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OPEN DEVICES AND SLICES:
EVIDENCE FROM WI-FI EQUIPMENT

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ABSTRACT

The study examines the quasi-natural experiments provided by the staggered introduction of open drivers in the supply chains for routers. It is rare to observe components become open and measure whether openness generates a statistical impact on more products and innovative products. This study collects novel data on all routers and subcomponents introduced between 2000 and 2018, characterizing each firm's position in a supply chain as either an upstream component provider or a downstream router assembler. Following prior literature, openness influences a firm's ability to negotiate with current and potential partners, which is labeled as autonomy. Evidence suggests that openness enhances supplier autonomy, increases the introduction of new products, and leads to a greater number of products located closer to the technical frontier. These estimates suggest that openness increased product introductions by enlarging the options available to component suppliers. The largest component suppliers benefited from greater sales, and no evidence indicates that openness aided entrants, small firms, or assemblers.

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An online appendix is available at http://www.nber.org/data-appendix/w34603

1. Introduction

This study examines the consequences of a supplier making a component open within a supply chain. Specifically, this study examines whether supply chains with newly opened components have a greater number of products and produce more innovative products than those that remain closed. These questions are examined in the United States router market, and this data covers the entire history of the mass-market for routers up to 2018.

The router market is an ideal setting for researching the introduction of new products. This large and vital market has experienced tremendous growth in its first two decades. Since the introduction of the first Wi-Fi router in 1999, the market for Wi-Fi router equipment has grown to nearly $12.5 billion worldwide by 2020.[2] Demand grew as wireless routers gained many use cases and as the opportunities for improvement expanded. Many firms entered the market with new designs, supporting a wide range of innovative products for various user segments. In turn, those products were supported by many different supply chains, involving many of the same suppliers and assemblers over time, as well as hundreds of new entrants.

The structure of the supply chains makes these activities highly suitable for analysis. First, the supply chains for routers are unusually well-documented and comprehensive, allowing for observations on every configuration. Observing so much in a supply chain is rare. Additionally, no firm has integrated into supplying the "entire stack". One set of companies provides CPUs, another supplies Wi-Fi chipsets, while yet another group assembles the products before they are distributed (see Appendix Table A3 for a Glossary). A few firms perform more than one activity. The general separation between the identities of upstream and downstream providers allows for observations of various configurations of upstream and downstream firms. Overall, there are 64 component suppliers, 34 of which specialize in building CPU chips, 13 in building Wi-Fi chips, and 18 supply both. This study covers the experiences of 263 assembler firms, comprising 3,239 observations.

The study focuses on the quasi-natural experiment associated with the release of open drivers. Some device drivers for router Central Processing Units (CPUs) became open source early in the router market's history. In contrast, others became open relatively late, and still others never did. After opening, the CPU supplier no longer controls who uses their component and how it is used. This motivates a statistical comparison between supply chains with open components and those without open components, and whether these are associated with similar, better, or worse outcomes.

The study examines a mechanism that shapes the consequences of openness. Based on prior analysis, openness might change a firm's ability to negotiate with a partner with whom it

[2] Wireless Router Market Revenue Worldwide (Statista, accessed June 2023).

interacts. This ability is labeled as *autonomy* (Hoetker et al. 2007). For suppliers, increased autonomy – potentially enabled by greater openness – offers better opportunities to sell their components to more potential assemblers. For assemblers, increased autonomy entails less reliance on a limited number of suppliers for key components. That can also be interpreted as the result of strong negotiating positions. If this interpretation holds, a positive association should exist between increasing autonomy and the introduction of new products by suppliers and assemblers. The research questions are: Does *autonomy* lead to more product introductions and more innovative products? If so, does it work better for some component suppliers, such as those that are larger or smaller in size?

The research question lends itself to a fixed effects regression analysis with additional controls, such as the firm's age and experience, as well as the duration of its portfolio of relationships with other suppliers. The approach is applied to the number of products and then to various measures of innovativeness. After establishing the robustness of these relationships, it is possible to focus solely on the impact of autonomy from openness. The latter part of the study measures the effects of openness using a staggered differences-in-differences approach, focusing on whether more autonomy leads to more products and more innovative products (Callaway and Sant'Anna, 2021). Using those estimates, it next investigates which size of firm had the most success.

The estimates suggest that a firm's position in the supply chain influences outcomes. Specifically, a firm's *autonomy* has a positive influence, with considerable heterogeneity in the impact. Changes in the level of autonomy are associated with significant changes in the number of devices introduced, with similar results for all the additional measures of innovativeness. These findings hold for the different Wi-Fi, CPU, and assembler supply chains. For Wi-Fi and CPU suppliers, the effect is large. A supplier moving from the median to the 75th percentile for the two groups translates into a 21.2% and 19.6% increase in devices, respectively. The estimated coefficients for Wi-Fi router assemblers are similar, with a 14.4% and 43.1% increase, respectively, for firms moving from the median to the 75th percentile.

Overall, the analysis reveals that when suppliers provide open-source drivers and make information accessible, their autonomy and product introductions increase compared to those of non-open suppliers. An increase in openness has a significant statistical effect on introducing new products, primarily through its impact on autonomy. The numerical evidence is large. The average treatment effect on the treated (ATT) for autonomy is 0.051, indicating that firms that become more open experience around a half-standard-deviation increase in autonomy. The ATT for the effect of openness on device counts is 16.092, suggesting that it leads to a 53.1% increase in device counts for firms that opened. Consistent with the creation of more innovative products, openness increases the number of products that use frontier protocols, implement standards immediately, use new radio frequency, and are more complex . Additionally, openness attracts younger assemblers, entrants, and those based in China or Taiwan, again consistent with the notion that openness increases autonomy.

The estimates for the staggered difference-in-difference suggest the mechanism did not work equally well for all suppliers. Larger suppliers and those supplying both Wi-Fi and CPU chips experience the most significant benefits from openness. In comparison, smaller suppliers and assemblers experience little to no benefit. These coincide with the earliest efforts to be open, which came from the largest firms. When large firms become open, device counts increase by 29.65 devices and autonomy by 0.077. For small firms, the effects are smaller, and the impact on product counts is statistically insignificant. The effects of opening are greatest in 2011, when Qualcomm, the largest supplier, released open source drivers. The most prominent firms (e.g., Broadcom, Qualcomm, Ralink, and Realtek) benefited from openness by expanding their autonomy.

The results are consistent with the notion that openness enables suppliers to innovate more quickly than their non-open counterparts. Since technological standards are accessible to all suppliers, firms must differentiate their products on other dimensions. In markets with short product lifecycles, one source of differentiation comes from lead time advantages (Simcoe and Watson 2019). Case studies of the Wi-Fi industry suggest a "profit from implementation" strategy where being first to market leads to differentiation (Eisenmann 2007). Notably, Craig Barratt, the CEO of Atheros in 2007, is quoted as saying, "The prize […] is the halo effect from being first to market. That allows you to win additional business" (Eisenmann and Barley 2007). The heterogeneity results, showing that the largest firms benefit more, are consistent with firms benefiting the most because of scale and complementary assets (Alexy et al. 2018), while openness allows for faster time to market, and thus opportunities for differentiation.

Despite its size and central role in networking, the router market has been a relatively underexplored area of research, aside from two prior studies that this study builds upon. Firstly, Kim (2019) discusses the role of openness in the first decade of router markets. The results highlight two key benefits of reducing information imperfections. First, in the case of software, to the extent that buyers can access source code ex ante, they can understand the characteristics of the components they need to buy and integrate into their systems. Second, open interfaces reduce search costs for final customers and allow buyers to monitor sellers (ex post). The current study examines a more extended time period and shifts the focus to supply chains. The findings of this study extend beyond the initial reduction in search costs, demonstrating how increased autonomy enables the creation of more products and more innovative products. Additionally, Fontana and Greenstein (2021) examine Intel's imposition of openness on the laptop supply chain, which led to the adoption of the IEEE 802.11 standard among router users and producers. The current study examines the supply chain over a longer period, across multiple supply chains, and focuses on autonomy to alter the supply chain.

2. *Contribution to Literature*

The conventional intuition that openness leads to more products can be traced (at least) to the introduction of the personal computer in 1981, when IBM introduced a modular design with published specifications and few limitations on who could make complementary components (David and Greenstein 1990, Langlois and Robertson 1992). Openness increased the short-term market value of IBM-supplied personal computers, highlighting the importance of compatible components and applications. The example also serves as a cautionary tale: IBM's open, modular design was imitated by clones. IBM lost market leadership in the long run, even as the system of compatible suppliers persisted (Bresnahan and Greenstein 1999). Since then, numerous studies have deepened the understanding of the broader questions surrounding openness. This study addresses several strands of the literature that have followed.

