Title: Government transparency affects innovation

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Abstract: The information environment deeply affects the innovative behavior of firms, but little empirical evidence exists on the effects of government-provided information on innovation. As the U.S. government ceases many data gathering and publishing activities, we evaluate the launch of a database detailing technical information about all wireless-enabled products on the U.S. market (N = 347 thousand). We find robust evidence that the launch approximately doubled the use of new technologies in the following ten years. The increase affected both products in the same and new categories, suggesting novelty; waned over several years, potentially due to an increase in secrecy and patenting; boosted foreign more than domestic competition; and increased market entry and exit. These results highlight the importance of government-provided information for the private sector.

Main Text:

Governments have long shaped the information environment in which firms innovate. Medieval Venice restricted the movement of glass workers to maintain a technological lead, the 18th-century British parliament paid inventors to exhibit machines for others to study, and in most countries today, the patent system offers exclusivity on the use of inventions in exchange for their publication (*1*–*3*). Innovation disclosure matters, as firms consistently report secrecy and lead time as more effective than patents in protecting their inventions (4). However, undisclosed innovation is difficult to observe and empirical analyses of the effects of transparency regulations outside of the patent system are sparse (*3*, *5*, *6*).

In the past months, the U.S. government ceased many data gathering and publishing activities (*7*). Such discontinuations will likely limit government accountability and public oversight (*8*–*10*), but their effect on the private sector is unclear. Here, we set to analyze the effects of government transparency on private sector innovation. By drawing on a unique dataset of high-tech products, we analyze if the launch of a government online database affected the introduction of new products, the use of secrecy and patenting, and market entry and exit.

Our setting originates with the U.S. Federal Communication Commission (FCC), which requires all wireless-enabled devices to comply with strict technical rules and document compliance in a submission to the FCC (*11*). Tens of thousands of high-tech products are submitted each year, including remote controllers, computers, phones, microwaves, hearing aids, and alarm systems. The documentation includes publicly accessible details of both patented and (the majority of) not-patented products. In 1998, the FCC digitalized the application process and launched a website that made the documentation significantly easier to access (*12*). We investigate how this government transparency shock affected innovation. (Supplementary materials detail dataset construction, empirical approach, and extended results.)

Database launch

We first examine if the transparency shock increased the use of innovative technologies, which we observe in products containing a new combination of wireless frequencies. Our focus is on the use of these technologies by competing firms in comparison to the firm that submitted the original product, as the original firm does not gain new information from the product documentation. Our main result estimates the transparency shock increasing the use of technologies by about 113 percent ($p < 0.01$) for products introduced in the following ten years (table S3), or about twice compared to what it would have been absent the transparency shock. Fig. 1A shows the increase peak in the fourth year with an average increase in use of 416 percent among domestic competitors, or about five times. This represents a large positive but time-constrained effect on the use of the new technologies.

The transparency shock was part of a broader openness trend, including the global liberalization of international trade. To investigate if the effect of transparency was contingent on trade liberalization, we next analyze if the shock was driven by foreign firms (table S5). As fig. 1A shows, both foreign and domestic firms increased their use of new technologies, but the former about twice as much as the latter (p 0.02) and similarly with respect to new technologies introduced by U.S. firms (p 0.04). We next inverse the selection to new technologies introduced in products by non-U.S. firms. The results estimate U.S. firms increasing their product introduction similarly to non-U.S. foreign firms (p 0.3), even if about half compared non-U.S. domestic firms (p 0.1). Overall, the evidence shows foreign firms gaining from the transparency shock somewhat more than domestic firms.

We further analyze what kinds of products and firms gained the most from the increased transparency (table S5). We first investigate if the increased use of new technologies was due to duplicates or novel products. The results estimate the increase being as much due to products in the same category as in new categories as the original product (p 0.87), implying that the new technologies spilled over to novel uses. We further investigate if the increase helped new entrants and new category entrants more than incumbents. The results estimate the increase affecting all three subpopulations similarly (p 0.42–0.88).

The response of firms

These changes to the use of new technologies are likely to affect the firm that introduced the original product. We next examine the time dynamics and the strategic response of firms to the transparency shock. Fig. 1B shows that the relevant period also saw an increase in the use of innovation appropriation mechanisms: patenting (from 18 to 38 percent six years prior and after the shock, respectively) and confidentiality claims in FCC applications (from 1.5 to 76 percent over the same time). Our results (table S6) estimate the transparency exposure sharply increasing the probability that a firm would patent before introducing its next product and claim confidentiality in its next submission by 11 percent (p 0.08) and 12 percent (p 0.05), respectively. This suggests that firms mitigated the increased transparency by reinforcing intellectual property protections, even as the patenting increase is part of a larger trend (*13*).

Further, we investigate the effects on the innovative behavior of the original firm, as the transparency-induced competition may have driven it out of the market or, inversely, encouraged it to compete with new products (*14*, *15*). The results (table S4B) estimate no negative effect on the original firm's introduction of new products with the new technology (one-tail p 0.86). However, further results (table S7) estimate the exposure to transparency decreasing firm survival by 8–11 percent in the next one to five years (p 0.07 and 0.04, respectively). This suggests the shock increased competitive pressure on the original firm, but overall, the consumer benefited from a wider product selection.

Transparency matters

Taken together, our results show an increased business dynamism in terms of both market entry and exit and an increased use of new technologies due to government transparency. The estimated negative effect on the survival of the original firm exposes a familiar tension in innovation policy: eased access to a new technology benefits competitors and consumers but may hinder the original firm's ability to offset the costs of developing the technology in the first place (*3*). Long-term, this may discourage innovation. These considerations restrain us from evaluating the overall effects of increased transparency on innovation as unequivocal positive—such evaluation requires modeling the strategic responses of firms as part of a dynamic equilibrium of the changed information environment.

The main message from our analysis is that government transparency can significantly affect business dynamism in ways that may not always be at the forefront of public discourse. As of the writing of this article, the FCC product database has not been affected by the discontinuations, but many other government websites were terminated (*7*). Our findings highlight the information frictions present in innovation markets, and the potential of government interventions to shape the information environment in which firms innovate.

