period constitute the baseline. Random effects standard deviation in squared brackets.
* p <0.1, ** p <0.05, *** p <0.01

Dependent Variable:	ForwardUse		
Bandwith (years):	Two	Four	Six
Model:	(1)	(2)	(3)
Variables			
Transparency × Competition	1.012***	1.394***	1.051***
	(0.333)	(0.308)	(0.294)
Competition	0.494*	0.539*	0.683**
	(0.292)	(0.285)	(0.277)
Transparency	-0.304	-0.365	0.105
	(0.369)	(0.294)	(0.237)
Competition × Pre-trend	-0.001*	-0.001*	-0.000
	(0.000)	(0.000)	(0.000)
Trend	0.000	0.000	-0.000*
	(0.000)	(0.000)	(0.000)
Random effects			
Product	Yes	Yes	Yes
	[1.1]	[0.93]	[0.886]
Fixed effects			
Competition	Yes	Yes	Yes
Transparency	Yes	Yes	Yes
Internet	Yes	Yes	Yes
AIPA		Yes	Yes
AIPA × Competition		Yes	Yes
Fit statistics			
Observations	4,466	7,324	11,322
R^2 marginal	0.121	0.210	0.170
R^2 conditional	0.444	0.423	0.373
AIC	5092.8	8944.1	13556.6
BIC	5150.4	9020.0	13637.3
Over-dispersion	0.215	0.141	0.127

Table 10: Difference-in-difference regression results, linear time trends.

Results of the linear time trends difference-in-difference specifications, fit on observations in four years prior and two, four and six years post the uptake period, uptake period observations omitted. Follow-on products by the same firm in the pre-treatment period constitute the baseline. Random effects standard deviation in squared brackets, standard errors clustered at the product level.

* p <0.1, ** p <0.05, *** p <0.01