Negotiating behavior. It has long been hypothesized that openness reduces switching costs and the risk of being locked into a particular system. (Farrell et al. 1998). This may deter one potential business partner from committing to another. Open components affect a firm's bargaining position within a supply chain and final assembly (Teece 1986, Reitzig 2004, Hoetker 2005). Introducing openness decouples drivers from other components, enabling specialization (Arora and Bokhari 2007, West and Wood 2014, Kretschmer et al. 2022, Kuan and West 2023). The reduced barriers to obtaining information lower the cost of entry for potential partners and increase their freedom to act independently of the component supplier. If the results are improvements that would not have occurred otherwise, then the increase in customer satisfaction could lead to growth in market size for products that use the component. Openness also enables independent operation, allowing for action without relying on a single business partner (Hoetker et al. 2007). The intuition is that a supplier (or buyer) might be dependent on another supplier (or buyer) if it sells (or buys) exclusively to (or from) that supplier (or buyer). Still, this dependence can be mitigated because the buyer (supplier) has few alternatives to buy from (supply to). Furthermore, suppliers of high-modular components have more independence than those of low-modular components (Hoetker et al., 2007). This study contributes to measuring autonomy in supply chains by building on the definitions and adapting them to account for events within routers, offering a new use case for study. It also offers empirical approaches to measuring heterogeneous effects.

Product sophistication. Like many electronic products, router markets have segments that divide (approximately) between home and business, where the latter typically supports a more extensive user base (Fontana and Greenstein 2021). Additionally, like many electronic equipment markets, users vary in technical sophistication, ranging from none to a high degree (Kim, 2019). Technically sophisticated users prefer open systems because they can customize the software to their needs. Non-technical users often prefer to hire third parties for maintenance and support and may sacrifice customization for lower support costs. Many proprietary systems aim to satisfy non-sophisticated users and forego the benefits of open systems, which are designed for sophisticated users. These differences can be significant in a business segment where the requirements for final products are unusual and technically challenging to address. Indeed, analyzing the impact of openness on demand, Kim (2019) finds that open-source drivers released by a technical user community improve demand for some products but not all, with the most sophisticated buyers valuing the change to openness the most. The empirical question in this context differs, as it focuses on openness over a longer period, large firms, and innovative products. It is an empirical question whether supply chains with open components produce products that reach the technical frontier more often than supply chains with comparable non-open components. It is also an empirical question whether large firms used openness more successfully than small firms.

Partnerships. If openness increases product variety by enabling more mixes and matches at a lower cost, in theory, it may yield a system of components with greater demand (Matutes and Regibeau 1988). Still, most examples typically have additional presumptions about exogenous modularity (Simcoe and Watson 2019). There is a further assumption about the role of standardized interfaces in complex products, specifically the presence of a critical component (de Figueiredo and Silverman 2012), as well as whether users or suppliers assemble the final products (Henderson and Clark 1990, Baldwin and Clark 2006). Components must share standard interfaces to work well together, and a coordinator's role is often essential (Kuan and West, 2023). In addition, modularity increases the range of components assemblers can choose to design their final products (Ethiraj and Levinthal 2004). If the potential partners are differentiated, it increases the combinations of different services. This study cannot determine which of these specific factors is most important. However, this study can provide empirical evidence on whether open components lead to a greater number of partners for the firm opening its component, supporting more products and more innovative ones.

Specialization in components. Prior work emphasizes that openness can lead to innovations in complementary hardware (Gawer and Henderson 2007, Boudreau 2010), which, in turn, can translate into significant benefits for the end customer. Introducing open drivers decouples drivers from other components and enables specialization by partners (Arora and Bokhari 2007, West and Wood 2014, Kretschmer et al. 2022). Standardization and stability of interfaces over time not only favor specialization and division of labor but also play a crucial role in increasing the flexibility of relationships between the supplier of the driver and any complement (Garud and Kumaraswamy 1993, Galunic and Eisenhardt 2001). Just as with the increase in partners, specialists among partners can provide either the same or differentiated components. This study also contributes by developing a novel approach to measuring whether products have reached the technical frontier.

3. *The Consequences of Openness.*

A close reading of prior literature reveals a range of definitions for “open.” Three distinct meanings arise in the context of supply chains in wireless markets. These different meanings relate to the release of drivers, the issuance of new standard protocols, and the behavior of varying supplier groups. Some historical details can clarify the possible roles of these three distinct meanings of “open” and how this paper measures them.

3.1. Origins

Apple first pioneered the mass-market Wi-Fi router using the IEEE standard 802.11b, the second design to emerge from the IEEE 802.11 committee. The Apple Airport—the first mass-market Wi-Fi product—debuted in July 1999 at a MacWorld convention in New York. Jobs famously took out a hoop during the presentation to convince the audience that there were no wires. The laptop expansion card was priced at $99 and came with a branded Apple product. The base station was sold separately. Apple distributed the entire system. The IBM-compatible market, which accounted for over 90 percent of the PC market, was first addressed by Dell Computer, one of the world's largest PC providers. Making Wi-Fi compatible with Windows was the main challenge, and a new version was released in 2001. It supported IEEE 802.11b in a Windows-based system. Once it was done for Dell, it also supported all other brands.

In 2001, Intel's management thoroughly examined the laptop supply chain and decided to shift priorities from desktops to laptops. Labeling this a “left turn,” the company considered how to enable Wi-Fi connectivity across all notebooks powered by Intel microprocessors. After considerable internal conflict and effort, “Centrino” was officially launched in March 2003. The redesign eliminated the need for an external card for the notebook, which is typically supplied by a firm other than Intel and installed by users or OEMs. Intel encountered several unanticipated crises, including insufficient parts for the preferred design, delays, and a trademark dispute over using its special symbol for the program. However, the most significant resistance came from the largest PC distributor, Dell Computer, the earliest IBM-PC-compatible firm to offer wireless features. Intel eventually prevailed, as Dell's reluctant cooperation emerged only a year later. One byproduct of these events was a uniform approach to wireless features on laptops, which standardized all supply chains on IEEE 802.11b and eliminated any possibility for proprietary features in the implementation (Fontana and Greenstein 2021).

Around the same time as the events mentioned above, firms that had helped pioneer the 802.11 standards formed the Wireless Ethernet Compatibility Alliance (WECA). WECA branded the new technology “Wi-Fi,” a made-up word for the mass market. WECA's members believed that “802.11b” was a less appealing label, and wanted to promote the adoption and use of Wi-Fi. WECA also arranged for testing to verify conformance to the standard, such as certifying the interoperability of antennae and receivers manufactured by different firms. In brief, while the IEEE committee designed the standard, an independent body (drawn from similar participating firms) performed conformance testing. Numerous businesses became early adopters of Wi-Fi and conducted directed experiments that supported what became known as hotspots—an innovative business concept.

Wireless router assemblers initially entered the market under agreements with Apple and Dell, and soon thereafter under their own brand names. With the standardization of laptops, more firms chose to enter the router market. The industry expanded from there as Wi-Fi gained popularity.

3.2. Unrestricted Information About Drivers.

Openness arises in this setting when CPU drivers are open. This meaning of open refers to a specific feature of the driver: no party controls access to information (West 2003, Boudreau 2010). Software drivers became open in this sense.

Specifically, a small community of technical users resented the limitations of proprietary router technologies, a young product in 2004. They reverse-engineered the wireless drivers for the Linksys WRT54G router, which led to the development of an open-source operating system for wireless routers (OpenWRT). Kim (2019) describes how, before the emergence of this open-source alternative, assemblers relied on purchasing software licenses from proprietary software companies. Once the open-source alternative became available, some (but not all) suppliers began releasing more drivers as open-source software, effectively making the technical standards available for some products within the 802.11 a/b/g/n segments. Appendix Table A14 lists all these releases.[3]

This study mainly focuses on the consequences of these open driver releases. Whether more openness leads to more products and more innovative products is an empirical question. A related question is whether these releases were equally effective for large and small firms across all generations of releases.

3.3. Unrestricted Access to and Use of Standardized Protocols.

Routers existed before the development of the IEEE 802 standards (Lemstra et al. 2010). However, these were based on proprietary definitions of the communications protocols. The deliberations and protocols of the IEEE 802.11 committee are "open," which illustrates another meaning of the term. Any firm can access this published standard without restriction (West 2007, Simcoe 2012).

Responding to growing demand for Wi-Fi, the 802.11 committees continued to revise the standards over the following years. These revisions improved error correction and data transmission rates, accommodating more users with reduced interference, among other design

[3] It has to be noted that an early version of a Linux-based open source driver had been released by Agere in 2001. Despite its early lead, this version ultimately proved unsuccessful due to the lack of a complementary Operating System. We list the case for completeness even though it is effectively not relevant for the analysis.

enhancements, which users experience as increased speed and enhanced reliability. New milestones were reached after 802.11b, notable ones being: 802.11g, released in 2003; 802.11n in 2008; 802.11ac in 2014; and 802.11ax in 2019. Again, access to these revisions remained unrestricted and available to anyone.

There was no variance in access to these protocols. However, despite equal access, there may be observable variance in how quickly new product releases incorporate improvements into the standardized protocols. These differences cannot be attributed to differential access to information. Instead, the preferred interpretation is that one set of suppliers developed a product closer to the frontier more quickly than another.[4] The unaddressed question is whether this achievement can be attributed to autonomy by component suppliers, which has led to supply chains for frontier products.