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Supplementary Materials

Materials

Methods

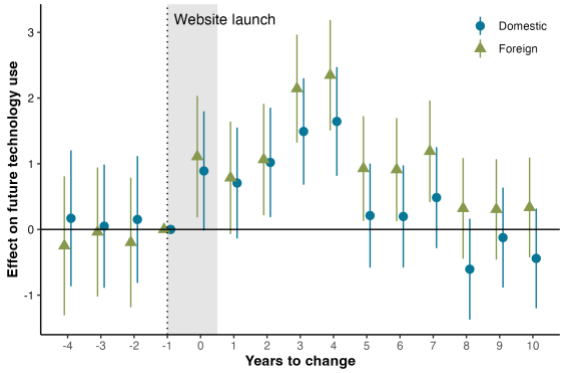
Supplementary Text

Figs. S1 to S4

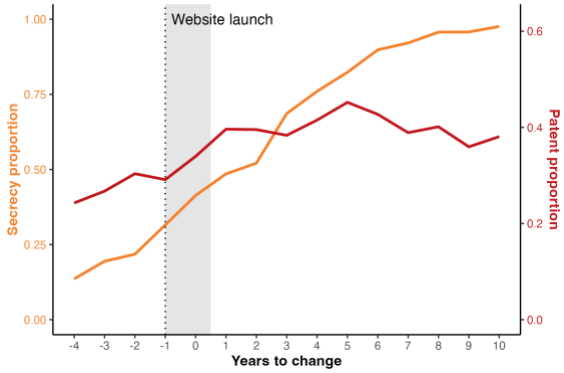
Tables S1 to S11

References (*13–45*)

Fig 1: The effect of government transparency on innovation



(A) The 1998 launch of the government website caused an increase in the use of new technologies, defined as new wireless frequency combinations in FCC product submissions. The increase was higher among foreign (green) than domestic (blue) competitors. (Difference-in-differences regression estimates, future use by the original firm as control, uptake period in gray.)



(B) The launch also contributed to a broader increase in secrecy (left, based on confidentiality claims in FCC product submissions) and patenting (right, based on firm-level linkage to USPTO patent data). (Uptake period in gray, discontinuity analysis in supplementary materials.)

Supplementary Materials for

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The PDF file includes:

Materials
Methods
Supplementary Text
Figs. S1 to S4
Tables S1 to S11
References (*16–44*)

Materials

Approach

The proliferation of secrecy obscures empirical research on innovation, as undisclosed innovation is difficult to observe. Most empirical work relies on innovation observable in patents, in which firms voluntarily disclose their inventions in exchange for legal protection (16–24). These findings show consistent evidence of a positive effect of patent disclosure on follow-on innovation. However, they are limited to the minority of inventions that are (eventually) patented, which skew towards large firms in some industries and are subject to the strategic choice of patent applicants.

A fruitful approach to overcoming the limitations of patent data relies on firms having to disclose their products when entering a market (25, 26). These studies confirm that most inventions were not patented, but do 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 effects on follow-on innovation, relying mostly on patent and academic publications data (5, 6, 27–29).

Our approach builds on 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 of intellectual property protections, and in a large high-tech industry.

Dataset origin

Well-established regulations govern the safety and reliability of the thousands of devices in our everyday life that emit electromagnetic signal. In the U.S., the Federal Communication Commission has been responsible for this regulation since the 1934 adoption of Section 302 of the Communications Act, following an increase in incidents of interference betwen unrelated devices such as cash machines and TV receivers (11).

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 the late

1990s, the period of focus of this paper, these products included hearing aids, domestic and industrial remote controllers, pagers, mobile phones, microwaves, and 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 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 to verify that marketed devices meet established standards. Today, the documents are publicly accessible on the 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, 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 technology globally. To our knowledge, the dataset is presented here for the first time in an academic study, apart from (27) who contemporaneously use it to analyze the effects of open-source drivers on Wifi router supply chains.

Dataset construction

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

[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.

It is akin to identifying innovative products based on new product characteristics (30) or tracking future patent applications in a patent class (31–33). 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 designs (see examples below).

We count separately the forward frequency used by the same firm as applied for the first product (*ForwardUse, Self*) and by other firms (*ForwardUse, Competition*). There are about five times fewer forward uses by the original firm than by competitors. For subsample analysis, we further split the sample of competition forward use between products in the same or different class as the original product (*InClass*, *OutClass*), products by incumbents, entrants in class, and new entrants (*Incumbent*, *NewClassEntrant*, *Entrant*), and products by domestic and (U.S. and non-U.S.) foreign firms (*Domestic*, *Foreign*, *ForeignUS*, *ForeignOther*).

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 code *Secrecy* (*SecrecyNext*) as a binary variable equal to 1 if the applicant claimed confidentiality (on their next product).[4]

We match the dataset to USPTO / PatentsView data by firm clean name and country. We code *RecentPatent* (*SecrecyPatent*) as a binary variable equal to 1 if the firm applied for at least one patent within three years prior to the (next) product application. We only consider U.S. patents even for foreign applicants, because the USPTO has jusrisdiction over products products under the FCC regulation. We code $Survival_{y,i}$, a binary variable indicating if the firm introduced a product y years after product i or later.

[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 (12). Applications classified for national security purposes are under stricter regime, and are not analyzed here.

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

We code *Internet* as a binary variable equal to 1 if the product uses a frequency that is associated with 3G, 4G, or Wifi internet connectivity. We also code products that were subject to deregulation by mapping the deregulated FCC rules. We exclude all deregulated products from the analysis for reasons discussed later. The rest of this section details the coding of deregulated and internet-connected products, Table S1 provides summary statistics.

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 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 (12, 34, 35). 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 or administrative, 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. Second, a decrease in applications during the time should be explained to these product categories. This is indeed the case: we see a drop in non-deregulated applications applications, but no drop among those that were not deregulated.

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 S2 summarizes the frequency thresholds we used in this coding. As 5G bands were established after the period 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.

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 S1 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 in a phone a year earlier. 32 exhibits from this application are available online (see Figure S2 for excerpts) three additional exhibits are claimed confidential by Samsung Electronics: the block diagram, schematics, and circuit description. The firm did patent during the three prior years.

Policy shock

In 1998, the FCC implemented several changes intended to streamline the authorization process. These changes were presented at a 1997 IEEE conference (11), shown for public consultation (35, 36) and enacted in two orders (12, 37). As the main change of interest, the FCC digitalized the application process and launched a publicly 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 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 sum, basic information became available on all products, but significantly more details became available on products submitted in the new digitalized process. The digitalization was voluntary in the first year since the announcement, but compliance built fast: one month later, in April 1998, over 90 percent of applications were digitalized, and in November, virtually all were.[5]

The policy shock did not change the public access regime of the authorizations or the technical requirements. The information available online since digitization had been available before through individual requests, as the FCC stated in response to concerns about confidentiality raised during the public consultation (12). The option to claim secrecy on some documents had also been available since before the policy change, but few applicants used it. In 1992, six years prior to the changes, only 1.5 percent of applications claimed secrecy. This increased dramatically around the time of the policy change, and in 2004, 76 percent of applicants claimed secrecy.

It was the availability of data on secrecy and the increase in its use that initially sparked our 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 the FCC. Detailed information on the 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, 4), could have moderated the effect of the policy over time. We estimate the causal effect of the transparency shock on follow-on innovation and strategic responses of firms. Figure S3 presents the timeline of events, including several related changes that occurred during this period that we outline in the next section.

Empirical context

Several other changes occurred during the relevant time period which 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 (38). We did not find any effect this would have beyond the

[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 (37, p. 11,333). In either case, the effect on information availability was the same.

transparency changes enacted detailed above.

The Telecommunications 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 (39, 40). 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 the 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 (21–24). 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 the FCC implemented in 1998 changed the regulatory regime of several product categories, mainly by deregulating some products that do not actively emit electromagnetic signal (12, 35). 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 products from the analysis, including those submitted prior to the policy change.

The period of interest also saw the entry of the 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.

Methods

Empirical strategy

We evaluate the effect of transparency on follow-on innovation on 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 products 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. To overcome these challenges, we primarily rely on the difference in differences design, which we supplement with regression discontinuity design to estimate the effects on alternative outcomes.

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:

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

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. $AIPA_i \cdot Competition$ and $AIPA_i$ control for the effects of AIPA whenever we include observations in its implementation period.

$\bar{Product}_i$ notes a vector of product random effects which we add to absorb the effects of product-level characteristics 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 pool information across products and generates stable conservative coefficient estimates (41, 42).

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 ten years post- the uptake period, with four years in the pre-period. We also estimate the 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 as robustness.

The causal identification rests on the assumption of parallel trends: absent the transparency shock, the forward 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 Table S10 (43) and Figure 1A in the main text plots staggered regression, neither of which shows significant pre-trends.

The presence of spill-overs could cause a violation of the parallel trends assumption in the post-period. An increase in competitors' product market entry could affect the original firm's 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). The next section describes a regression discontinuity design, where we substitute the outcome variable in the regression

[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.

discontinuity design, and show that the transparency shock had no significant effect on forward use by the original firm (despite a potential negative effect on firm survival). As the forward use by the original firm servers as the baseline in the difference-in-differences, this result provides evidence that the average spill-over effect is close to zero. The regression discontinuity design on the main outcome of interest also has the advantage of not relying on a control group, serving as a further robustness check.

Discontinuity

We leverage the sharp discontinuity in the availability of information for products registered just before and after the transparency shock. Whereas products authorized in February 1998 did not have exhibits available online, over 90 percent of products authorized in April did, and so did virtually all products authorized in November of the same year. When other firms developed their products, they had significantly more information on the latter products, even though they were registered just a few weeks later. We compare products just before (control) and after the transparency shock (treatment). We specify:

$$Y_t = \alpha + \beta_1 \cdot Transparency_t \cdot Distance_t$$
$$+\beta_2 \cdot Transparency_t + \beta_3 Distance_t + \varepsilon_i$$

where t is time in weeks, and Y_t is the weekly mean of one of the following values over products i introduced in the week t: $Log(ForwardUse, Competition_i + 0.01)$, $Log(ForwardUse, Self_i + 0.01)$, $NextSecrecy_i$, $NextPatent_i$, and $Survival_{y,i}$ for $y \in \{1, 3, 5\}$ (see above for definitions). $Transparency_i$ notes the treatment period, $Distance_i$ is the running variable, measuring the number of weeks until or from the treatment.

We use the sharp regression discontinuity design (44), which fits a non-parametric local regression. We rely on robust estimates and report results from polynomials of degree one (main), two, and three, and let the algorithm choose optimal bandwidth from ten years of observations prior and post the shock and use the triangular kernel.

The uptake period complicates the discontinuity design (45). Excluding observations from the uptake period (so-called donut model) risks introducing artificial discontinuity and noise. Including observations from the uptake period risks underestimating the treatment

effects, because treatment was incomplete. Thanks to the fast uptake (over 90 percent in April 1998), this downward bias might be limited. We present results from both approaches, which are broadly consistent. We refer to estimates from the specifications inclusive of the treatment period as the main (conservative) results.

We further test the significance of the findings by estimating the main model for each outcome variable on 6,942 placebo dates. These are all dates from ten years prior- and post-the true event, excluding one year closest on each side. We then calculate the bootstrapped p-value by comparing the coefficient sizes of the true event and the placebo estimations.

Supplementary Text

Tabulated results

Table S3 details results from the main difference-in-differences specification. Model specifications that rely on observations from the first four years (columns 2 and 3) show a larger effect than two and ten years (1, 4, and 5). Focusing on the ten-year estimates with all control variables (column 5), the model estimates that transparency treatment increased the number of products that used the new frequency combination by $exp(0.755) = 2.13$, or by 113 percent. The dynamic treatment effect, included in the main text, shows a decline of this effect after the fourth year, corresponding to a higher estimate in the four-year bandwidth.

The main regression discontinuity design results, presented in Table S4A, show a sharp increase in forward use of about 119 percent (robust estimate in panel 1). This corresponds to the initial smaller increase found in the difference-in-differences results, but could also be affected by the inclusion of uptake period observations. The results from higher-order polynomials and with the uptake period omitted (panels 2–6) are broadly consistent and statistically significant. The bootstraped p-value of < 0.01 indicates the results are not due to noise in the data.

Sub-populations

Table S5 presents detailed sub-population results. It uses the four-year bandwidth for maximum statistical power of the estimates for between-subpopulation comparisons. Panel (1) splits the outcome variable between products in the same class (low novelty) or a

different product class (high novelty). The two coefficients are comparable (p-value 0.87), indicating that the future use of new frequencies also included novel products. Panel (2) splits the outcome variable between new entrants, new entrants in class (but incumbents in the dataset), and incumbents. The coefficients are also of comparable size (p-values of 0.52 and 0.42 for NewClassEntrant and Incumbent with respect to NewEntrant, respectively), indicating that all these subpopulations benefited from the transparency shock.