3.4. Comparative Firm Behavior in a Supply Chain

Over the next two decades, the supply chain for routers expanded, eventually involving hundreds of companies that produce products for end markets worth billions of dollars. Several assemblers developed large portfolios of products and recognizable brand names, such as Cisco, Netgear, and Linksys. Some component suppliers also involved recognizable names, such as Qualcomm and Broadcom. From the outset, these supply chains involved supply, assembly, and distribution on a global scale. As they grew, U.S. and Asian companies continued to play the most predominant roles.

The structure of supply chains helps with measurement. The structure of the Wi-Fi supply chain emerged as ‘horizontal’ with several companies specializing in different ‘slices’ of the industry. One set of companies provides CPUs, another provides Wi-Fi chips, and some suppliers offer both (Table A4 lists all suppliers). In contrast, another (much larger) group of companies assembles the products and distributes them under their brands. Firms did not vertically integrate between parts supply and assembly. This clear separation between the identities of upstream and downstream firms is helpful for analysis. It enables questions about how the characteristics of the upstream and downstream structures of the supply chain shape the introduction of new devices across distinctly different slices.

A feature of these supply chains illustrates another distinct meaning of “open.” Some component suppliers have been more “open” and willing to release open-source software voluntarily, while others have not been willing to (Henkel 2006, Nagle 2018). Specifically, CPU suppliers have a reputation for being more willing to support compatibility with open-source software, while Wi-Fi chip suppliers do not possess this reputation. This stance is reflected in many statements and

[4] An alternative interpretation, for which we have no evidence, is that participation in the IEEE 802.11 committees gives some component suppliers and assemblers a privileged position, and this translates into their components supporting products that reach the frontier fast. This is a challenging topic for future work.

incremental decisions for designs and distribution. It is thought that this difference demonstrates the ability of CPU suppliers to generate margins through branding and performance improvements, thereby suffering the downsides of openness less than chip suppliers. It also reflects long-standing strategic actions by some providers to grow the market by reducing the costs of complementary products, such as chips. Relatedly, it also reflects the limited ability of Wi-Fi chip suppliers to gain leverage in any negotiation due to competitive forces. The contrast in autonomy between these two types of firms offers another potential opportunity to measure openness in supply chains.

4. Data and Econometric Model

The statistical analysis primarily focuses on whether open-source drivers are associated with a greater number of products and more innovative products. If openness creates no benefits, then there should be no association between openness and downstream change. If it works through one of these mechanisms identified in the literature, a positive association should emerge in the estimation. Further analysis will refine causal evidence about whether the actions of large or small firms, and which generation, had the most impact. Statistical analysis will also examine similarities and differences between CPU and Wi-Fi chip suppliers, though this will not be the study's primary focus.

4.1. The Sample

It is possible to collect data for all routers sold in the U.S. between 2002 and 2018. This market is observable due to a requirement of U.S. regulatory oversight. Every router for sale uses unlicensed spectrum (in the 2.4 and 5 GHz frequency bands), and, by law, the FCC must inspect and verify that it does not interfere with other products using adjacent spectrum. That makes each entrant's action a matter of public record (albeit the records *are not* easily obtained and decoded). From such documents, and with appropriate supplements, a firm's position in a supply chain can be inferred. Every assembler seeks FCC approval, so this data set covers virtually all routers designed for the US and global markets.

More specifically, the data comes from filings of all router firms for authorization to use unlicensed spectrum. The FCC has maintained a database of all such products since 1980. This study utilizes data from 2002 onward, when the IEEE 802.11 standards became widely adopted across routers. The FCC data is combined with information from Wikidevi, a crowdsourced database of computer hardware. Wikidevi provides information about the hardware and software components of consumer electronic devices. Wikidevi includes information about routers' Wi-Fi and CPU chips, often with supporting links. The supplier information enables the construction of supplier-buyer relationships for CPU suppliers and assemblers, as well as Wi-Fi chip suppliers and assemblers.[5]

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[5] Through our time period, there are several (supplier and assembler) merger events. We deal with mergers and acquisitions by treating firms as separate before mergers, and maintain continuity for the acquiring firm after the

Finally, information about suppliers' openness comes from their release of open-source drivers. That information is available because open-source software development is a transparent process. Specifically, the earliest dates on which firms wrote open-source drivers can be inferred from the Linux kernel's commit history and the Linux Kernel Mailing List.

4.2. Variables

The dependent variable will be **Device Count**, which represents the number of devices a firm releases to the market in a year. Firms take on different roles as assemblers of routers and suppliers of CPUs and Wi-Fi chips. The average CPU firm offers 13 products for sale, while the average Wi-Fi supplier offers 22 products for sale.[6]

Figure 1 plots the distribution of the products provided for sale each year. There is variance across firms. The assemblers of final products buy these components and sell routers. The average router assembler in this data has 3.5 products for sale. Again, there is variance in the number of routers they offer for sale. Appendix Table A4 lists all suppliers covered in the dataset, along with the type of chip they supply.

[Insert Figure 1 about here]

The composition of this data reflects the different structures of the component supply and router assembly markets. For example, most CPUs and Wi-Fi chips are a concentrated market. In this sample, more than half come from firms with ten or more years of experience. In contrast, routers come from many assemblers, experienced and inexperienced firms, from various countries. There is also considerable turnover among them. In this sample, more than half are less than five years old.

The descriptive statistics reveal a basic pattern. The CPU and Wi-Fi chip suppliers can negotiate with many different assemblers. In contrast, the assemblers have more limited options among the suppliers they can negotiate with. While this statement pertains to the stability of the market structure, it is also relevant for econometric identification. It is possible to observe more variance in the options available to CPU and Wi-Fi chip suppliers than among the options available to assemblers. The next set of figures will confirm this intuition.

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event. For example, "Atheros" and "Qualcomm" exist as separate entities until Qualcomm acquires Atheros in 2011, at which point the merged company is treated as "Qualcomm".

[6] The summary statistics broken down by type of supply are in Appendix Table A1, and the correlation tables are in Appendix Table A2.

These data enable the measurement of many variables that are critical for the analysis. **Customer Share** will measure *autonomy*.[7] It is measured as the ratio between the number of customers and the total number of buyers. The following equation describes the measure of customer share:

$$CustomerShare_{it} = \frac{\#Partner\ Assemblers_{it}}{\#Total\ Assemblers_{t}}$$

There are several ways to determine whether a router embodies innovative technology. One measure is **Frontier Technology.** It counts the number of routers that implement the most up-to-date standards at the time of release. Relatedly, **Early Adoption** measures the number of routers whose release date is not after the new standard release date, measured in years. For example, a router using 802.11g (the standard adopted in 2003) released in 2003 would count towards Early Adoption, whereas one released in 2004 would not. Both routers would count towards Frontier Technology. Other possible indicators of innovativeness capture the product complexity. One measure of complexity is **Multiple RF Bands.** It counts routers that implement the 5 GHz bandwidth and more. Another is **Multiple Wi-Fi Standards.** It counts routers that implement at least three IEEE 802.11 standards.

Other variables of interest are features of firms. For example, **Assembler is Entrant** is a count of assemblers founded in the prior two years (in relation to the year of observation). **A Chinese assembler** is a company that has a headquarter in China or Taiwan. Also included are controls for firm features that change over time, such as the maximum/average relationship duration, and dummies for firm age (with the omitted category being age > 10).

4.3. Econometric Model: Staggered Differences-in-Differences

This study employs a difference-in-difference model to address three questions. 1) What are the short-run impacts of releasing open-source device drivers on product numbers and innovative products? 2) Has the effect of releasing open-source device drivers changed over time? 3) Do the impacts from openness fall heterogeneously across different company characteristics?

A difference-in-difference approach initially seems natural for measuring the impact of autonomy. Following the quasi-experimental emergence of OpenWRT, some suppliers opted to integrate the platform via open-source device drivers at various points in time. One way to measure the effect of releasing open-source device drivers is to estimate a Two-Way Fixed Effects regression with an indicator for post-periods among firms that release open-source

[7] It has to be noted that this measurement is computed differently from 'autonomy' in Hoetker et al (2007), but it is functionally equivalent. Early drafts employed the precise formula for autonomy proposed by Hoetker et al (2007) and got qualitatively similar results. Customer share is a simpler measure to understand and gives identical insights. Section A2 in the Appendix provides a detailed comparison of the customer share measure with the autonomy measure proposed by Hoetker et al (2007). We thank an anonymous reviewer for this suggestion.

drivers. However, recent work suggests that simple TWFE estimates can be biased (Callaway and Sant'Anna 2021, Goodman-Bacon 2021, Borusyak et al. 2022).

This study follows Callaway Sant'Anna (2021) in estimating the treatment effects using a staggered difference-in-difference approach. In contrast to the traditional TWFE estimates, staggered differences in differences first construct a building block causal parameter and then aggregate these parameters across different groups and time periods. A benefit of this approach is that researchers can be more explicit about the assumptions required for a causal interpretation, as well as answer policy questions. We provide a detailed discussion of our framework in Appendix Section A3.

We start by defining $ATT(g, t)$ as the average treatment effect of opening device drivers in the year g relative to never opening, at the time t, among suppliers that opened in the period g. Provided that the assumptions about no anticipation and parallel trends are satisfied, Callaway and Sant'Anna (2021) propose estimating the treatment effects as follows:

$$ATT(g, t) = E\left[Y_{i,t} - Y_{i,t=g-1} \middle| G_i = g\right] - E\left[Y_{i,t} - Y_{i,t=g-1} \middle| G_i > max\{g, t\}\right]$$

Here, $Y_{i,t}$ measures product innovation for the supplier i in year t, G_i denotes the year when the supplier i opened, and is set to infinity if i never opens. To illustrate, consider $ATT(2005, 2006)$. This parameter compares the level of product innovations in 2006 by Atheros (one of the companies that released open-source drivers in 2005) with that of other companies that had not yet done so. In short, $ATT(g, t)$ measures the increase in product innovation levels in a year t, for suppliers who opened in the year g.

We then proceed to aggregate our building block measures to summary measures and answer our research questions. First, to measure the short-run impact of releasing open-source software, calculate the average ATT for all treated suppliers within their first 5 years of releasing open-source device drivers. Formally, this is the following summary parameter:

$$ATT_{sr} = \sum_{e \leq 5} \sum_{g < \infty} ATT(g, g + e) \tag{1}$$

This measure provides the average impact of releasing open-source device drivers on product innovation over the first five years, across all suppliers who released open source device drivers. Five years is the natural choice as the short-term period because the median time between new IEEE 802.11 standards releases during this period is between four and six years.

Next, to test whether the effect of releasing open-source device drivers changed over time, aggregate the data by calendar year and examine trends in effect sizes over time. This is the following summary parameter:

$$ATT_{cal}(t) = \sum_{g<\infty} ATT(g,t) \tag{2}$$

This measure allows for the comparison of whether effects are increasing or decreasing over time. For instance, a comparison of $ATT_{cal}(2005)$ against $ATT_{cal}(2018)$ can test whether the effect of releasing open source device drivers on product innovation was greater in the early periods near 2005, or in the later periods of 2018.

Finally, subsample analysis can test whether the benefits from open source fall heterogeneously across different company characteristics. Companies are either large or small based on their historical employee count and revenue. Then, for each group of large and small companies, it is possible to calculate the $ATT(g,t)$ above and aggregate to ATT_{st}. For the heterogeneous effects to be identified, the comparison is restricted to years in which both treated and eventually treated groups exist. Specifically, the heterogeneity analysis is limited to the years 2007 and 2009.

4.4. Identification Assumptions

To identify the building block causal parameter, we make two key assumptions: (i) no anticipation and (ii) parallel trends based on not yet treated groups. This section first states the assumptions explicitly, then elaborates on the threats to identification, as well as the circumstances under which those assumptions are likely to hold.[8]

*No anticipation***.** This assumption states that the treatment effect should be zero in all pre-periods. Violations may occur, for instance, if individuals "anticipate" the treatment via announcements and respond before it actually occurs. In this setting, this concern translates to situations where product innovation increases because assemblers anticipate suppliers' release of open-source device drivers, even before those drivers are made available.

*Parallel trends based on not-yet-treated groups***.** The parallel trends assumption states that, in the absence of treatment, the average untreated potential outcome evolution is the same for both treated and control groups,[9] This assumption can be violated if units select into treatment based on their potential outcomes. For instance, if suppliers have perfect information about their untreated potential outcomes, they could time their open source driver release to maximize

[8] See also Appendix Section A3.2 for detailed identification assumptions, A3.3 for the estimation method, and A3.4 for assumptions regarding heterogeneity analysis.

[9] Note that the assumption pertains to the evolution of unobserved potential outcomes across groups, and thus it is fundamentally untestable.

innovation outcomes and generate different trajectories for untreated potential outcomes. Recent literature shows that some types of selection can be consistent with parallel trends (Marx et al. 2024, Ghanem et al. 2025, Baker et al. 2025). In particular, the literature finds that parallel trends can hold if units select into treatment based on *time-invariant* factors.

We believe the no-anticipation assumption holds for several reasons. First, the time interval between a firm's announcement of open-source device drivers and the actual software appearing in the open-source community is relatively short. Second, the event study plots indicate that all estimates in the pre-treatment period are statistically insignificant from zero, consistent with the no-anticipation hypothesis. Finally, given the short product life cycle of the wireless router industry, fast implementation of technologies is more important than the supplier's commitment to an open source strategy (Eisenmann and Barley 2007).

The parallel trends assumption will hold under three conditions: suppliers decide to release open source drivers primarily to 1) meet legal requirements, 2) in accordance with company culture, and 3) for reasons related to the router product design. Prior work on selective revealing indicates that legal concerns significantly influence firms' decisions to open (Henkel 2006). Additionally, firms often cite a culture of "giving back to the community" as a significant factor to open (Henkel 2006, Musk 2014). Finally, because router production follows modular development practices, firms may be more likely to open devices once an architecture is established and interfaced are defined (Ulrich 1995, Baldwin and Clark 2006, Henkel et al. 2013). Importantly, these three factors tend not to change abruptly over time, and are difficult to shift in the short term (MacDuffie 2013).

Threats to identification arise when time-varying factors influence both a firm's decision to open and its innovation outcomes. One example of a threat is learning. If open source has a positive effect on innovation, and therefore on firm performance, competitors could observe this effect and make informed decisions about their own openness. To the extent that learning is a threat to identification, it should only affect the decision of assemblers later in the sample. As discussed above, suppliers that decided to open early did so not because of the innovation potential, but rather for legal reasons and/or a general ethical requirement toward the community. In Appendix Section 3.5, we discuss the threats to identification in detail. In particular, we find that our results are robust to restricting our sample to firms that released open-source device drivers before 2011, and are therefore less likely to have been exposed to learning.

5. Results

5.1. Summary Statistics

Figure 2 presents descriptive statistics, including the HHI, total number of firms, incumbents, and entrants, over time. Over the past decade, the supplier market has become more concentrated, while the opposite appears to be true for downstream assemblers. The HHI is much larger for CPU and Wi-Fi suppliers than for router assemblers. This is due to the growing number of router incumbents and the relatively flat number of suppliers. Finally, entry into the assembler market is much greater than into the supplier market.

[Insert Figure 2 about here]

Figure 3 presents how the main independent variables change over time for the supplier and assembler groups. Each panel in Figure 3 is a binned scatter plot of the independent variables and years. Figure 3 suggests that suppliers' autonomy and bargaining power increase over time. *Autonomy*, as measured by customer share, is generally greater for suppliers than for assemblers. Notably, Wi-Fi chip suppliers have the greatest autonomy.

[Insert Figure 3 about here]

Further indications of the independent variables can be obtained by examining the summary statistics for the firm-year level observations in Table 1.

[Insert Table 1 about here]

There are approximately 14 years per firm, on average, for the 36 Wi-Fi supplier firms. As can be seen from the low mean and high standard deviation of the Device Count variable, many observations are zero. Zero accounts for approximately 65% (not shown). Customer share ranges from 0 to 0.79, suggesting a high concentration of supplier bargaining power across years. Of the 7.8 devices released annually, 1.5 devices utilize frontier technology (i.e., implement the latest standard), 1.95 devices use multiple RF bandwidths (e.g., 5 GHz), and 4.6 devices implement numerous standards. The average age of an assembler is 19 years, which is consistent with some assemblers being long-established companies in the electronics industry. Entrant firms exist, with 0.25 new assemblers per firm-year joining the sample, and 1.49 assemblers are located in China or Taiwan.

5.2. Autonomy and Device Counts

This section examines the relationship between their autonomy and the number of devices released to the market, presenting preliminary correlations from the estimation of Poisson pseudo-likelihood regressions that include firm and year-fixed effects. Fixed effects for firms measure the many unobservable features that persist over time, such as the average quality of their products, the average reliability of their delivery, and the average level of negotiating leverage with business partners. In addition, fixed effects for time account for the various factors that simultaneously shift supply and demand conditions for all firms, such as macroeconomic fluctuations (e.g., the 2009 downturn) and the introduction of new protocols (e.g., 802.11n in 2008, and 802.11ac in 2014). Fixed effects also imply that statistical identification arises from changes in a firm's situation over time. That also limits the set of controls. Each regression includes controls for firm features that change over time, such as the maximum/average relationship duration, and dummies for firm age (with the omitted category being age > 10).

Results are reported in Table 2, separated by suppliers, columns (1) and (2), and assemblers (columns (3) and (4)). Section A1.2 in the Appendix demonstrates that these results are robust to the use of ordinary least squares and log-transformed dependent variables.[10]

[Insert Table 2 about here]

Autonomy is positively associated with device counts, especially for suppliers. Moreover, the estimates are precise. Overall, the estimated coefficients suggest that autonomy significantly influences outcomes. Consider Wi-Fi and CPU suppliers. Moving from the median to the 75th percentile (an increase of 0.0329 for Wi-Fi and 0.02 for CPU suppliers) corresponds to a 23.46% increase in the number of devices for Wi-Fi suppliers and a 19.7% increase for CPU suppliers.