We next turn to foreign competition. Panel (3) splits the outcome variable between these from the same country as the original firm (domestic) and other countries (foreign). The results show a significant difference, with foreign firms increasing their use by $exp(1.512)/exp(0.871) = 1.9$, or about twice as much as foreign firms (p-value 0.02). Restricting the sample to products by U.S. firms only (panel 4) yields a similar difference between foreign and domestic of $exp(1.127)/exp(0.459) = 1.95$ (p-value 0.04). Finally, panel (5) restricts the sample to products by non-U.S. firms only. The results show a significantly somewhat lower increase in forward use among U.S. firms compared to domestic firms (p-value 0.1), and no statistically significant difference between domestic and other foreign non-U.S. competitors (p-value 0.47), or between U.S. and non-U.S. foreign competitors (p-value 0.3).

Alternative outcomes

We next turn to the results of alternative outcomes. Table S4B shows no statistically significant increase or decrease in forward use by the original firm. The coefficients are meaningfully positive but statistically insignificant (bootstrapped p-value 0.16 for the main coefficient of 0.25). We interpret this in supporting the assumption of no net spill-overs from the treatment group in the difference-in-differences design. Table S6 shows an increase in secrecy (panel A) and patenting (panel B) in the subsequent product of about 11 and 12 percent, respectively, although statistically significant only at the 90 percent level (bootstrapped p-value 0.02 and 0.04, respectively). This represents a meaningful increase in innovation appropriation measures.

Table S7 shows a decrease in survival of firms exposed to secrecy of 8 and 11 percent in one and five years, statistically significant at 90 and 95 percent levels (bootstrapped p-value 0.06 and 0.08), respectively. This presents evidence that transparency exposure increased

market exit in the following years, potentially due to increased competition. Across these alternative outcome results, the donut specification with omitted uptake period (models 4–6 on each subplot) shows broadly consistent results.

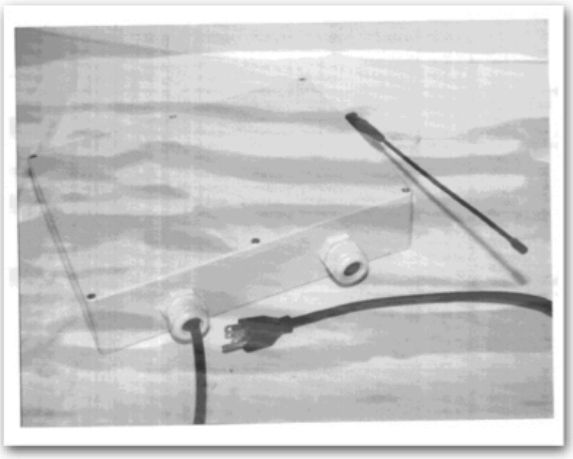
Robustness

As further robustness checks to our main difference-in-differences specification, we first estimate two complementary specifications: a logistic regression where the outcome is binary rather than a count, indicating if at least one further product used the frequency combination, with product random effects, and 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 effects absorb all the product-level constant variables included in the main specification. We further include linear time pre-trends in the main specification and vary the dependent variable to count three, five (main), and seven years of forward use.

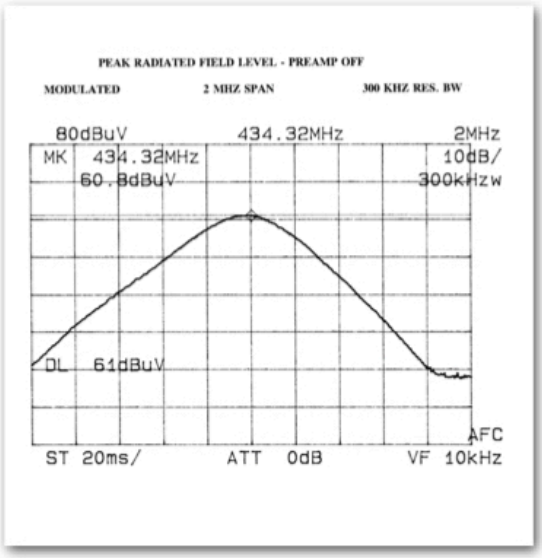
All results are consistent with the main findings. Treated products have a higher probability of at least one follow-up product in the same frequency (table S8), and among those that have at least one follow-up, the count is higher (table S9). The linear time pre-trend is insignificant and does not significantly change the main coefficient of interest (table S10). Variations on the dependent variable result in comparable estimates, with the three-year definition resulting in a smaller effect and the seven-year definition resulting in a larger effect.

List of Figures

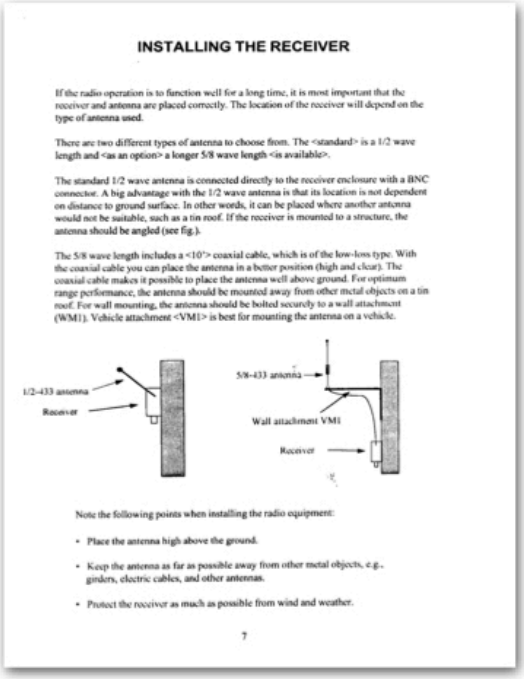
S1 Product example, FCC ID CBFCRANET1 16
S2 Product example, FCC ID A3LSCH855 17
S3 Timeline of relevant events 18
S4 Discontinuity plots 19