The estimate for maximum duration has the expected sign for suppliers and is statistically significant. It is moderately influential. Wi-Fi and CPU suppliers with the oldest relationships (four or five years) manage to introduce half of the devices. That is small against the mean number of devices. In the case of Wi-Fi and CPU assemblers, maintaining an established relationship for four years also results in the introduction of half a device, which is moderate compared to the mean level of devices.

Finally, the estimates for a firm's age generally have little effect and are not estimated with precision. If experience matters at all, it matters to the extent that firms can maintain relationships over extended periods of time. Even in this case, it matters only moderately.

Altogether, these estimates confirm that autonomy is the most critical factor in shaping the introduction of new devices. Because the devices embody innovative new designs, these findings suggest that the structure of the supply chain significantly influences the rate at which innovation reaches consumers.

Overall, Table 2 paints a picture in which the role of autonomy is similar for both Wi-Fi and CPU firms. Autonomy is positively associated with device counts, and young firms tend to have fewer devices. Does autonomy also impact the quality of products created? For this question, the

[10] Similar results emerge from estimating the same specification using alternative definitions for autonomy and log device counts as the dependent variable. See Appendix Tables A5A, and A12 and A13.

sample focuses solely on Wi-Fi suppliers, as they are the most significantly impacted by open-source device drivers.

[Insert Table 3 about here]

Table 3 estimates a Poisson pseudo-likelihood regression to measure the impact of autonomy on technological innovations. Specifically, the endogenous variables are: the number of products using Frontier Technologies (Column 1), Early Adoption (Column 2), Products with multiple radio frequency bands (Column 3), and Products that support multiple Wi-Fi standards (Column 4).

Across all specifications, a positive association exists between autonomy and innovative products. Again, a firm moving from the median to the 75th percentile of autonomy (increase in customer share of 0.0329) is associated with a 14.87% increase in products using frontier technologies, a 18.76% increase in products introduced by early adopters, a 16.17% increase in products implementing multiple radio frequency bands, and a 22.3% increase in products that support multiple Wi-Fi standards.

5.3. Staggered Difference in Differences

This exercise first examines the short-term effects of releasing open-source software on product innovation. Table 4 reports the result of estimating the summary parameter in equation (1) using the Callaway Sant'Anna (2021) method. The not-yet-treated groups are controls, clustering standard errors at the firm level.

[Insert Table 4 about here]

Panel A of Table 4 indicates that releasing open source drivers has a positive overall impact on product innovation. Column (1) shows that, on average, firms experience an increase of 16 in the number of products released as open source within the first 5 years. Consistently with the main hypotheses, this appears to be the consequence of an increase in supplier bargaining power (see Column 2). In addition to having more products overall, columns 3-5 show that these products are more innovative overall (Column 3 and Column 4), and more complex as they are more likely to implement multiple radio frequency bands (Column 5), and more likely to implement multiple wireless standards (Column 6) than the control group suppliers. Panel B estimates the effects separately for each cohort. Casual observations suggest that the returns to opening are decreasing over time. Firms that released open source before 2011 see positive effects on product innovation and customer share, but the effect is negative for firms that open later.[11]

[11] Appendix Table A9 show qualitatively similar results when using log-transformed outcome variables.

Next, Figure 4 shows event study plots for the variables during this period. It documents the time evolution of effect sizes and check for pre-trends. Across all the graphs, the effect sizes are zero for the pre-treatment periods, suggesting that the no-anticipation assumption holds. As for the time evolution of effects, increases in device counts peak around year 4 of opening. For autonomy and products with frontier technologies, the effects peak around year 2. This is consistent with wireless routers' short product life cycles.

[Insert Figure 4 about here]

Finally, Table 5 estimates the impact of opening by suppliers on the type of assemblers they attract. Overall, the table is consistent with the notion that open-source device drivers lower barriers to entry for assemblers. Column (1) shows that, on average, the assemblers with which a supplier works are around 9 years younger. Similarly, column (2) shows that assemblers are more likely to be firms that entered within the previous three years. On average, when suppliers release open source device drivers, they interact with 0.55 more assemblers that were founded within the previous two years. Interestingly, these assemblers tend to be foreign assemblers. Column (3) shows that suppliers that release open source drivers work with 2.2 more Chinese assemblers than firms that do not. Appendix Figure A1 plots event study graphs for Table 5.

[Insert Table 5 about here]

5.4. Heterogeneous Effects

Appendix Table A14 outlines the timeline for releasing open-source drivers. This section tests for heterogeneous effects across time and across different company types. For this, the $ATT(g,t)$ metrics are aggregated across calendar years, as in equation (2), and a figure plots them over time. If an upward trend in the estimates exists, this suggests that the benefits of open source increase over time. In contrast, a downwards trend would indicate that the benefits of open source are concentrated in the early periods, and that first movers are more advantageous for product innovation.

Figure 5 plots the results of the estimation equation (2) across calendar years. For the product count (panel a), the effects are positive and significant for the first half of the sample period, but are mostly insignificant from zero in the latter periods. This suggests that the benefits of releasing open-source software are concentrated in the early stages of open-source development. Panel b is consistent with this evidence. There are positive and significant increases in supplier bargaining power in the same early periods. Panel c shows again that for earlier years, open source attracts first-time assemblers. Notably, in 2005 and 2011, open-source software appeared to have attracted first-time makers of wireless routers. Finally, panel d shows that open source allows foreign firms, particularly Chinese and Taiwanese firms, to develop products for sale in the US.[12]

[Insert Figure 5 about here]

The third and last question asked whether the effect of releasing open source is different for large and small companies. Table 6 presents estimates of equation (1) using subsamples of different companies. Appendix Table A14 lists the suppliers, along with their categorization into large and small companies.

There are two panels in Table 6. Each of them repeats the results of Table 2. Panel A displays the results for large companies, while Panel B presents the results for small companies. Across all metrics, large companies are responsible for the increase in product innovation. Coefficient estimates for the subset of small companies are smaller and statistically insignificant. These results are consistent with the hypothesis that open source software requires scale a complementary asset. When releasing open-source software, the uncertainty surrounding smaller firms, and perhaps the relative lack of complementary assets, negates the benefits of having more flexible development methodologies, particularly when small firms are entrants and/or foreign assemblers. Therefore, even if small companies release open-source software, they are unable to attract developers and do not experience a corresponding increase in their market share or bargaining power.

[Insert Table 6 about here]

All in all, the staggered difference-in-differences results highlight how open-source strategies enable suppliers and assemblers to "profit from implementation." First, the results demonstrate that openness leads to increased autonomy for suppliers of Wi-Fi chips, as well as an increase in the number of products they create. Consistent with suppliers' increased autonomy, openness leads to partnerships with younger assemblers, new market entrants, and foreign assemblers. Furthermore, openness allows suppliers to innovate faster. Their products are closer to the frontier and more complex, as measured by the latest 802.11 standards and radio frequencies. These effects seem to be concentrated in large suppliers, consistent with the idea that they tend to benefit from a scale advantage and complementary assets compared to smaller firms.

6. Conclusion

[12] In the Appendix Table A7, we provide the point estimates and standard errors in table form. Additionally, in Appendix Figure A2, we present the calendar year plots for our other dependent variables.

This study examines the influence of openness on the relationship between a firm's position in the supply chain and its introduction of new products. The study finds evidence of an association between a firm's role in the supply chain and its ability to introduce new products. Specifically, a firm's *autonomy* has a positive influence. These findings apply to various supply chains, including those of Wi-Fi chip suppliers and CPU suppliers.

When suppliers provide open-source drivers and share information, their autonomy and product introductions increase compared to those that do not introduce open-source drivers. The study finds that an increase in openness has a significant statistical effect on introducing new products, primarily through its impact on autonomy. The numerical evidence is substantial and can be interpreted as a measure of the change in options that influence a firm's negotiating position.

These estimates provide evidence that openness increased product introductions by enlarging the number of options available to component suppliers. It enables them to not only introduce more products but also more innovative ones (i.e., closer to the frontier) and complex ones.

The mechanism did not work equally well for all suppliers. Larger suppliers and suppliers of both Wi-Fi and CPUs experience the biggest benefits. No evidence suggests that smaller suppliers and assemblers experience much of a benefit. Differences between Wi-Fi and CPU suppliers do not arise. The interpretation is that large suppliers benefit the most due to numerous existing relationships, scale, and complementary assets.

Our study contributes to the literature on the effect of openness on the frequency and the nature of product innovation. It shows that openness leads to more products and a greater number of products on the frontier, and identifies the underlying mechanism. The identification of autonomy as a crucial variable through which openness benefits firms, is also a contribution to the literature on buyer-supplier interactions as supplier openness attracts assemblers, increase their bargaining power, and have a faster time-to-market. Finally, the study also contributes to the literature on openness and entrepreneurship by highlighting that openness can attract entrant assemblers. Assemblers in this market suffer from high entry costs from software licenses, as well as fear being locked into a particular platform. Foreign assemblers looking to enter the US market face higher risks. The evidence is consistent with openness lowering these costs, allowing innovative firms to enter the market. Furthermore, these firms tend to create more innovative products faster.

The study suffers from two main limitations that pave the way for future analyses. First, we lack information about product-level sales data. We see that openness leads to an increase in product innovation and quality, but we do not directly observe the effect on sales or market outcomes. Given that the product portfolio for both assemblers and suppliers is diverse, we do not observe the firm-level implications for revenue. Future analyses on the impact of openness on firm performance could document whether products created by open suppliers generate higher sales volumes, have higher margins, or have brand longevity.

A second limitation is that these results pertain to a specific industry, wireless routers, that established a standard at an early stage in product development and continually improved it over time. Investigating whether the insights hold in other markets that display these “horizontal” features over the long term would be worthwhile. It would also be interesting to learn if the impact holds when standards emerge long after product markets are established. The results also indirectly raise questions about vertically organized production, which may potentially lose the benefits of new partnerships because it cannot capitalize on openness. Further research could investigate the costs of these missed opportunities.

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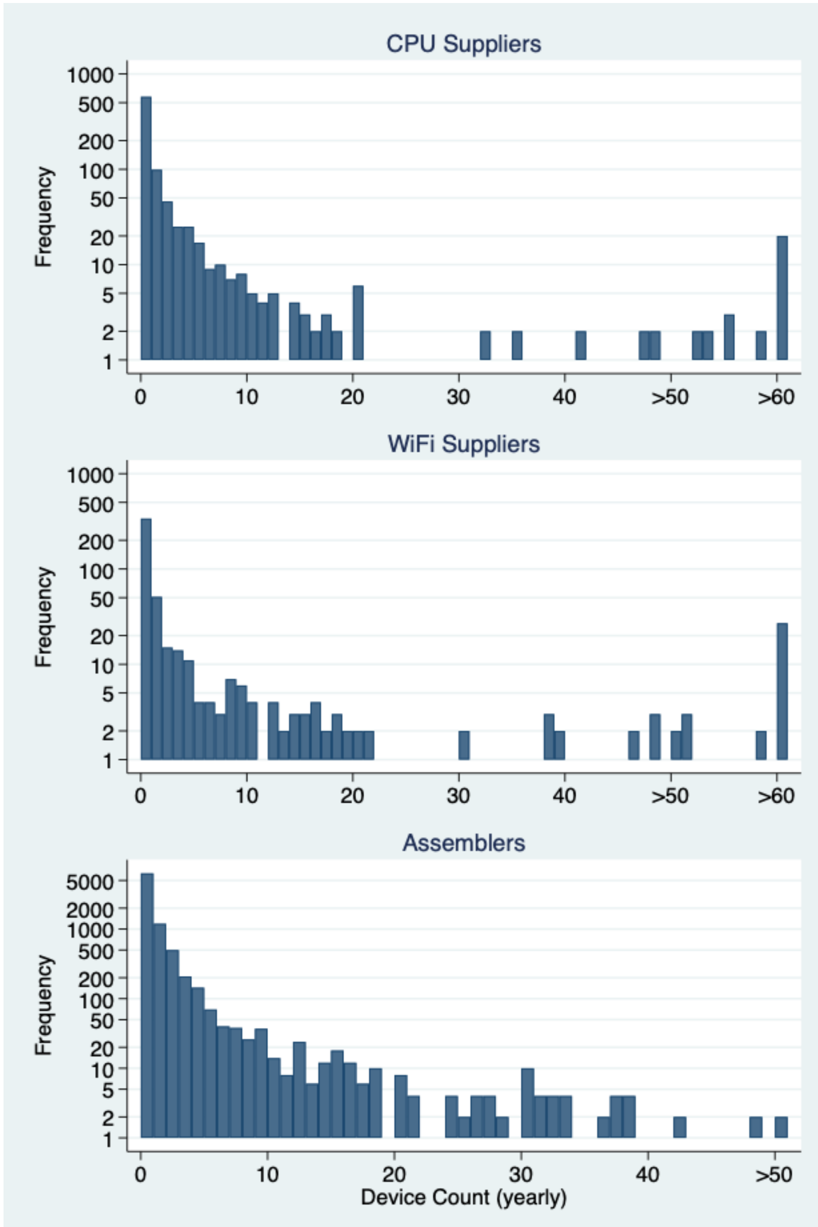
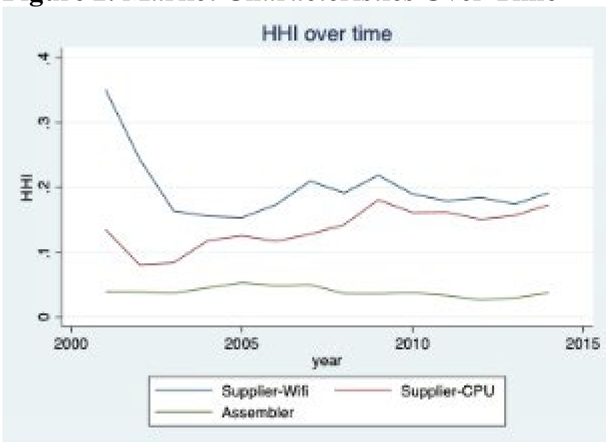
Figure 1. Distribution of product counts

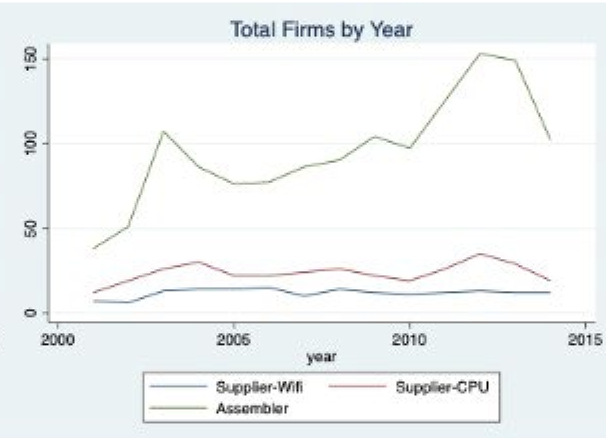


Notes. Histograms of the number of new devices released by suppliers in a given year. Each bar denotes the number of firm-year observations with 0 devices, 1 device, and so forth. For Wi-Fi suppliers, the maximum number of devices is 128 in a single year. For CPU suppliers, the maximum is 115 devices, and for assemblers it is 53.