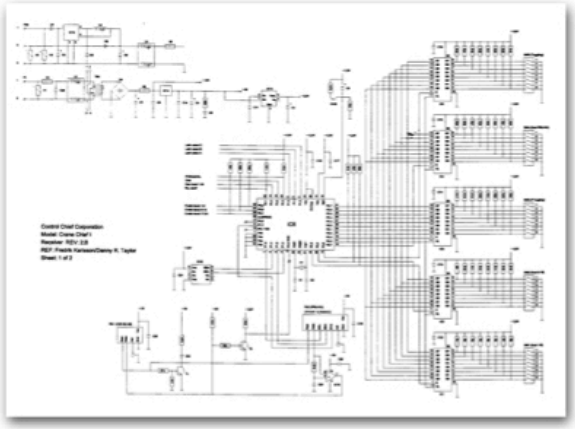
A



B



C

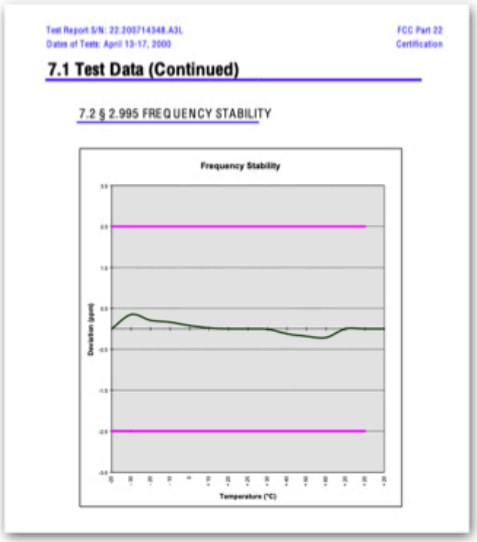


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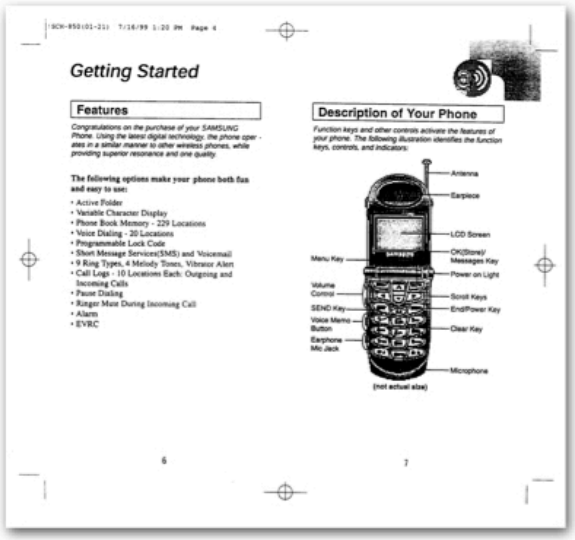
Figure S1: Product example, FCC ID CBFCRANET1
Excerpts from documentation submitted to the FCC as part of the equipment authorization process, and available online: A) external photos, B) test results, C) user manual excerpt, D) schematics.



A



B



C

Figure S2: Product example, 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.

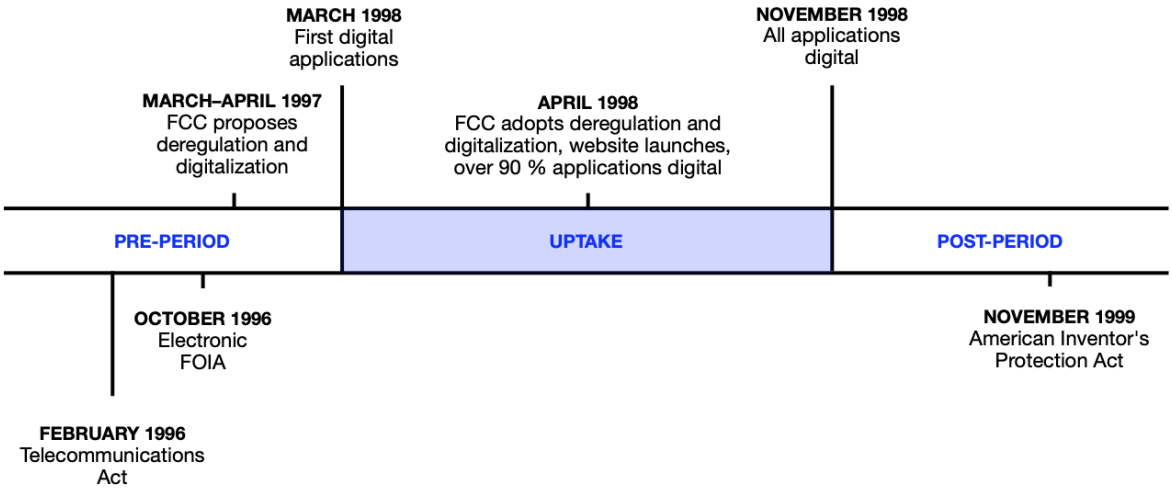
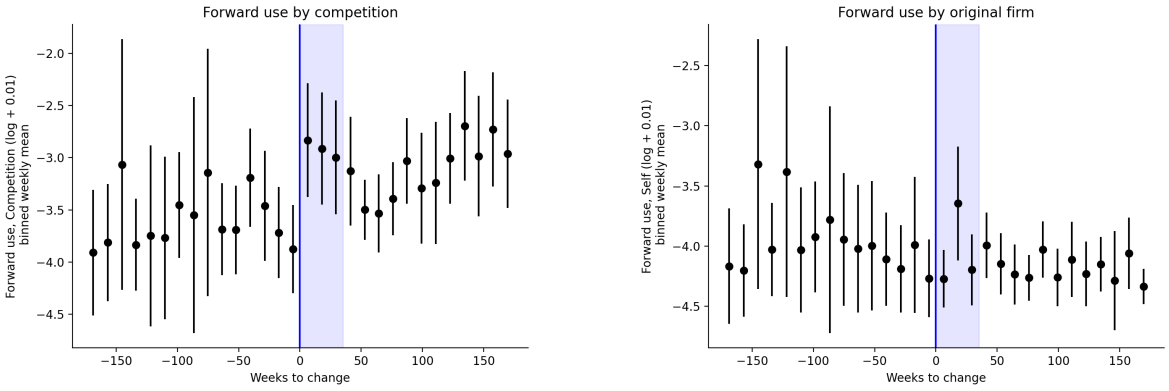
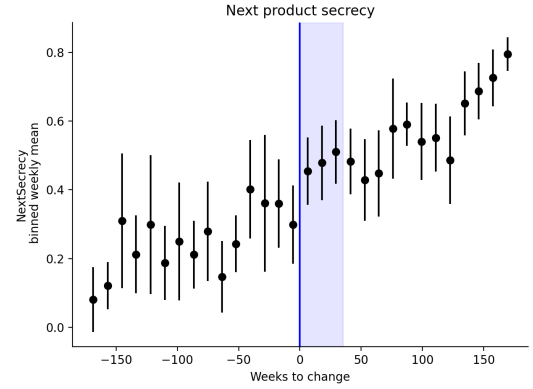


Figure S3: Timeline of relevant events

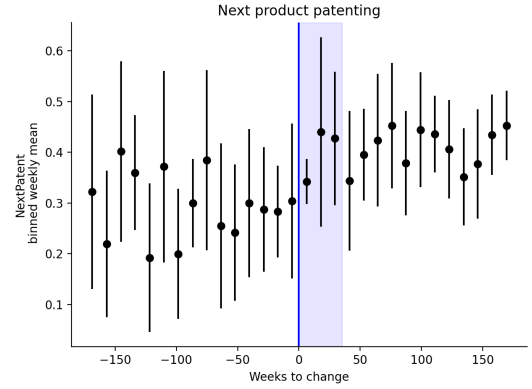


(A)

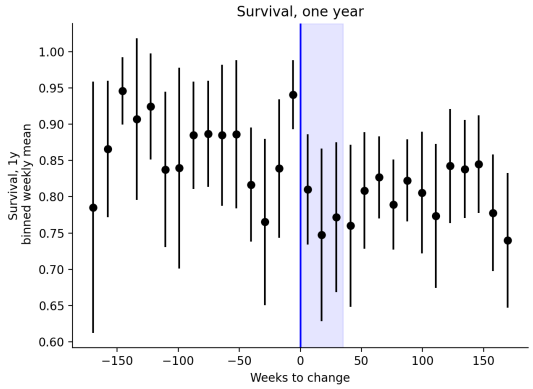
(B)



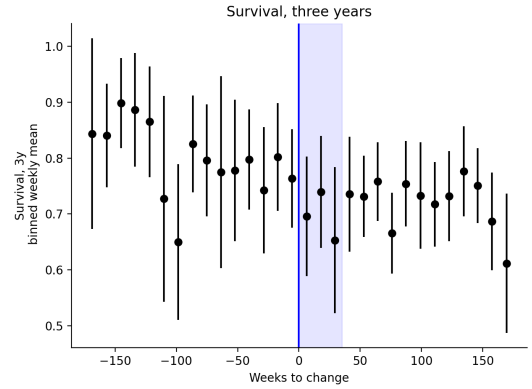
(C)



(D)



(E)



(F)

Figure S4: Discontinuity plots

Forward use by (A) competition and (B) the original firm, (C) secrecy in the next product, (D) patenting before the next product, and (E) survival after one and (F) three years around the transparency policy shift. Blue shading indicates the uptake period, weeks to initial change on the x-axis, weekly means binned by 11–12 weeks, 95 percent confidence interval.

List of Tables

S1 Summary statistics 21
S2 U.S. internet bands 22
S3 Main difference-in-difference regression results 23
S4 Regression discontinuity design results, forward use 24
S5 Difference-in-differences, sub-populations 25
S6 Regression discontinuity design results, secrecy, and patenting 26
S7 Regression discontinuity design results, survival 27
S8 Logistic difference-in-differences regression results 28
S9 Difference-in-difference regression results, non-zero future use products . . 29
S10 Difference-in-difference regression results, linear time trends 30
S11 Difference-in-difference regression results, dependent variable variations . . 31

	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			
Survival, 1y	0.84	0.37				0.83	0.37			
Survival, 3y	0.78	0.42				0.75	0.43			
Survival, 5y	0.71	0.45				0.69	0.46			
ForwardUse, Self	0.19	0.76	0	0	1	0.17	1.13	0	0	0
ForwardUse, Other	1.06	7.73	0	0	2	1.60	6.57	0	0	3
– InClass	0.72	7.03	0	0	1	0.97	4.94	0	0	2
– OutClass	0.34	2.74	0	0	0	0.63	3.66	0	0	1
– Incumbent	0.78	6.59	0	0	1	1.26	5.40	0	0	2
– ClassEntrant	0.14	0.81	0	0	0	0.16	0.68	0	0	0
– Entrant	0.14	0.73	0	0	0	0.18	0.86	0	0	0
– Domestic	0.41	2.50	0	0	1	0.51	2.27	0	0	1
– Foreign	0.65	6.93	0	0	1	1.09	5.17	0	0	2
– US	0.61	4.02	0	0	1	0.65	2.82	0	0	1
– NonUS	0.45	4.12	0	0	0	0.94	4.04	0	0	2

Table S1: 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 the 10th and the 90th percentile values, 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.

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 S2: U.S. internet bands

Dependent variable:	ForwardUse				
Bandwidth (years):	Two	Four		Ten	
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Transparency × Competition	0.869***	1.381***	1.323***	0.606***	0.755***
	(0.225)	(0.207)	(0.216)	(0.184)	(0.189)
Random effects					
Product	Yes	Yes	Yes	Yes	Yes
	[1.09]	[1.05]	[1.04]	[1.012]	[1.014]
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	23,484	23,484
Underlying products	2,233	3,662	3,662	11,742	11,742
R^2 marginal	0.188	0.279	0.282	0.181	0.185
R^2 conditional	0.480	0.511	0.508	0.426	0.429
AIC	6228.2	11024.8	11024.0	29538.0	29527.9
BIC	6273.1	11073.1	11086.1	29594.5	29600.5
Over-dispersion	0.187	0.137	0.136	0.123	0.124

Table S3: Main difference-in-difference regression results

Results of the main difference-in-difference specifications, estimated on observations four years prior and two, four, and ten 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

(A) Dependent variable: FordwardUse, Competition						
Uptake period:		Included			Omitted	
Polynomial:	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
	(1)	(2)	(3)	(4)	(5)	(6)
Estimates						
Conventional	1.066***	1.319***	1.437***	0.602**	2.375***	3.041***
	(0.268)	(0.331)	(0.355)	(0.270)	(0.701)	(0.845)
Bias-corrected	1.185***	1.433***	1.503***	0.628**	2.657***	3.289***
	(0.268)	(0.331)	(0.355)	(0.270)	(0.701)	(0.845)
Robust	1.185***	1.433***	1.503***	0.628*	2.657***	3.289***
	(0.297)	(0.361)	(0.386)	(0.336)	(0.756)	(0.916)
Bandwidth (weeks)	98	131	200	128	109	166
Bandwidth type	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal
Kernel type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