Figure 2. Market Characteristics Over Time

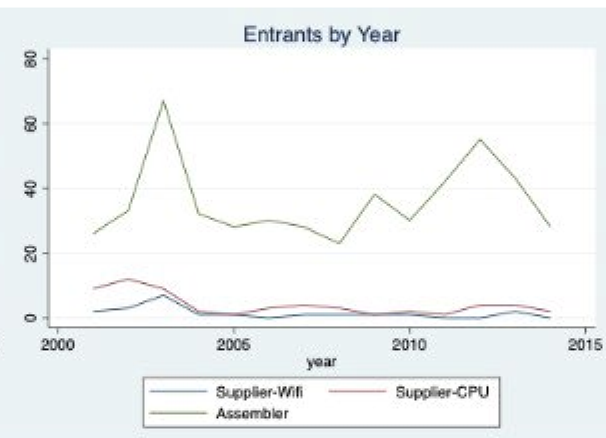


(a) HHI



(b) Total Firms

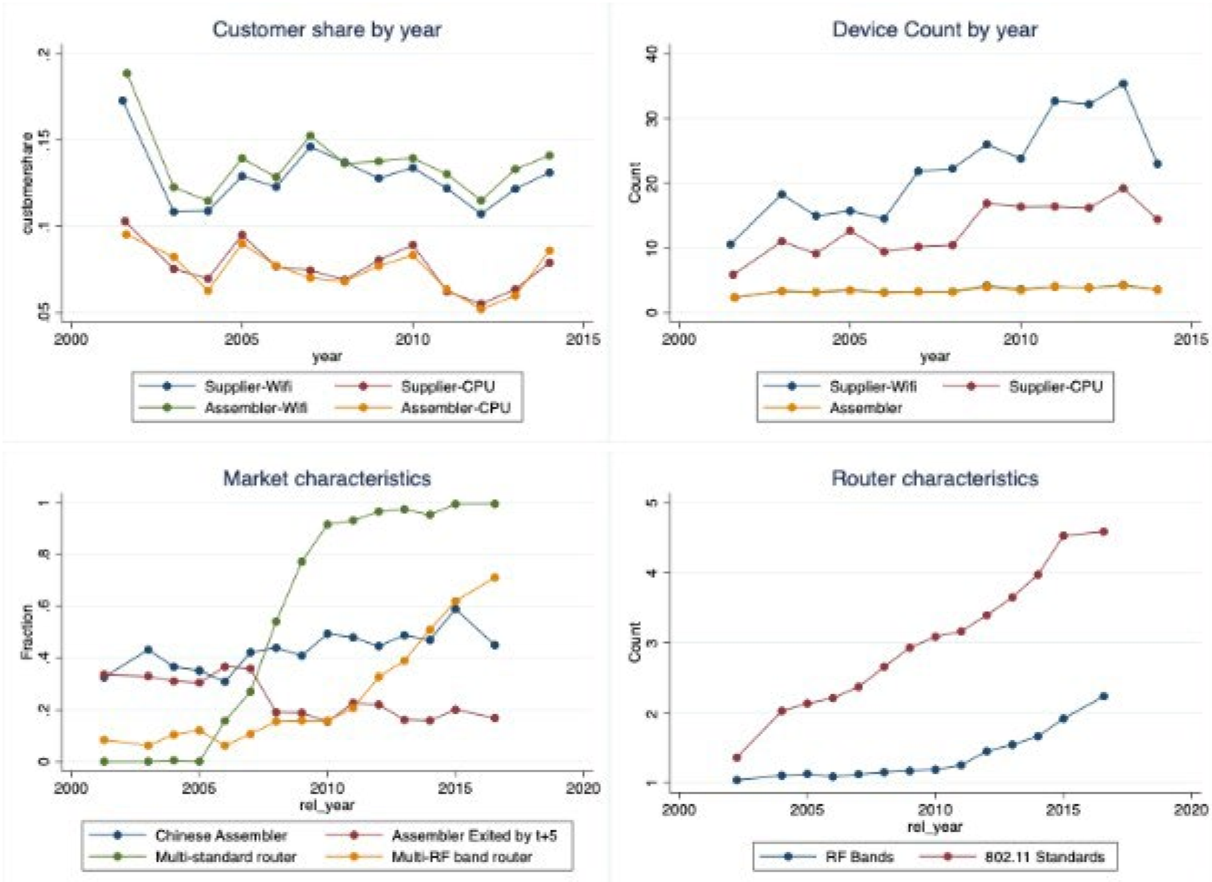
(c) Incumbent Firms



(d) Entrants

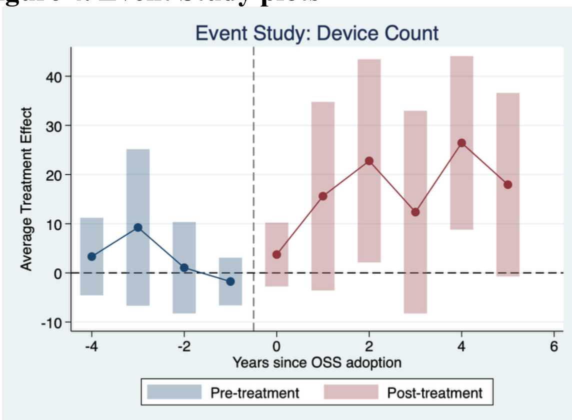
Notes. Plots of the HHI (Panel A), Total number of firms (Panel B), Incumbent firms (Panel C), and Entrants (Panel D) over time for suppliers and assemblers. Incumbents are firms that released new products in that year, who were not entrants.

Figure 3. Binned Scatterplots of Independent Variables

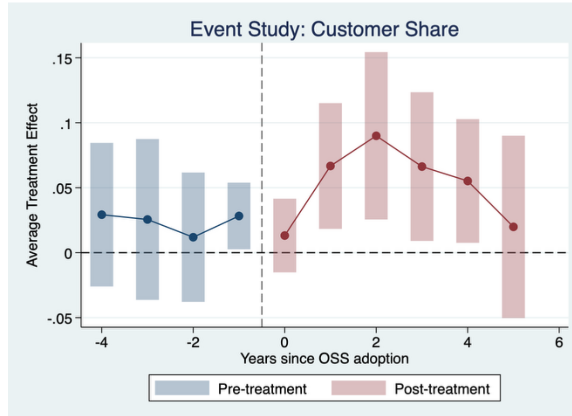


Notes. Binned scatterplots using the "binscatter2" command in STATA. Panels present autonomy as measured by Customer share (Panel A), Device count (Panel B) over time for assemblers and suppliers, Market characteristics (Panel C), and Product characteristics (Panel D). Each point on the graph is the average value of the variable across all firms that released a product in that year.

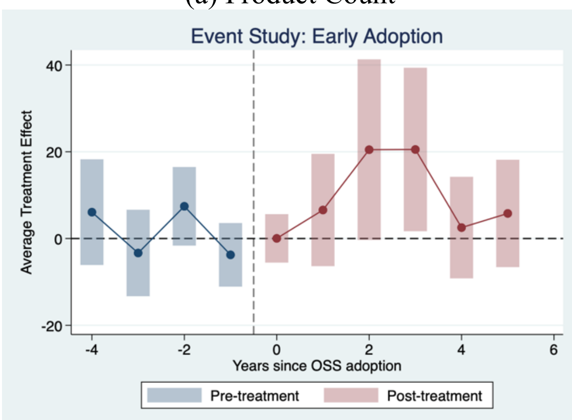
Figure 4. Event Study plots



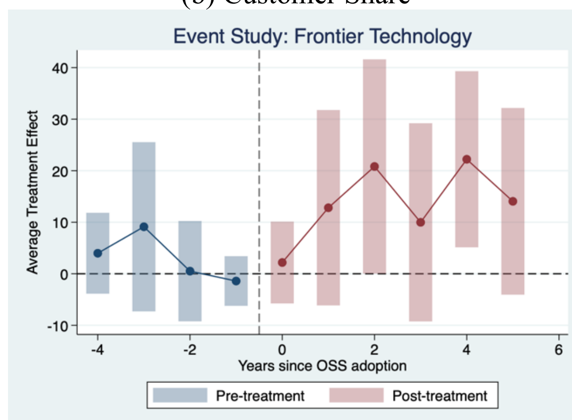
(a) Product Count



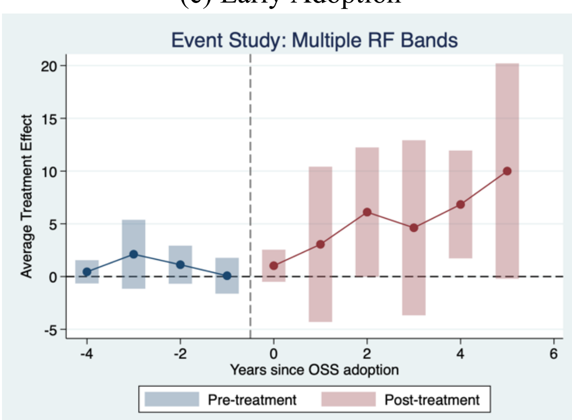
(b) Customer Share



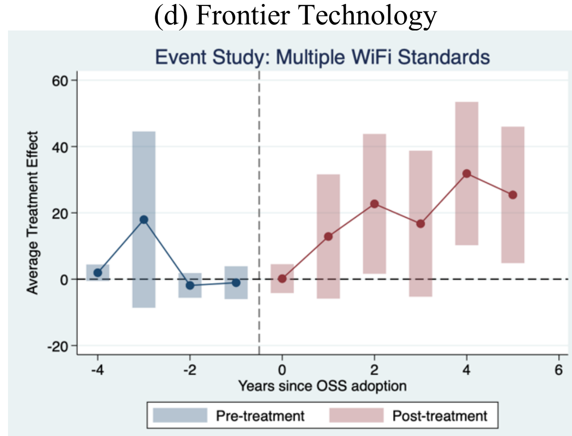
(c) Early Adoption



(d) Frontier Technology



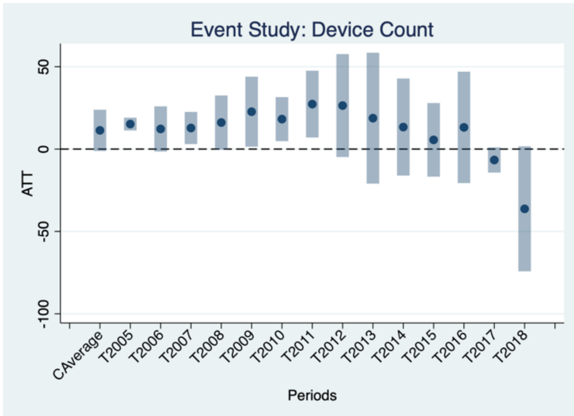
(e) Multiple RF Bands



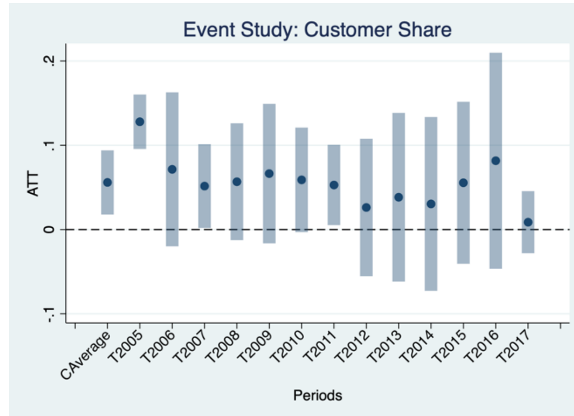
(f) Multiple Wi-Fi Standards

Notes. Aggregate event study plots using the "csdid_plot" command from the csdid package in STATA. The x-axis denotes the years since a firm releases open source device drivers. The y-axis measures the estimated average treatment effect for a particular point in time. Each point aggregates the ATT(g,t) across all treated groups at a given point in time. There is no "baseline" year, as with standard two-way fixed effects estimators, as the ATT(g,t) compares the average at some t compared to t=-1. Dependent variables for panels are (a) product counts, (b) customer share, (c) early adoption (product adopted standard within 1 year), (d) frontier technology (product uses frontier standard), (e) product uses multiple RF bands, (f) Product implements multiple Wi-Fi standards.