(B) Dependent variable: FordwardUse, Self						
Uptake period:		Included			Omitted	
Polynomial:	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
	(1)	(2)	(3)	(4)	(5)	(6)
Estimates						
Conventional	0.196	0.271	0.081	0.131	0.290	0.021
	(0.195)	(0.208)	(0.275)	(0.279)	(0.311)	(0.599)
Bias-corrected	0.250	0.304	0.020	0.189	0.328	-0.075
	(0.195)	(0.208)	(0.275)	(0.279)	(0.311)	(0.599)
Robust	0.250	0.304	0.020	0.189	0.328	-0.075
	(0.229)	(0.235)	(0.297)	(0.350)	(0.367)	(0.692)
Bandwidth (weeks)	116	230	193	102	206	178
Bandwidth type	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal
Kernel type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

Table S4: Regression discontinuity design results, forward use

Linear (1, 4), quadratic (2, 5), and cubic (3, 6) discontinuity estimates of the effect of the policy change on (A) forward use by competition and (B) forward use by the original firm. The uptake period included with discontinuity on March 1, 1998 (1–3) and excluded with discontinuity on July 1, 1998 (4–6).

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

Dependent variable:	ForwardUse				
Bandwidth (years):			Four		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Transparency × InClass	1.248***				
	(0.200)				
Transparency × OutClass	1.199***				
	(0.210)				
Transparency × NewEntrant		1.247***			
		(0.162)			
Transparency × NewClassEntrant		1.082***			
		(0.200)			
Transparency × Incumbent		1.039***			
		(0.200)			
Transparency × Domestic			0.871***	0.459**	2.427***
			(0.194)	(0.218)	(0.366)
Transparency × Foreign			1.512***	1.127***	
			(0.192)	(0.233)	
Transparency × ForeignUS					1.655***
					(0.295)
Transparency × ForeignOther					2.091***
					(0.292)
Random effects					
Product	Yes	Yes	Yes	Yes	Yes
	[2.554]	[2.787]	[2.661]	[2.89]	[2.784]
Fixed effects					
Transparency	Yes	Yes	Yes	Yes	Yes
Internet	Yes	Yes	Yes	Yes	Yes
AIPA	Yes	Yes	Yes	Yes	Yes
OutClass + InClass	Yes				
AIPA × InClass	Yes				
AIPA × OutClass	Yes				
NewEntrant + NewClassEntrant + Incumbent		Yes			
AIPA × NewEntrant		Yes			
AIPA × NewClassEntrant		Yes			
AIPA × Incumbent		Yes			
Domestic + Foreign			Yes	Yes	Yes
AIPA × Domestic			Yes	Yes	Yes
AIPA × Foreign			Yes	Yes	
ForeignUS + ForeignOther					Yes
AIPA × ForeignUS					Yes
AIPA × ForeignOther					Yes
Fit statistics					
Observations	10,986	14,648	10,986	7,356	4,840
Underlying products	3,662	3,662	3,662	2,452	1,210
R^2 marginal	0.055	0.071	0.050	0.024	0.121
R^2 conditional	0.839	0.900	0.862	0.885	0.908
AIC	13537.1	14486.1	13626.4	7793.5	6934.4
BIC	13624.8	14600.0	13714.0	7876.3	7031.7
Over-dispersion	0.457	1.09	0.592	0.814	1.15

Table S5: Difference-in-differences, sub-populations

Results of the sub-population difference-in-differences specification of (1) in-class and out-class, (2) new entrants, new entrants in class, and incumbent, (3) domestic and foreign, (4) domestic on a subset of U.S. firms, (5) domestic, U.S., and non-U.S. foreign on a subset of non-U.S. products. Follow-on products by the original firm in the pre-treatment period constitute the baseline.

(A) Dependent variable: NextSecrecy						
Uptake period:		Included			Omitted	
Polynomial:	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
	(1)	(2)	(3)	(4)	(5)	(6)
Estimates						
Conventional	0.098*	0.105*	0.117*	0.069	0.102	0.167
	(0.053)	(0.060)	(0.068)	(0.071)	(0.108)	(0.162)
Bias-corrected	0.111**	0.119**	0.121*	0.072	0.123	0.189
	(0.053)	(0.060)	(0.068)	(0.071)	(0.108)	(0.162)
Robust	0.111*	0.119*	0.121	0.072	0.123	0.189
	(0.063)	(0.066)	(0.074)	(0.088)	(0.126)	(0.187)
Bandwidth (weeks)	141	236	296	153	189	220
Bandwidth type	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal
Kernel type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

(B) Dependent variable: NextPatent						
Uptake period:		Included			Omitted	
Polynomial:	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
	(1)	(2)	(3)	(4)	(5)	(6)
Estimates						
Conventional	0.109**	0.091	0.082	0.148*	0.159	0.149
	(0.053)	(0.076)	(0.084)	(0.086)	(0.109)	(0.150)
Bias-corrected	0.122**	0.079	0.064	0.161*	0.151	0.125
	(0.053)	(0.076)	(0.084)	(0.086)	(0.109)	(0.150)
Robust	0.122*	0.079	0.064	0.161	0.151	0.125
	(0.063)	(0.086)	(0.092)	(0.108)	(0.130)	(0.172)
Bandwidth (weeks)	184	190	271	121	202	258
Bandwidth type	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal
Kernel type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

Table S6: Regression discontinuity design results, secrecy, and patenting

Linear (1, 4), quadratic (2, 5), and cubic (3, 6) discontinuity estimates of the effect of the policy change on (A) patenting in the next application and (B)secrecy in the next application. The uptake period included with discontinuity on March 1, 1998 (1–3) and excluded with discontinuity on July 1, 1998 (4–6).
* p <0.1, ** p <0.05, *** p <0.01

(A) Dependent variable: Survival, 1 year						
Uptake period:		Included			Omitted	
Polynomial:	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
	(1)	(2)	(3)	(4)	(5)	(6)
Estimates						
Conventional	-0.085**	-0.110**	-0.134**	-0.100**	-0.350***	-0.454***
	(0.038)	(0.049)	(0.055)	(0.051)	(0.105)	(0.140)
Bias-corrected	-0.082**	-0.123**	-0.142**	-0.093*	-0.398***	-0.503***
	(0.038)	(0.049)	(0.055)	(0.051)	(0.105)	(0.140)
Robust	-0.082*	-0.123**	-0.142**	-0.093	-0.398***	-0.503***
	(0.045)	(0.053)	(0.059)	(0.063)	(0.117)	(0.150)
Bandwidth (weeks)	157	172	181	140	119	160
Bandwidth type	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal
Kernel type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

(B) Dependent variable: Survival, 3 years						
Uptake period:		Included			Omitted	
Polynomial:	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
	(1)	(2)	(3)	(4)	(5)	(6)
Estimates						
Conventional	-0.082**	-0.121**	-0.129*	-0.120**	-0.342**	-0.323**
	(0.041)	(0.059)	(0.067)	(0.053)	(0.144)	(0.157)
Bias-corrected	-0.083**	-0.140**	-0.132*	-0.111**	-0.393***	-0.374**
	(0.041)	(0.059)	(0.067)	(0.053)	(0.144)	(0.157)
Robust	-0.083*	-0.140**	-0.132*	-0.111*	-0.393**	-0.374**
	(0.049)	(0.065)	(0.074)	(0.065)	(0.160)	(0.168)
Bandwidth (weeks)	155	148	194	149	118	192
Bandwidth type	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal
Kernel type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

(C) Dependent variable: Survival, 5 years						
Uptake period:		Included			Omitted	
Polynomial:	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
	(1)	(2)	(3)	(4)	(5)	(6)
Estimates						
Conventional	-0.099**	-0.128**	-0.149**	-0.102*	-0.178	-0.284**
	(0.046)	(0.058)	(0.068)	(0.061)	(0.138)	(0.140)
Bias-corrected	-0.110**	-0.143**	-0.164**	-0.100	-0.228*	-0.317**
	(0.046)	(0.058)	(0.068)	(0.061)	(0.138)	(0.140)
Robust	-0.110**	-0.143**	-0.164**	-0.100	-0.228	-0.317**
	(0.054)	(0.064)	(0.074)	(0.076)	(0.154)	(0.156)
Bandwidth (weeks)	132	170	205	146	130	226
Bandwidth type	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal
Kernel type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

Table S7: Regression discontinuity design results, survival

Linear (1, 4), quadratic (2, 5), and cubic (3, 6) discontinuity estimates of the effect of the policy change on the survival of firms after (A) one, (B) three, and (C) five years. The uptake period included with discontinuity on March 1, 1998 (1–3) and excluded with discontinuity on July 1, 1998 (4–6).

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

Dependent variable:	ForwardUse > 0		
Bandwidth (years):	Two	Four	Ten
Model:	(1)	(2)	(3)
Variables			
Transparency × Competition	0.673***	0.856***	0.482***
	(0.190)	(0.166)	(0.143)
Fixed effects			
Internet	Yes	Yes	Yes
Competition	Yes	Yes	Yes
AIPA		Yes	Yes
AIPA × Competition		Yes	Yes
Random effects			
Product	Yes	Yes	Yes
	[1.191]	[1.087]	[1.233]
Fit statistics			
Observations	4,466	7,324	23,484
Underlying products	2,233	3,662	11,742
R^2 marginal	0.060	0.085	0.051
R^2 conditional	0.343	0.327	0.351
AIC	3695.3	6059.3	17735.5
BIC	3733.8	6114.5	17800.0

Table S8: Logistic difference-in-differences regression results

Results of the logistic difference-in-difference specifications, fit on observations in two, four, and ten years prior and post the uptake period (uptake period observations omitted). Follow-on products by the original 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 | ForwardUse > 0		
Bandwidth (years):	Two	Four	Ten
Model:	(1)	(2)	(3)
Variables			
Transparency × Competition	0.889***	1.27***	0.734***
	(0.259)	(0.224)	(0.181)
Fixed effects			
Competition	Yes	Yes	Yes
Product	Yes	Yes	Yes
AIPA		Yes	Yes
AIPA *times* Competition		Yes	Yes
Fit statistics			
Observations	948	2,064	5,616
Underlying products	474	1,032	2,808
Squared Correlation	0.83900	0.90320	0.71686
Pseudo R^2	0.27241	0.28706	0.24543
BIC	5,856.9	13,905.5	39,971.8
Over-dispersion	7.7435	10.269	3.4667

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

Table S9: Difference-in-difference regression results, non-zero future use products

Results of the difference-in-difference specifications, estimated on observations four years prior and two, four, and ten 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 original 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		
Bandwidth (years):	Two	Four	Ten
Model:	(1)	(2)	(3)
Variables			
Transparency × Competition	1.019***	1.487***	0.898**
	(0.350)	(0.363)	(0.352)
Competition	0.984***	0.996***	1.041***
	(0.313)	(0.339)	(0.344)
Transparency	-0.025	-0.226	-0.329
	(0.281)	(0.288)	(0.277)
Competition × Pre-trend	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Pre-trend	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Random effects			
Product	Yes	Yes	Yes
	[1.077]	[1.025]	[1.012]
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
Underlying products	2,233	3,662	5,661
R^2 marginal	0.190	0.283	0.185
R^2 conditional	0.476	0.505	0.429
AIC	6228.9	11025.3	29531.2
BIC	6286.6	11101.2	29619.9
Over-dispersion	0.185	0.135	0.124

Table S10: 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 ten years post the uptake period, uptake period observations omitted. Follow-on products by the original 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

Dependent variable:	ForwardUse		
Definition (years):	Three	Five	Seven
Bandwidth (years):		Ten	
Model:	(1)	(2)	(3)
Variables			
Transparency × Competition	0.481***	0.755***	0.951***
	(0.157)	(0.189)	(0.189)
Random effects			
Product	Yes	Yes	Yes
	[3.04]	[1.014]	[1.118]
Fixed effects			
Competition	Yes	Yes	Yes
Transparency	Yes	Yes	Yes
Internet	Yes	Yes	Yes
AIPA	Yes	Yes	Yes
AIPA × Competition	Yes	Yes	Yes
Fit statistics			
Observations	23,484	23,484	23,484
Underlying products	11,742	11,742	11,742
R^2 marginal	0.033	0.188	0.241
R^2 conditional	0.887	0.436	0.507
AIC	24129.2	29527.9	33344.9
BIC	24201.8	29600.5	33417.4
Over-dispersion	0.906	0.124	0.127

Table S11: Difference-in-difference regression results, dependent variable variations

Results of the robustness difference-in-difference specifications, estimated with dependent variable based on three, five, and seven years of observations, ten year bandwidth. Follow-on products by the original 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