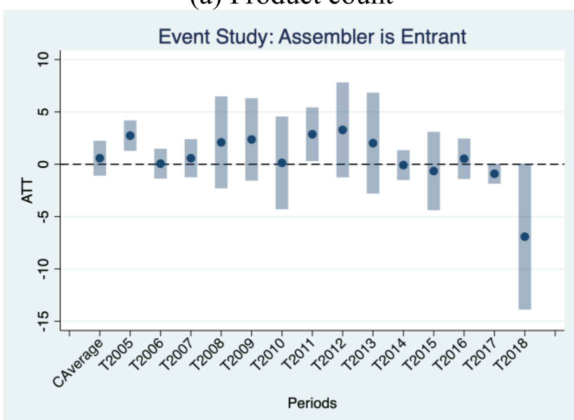
Figure 5. Heterogeneous effects across time



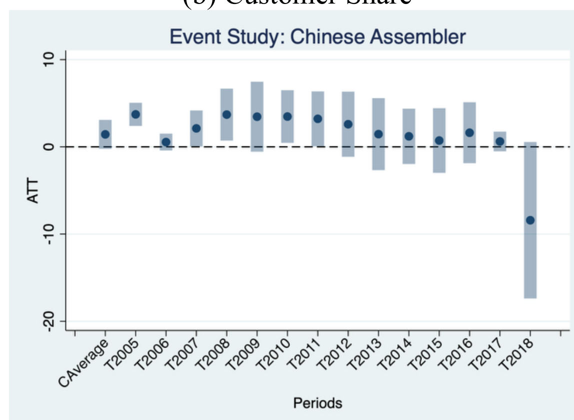
(a) Product count



(b) Customer Share



(c) Assembler is an entrant



(d) Chinese assembler

Note. Calendar year plots of effect sizes using the "csdid_plot" command from the csdid package in STATA. The x-axis denotes a calendar year, and the y-axis denotes the average of the ATT(g,t) for a calendar year. $ATT_{cal}(t)$.

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Table 1. Summary Statistics

	count	mean	sd	min	max
Device Count	510	8.39	20.90	0	128.00
Customer Share	510	0.05	0.12	0	0.79
Frontier Technology	510	1.47	7.90	0	106.00
Multiple RF Bands	510	2.53	7.93	0	59.00
Multiple Wi-Fi Standards	510	5.18	17.58	0	120.00
Large Company	510	0.32	0.47	0	1.00
Entrant Assemblers	510	0.25	0.80	0	8.00
Chinese Assemblers	510	1.63	3.85	0	23.00
Supplier Age	492	17.72	16.96	0	87.00
Assembler Exited (within 3 years)	203	0.09	0.30	0	2.00
Avg. Assembler Age	203	18.87	13.26	0	99.00
Max Relationship Duration	203	3.79	3.98	0	15.00
Average Relationship Duration	203	1.63	1.93	0	9.00

Note. Summary statistics for the main variables in the Wi-Fi supplier data at the supplier firm-year level. The number of observations for Supplier Age and below is smaller than the total count because those variables are not defined when a firm does not produce any devices in a given year.

Table 2. Are Device Counts associated with the change in Autonomy?

	(1) WLAN-Supplier	(2) CPU-Supplier	(3) WLAN-Assembler	(4) CPU-Assembler
Customer Share	6.409***	8.991***	6.741***	10.542***
	(0.763)	(1.020)	(1.043)	(1.644)
Max Relationship Duration	0.221***	0.161***	-0.077*	-0.013
	(0.054)	(0.042)	(0.044)	(0.040)
Average Relationship Duration	-0.034	-0.000	0.224***	0.207***
	(0.046)	(0.053)	(0.050)	(0.047)
Firm Age<5	-1.081***	-1.020***	-0.352	-0.531**
	(0.405)	(0.214)	(0.227)	(0.217)
Firm Age>5 but <=10	-0.684**	-0.364**	-0.114	-0.266*
	(0.274)	(0.162)	(0.136)	(0.140)
Constant	0.666**	0.510**	-0.462*	-0.622***
	(0.285)	(0.230)	(0.250)	(0.232)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Log-Likelihood	-828.61	-1231.71	-3181.26	-3183.67
Observations	492	859	4099	4145

Note. Coefficient estimates from a Poisson pseudo-likelihood regression with fixed effects using the ppmlhdfe package in Stata. Observations are at the firm-year level. Outcome variable counts the number of devices released in a firm-year. Customer Share measures the autonomy of a firm. Relationship Duration and Firm Age are for the focal firm, and measure supplier age (columns 1 & 2) or assembler age (columns 3 & 4). Standard errors in parentheses, clustered at the firm level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Are Frontier Products associated with the change in Autonomy?

	(1) Frontier Technology	(2) Early Adoption	(3) Multiple RF Bands	(4) Multiple Wi-Fi Standards
Customer Share	6.711***	5.226***	4.669***	6.175***
	(0.770)	(0.747)	(1.202)	(0.706)
Max Relationship Duration	0.243***	0.279**	0.171**	0.237**
	(0.066)	(0.124)	(0.074)	(0.096)
Average Relationship Duration	-0.019	-0.177	-0.017	-0.033
	(0.064)	(0.173)	(0.101)	(0.044)
Firm age<5	-1.015**	-0.166	-0.204	-1.757***
	(0.424)	(1.028)	(0.735)	(0.609)
Firm age>5 but <=10	-0.609**	-0.115	0.272	-0.338
	(0.297)	(0.350)	(0.481)	(0.261)
Constant	0.356	0.481	0.082	0.156
	(0.266)	(0.505)	(0.432)	(0.660)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Log-Likelihood	-777.77	-243.93	-434.47	-370.51
Observations	406	131	337	163

Note. Coefficient estimates from a Poisson pseudo-likelihood regression with fixed effects using the ppmlhdfe package in Stata. Observations are at the firm-year level. Outcome variables are counts of the number of devices satisfying a particular product characteristic, released in a firm-year. Customer Share measures the autonomy of a firm. Relationship Duration and Firm Age are for the focal firm, and measure supplier age (columns 1 & 2) or assembler age (columns 3 & 4). Standard errors in parentheses, clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Short-run effects of openness on innovation

Panel A: Simple Weighted Average ATT

			Technological Frontier		Product Complexity	
	Device Count	Customer Share	Frontier Technology	Early Adoption	Multiple RF Bands	Multiple Wi-Fi Standards
ATT	16.092**	0.051***	13.559**	9.510*	5.082*	17.889**
	(7.113)	(0.019)	(6.892)	(5.577)	(2.793)	(7.572)

Panel B: Group-Specific ATT by Treatment Cohort

	Device Count	Customer Share	Frontier Technology	Early Adoption	Multiple RF Bands	Multiple Wi-Fi Standards
GAvg	13.627***	0.044***	10.849***	8.922***	4.355***	15.624***
	(2.546)	(0.007)	(2.429)	(3.045)	(0.813)	(3.192)
G2005	22.650***	0.051***	13.491***	33.935***	-1.087***	33.135***
	(1.787)	(0.017)	(1.564)	(0.438)	(0.394)	(0.438)
G2006	1.307	0.007	1.191	-0.665	-0.052	-0.596
	(1.097)	(0.008)	(1.064)	(0.438)	(0.401)	(0.369)
G2007	29.944***	0.088***	29.113***	17.625**	7.677***	34.325***
	(7.142)	(0.017)	(6.760)	(7.579)	(2.332)	(9.207)
G2009	-1.686	-0.013	-2.429	-1.644	-0.874	-1.635
	(2.059)	(0.011)	(2.084)	(1.065)	(0.532)	(1.985)
G2011	59.038***	0.163***	48.696***	-10.865***	30.511***	52.954***
	(1.986)	(0.008)	(1.918)	(0.031)	(0.546)	(1.905)
G2012	-1.916	-0.009	-2.532	-0.400	-0.662	-2.027
	(1.959)	(0.008)	(2.268)	(0.390)	(0.556)	(1.878)
G2015	-27.455***	0.018***	-35.664***		0.119	-24.507***
	(0.170)	(0.001)	(0.176)		(0.074)	(0.165)
G2017	-6.500***	-0.025***	-6.583***		-5.528***	-5.500***
	(0.104)	(0.003)	(0.081)		(0.100)	(0.104)

Note. This table reports treatment effects from the Callaway and Sant'Anna (2021) estimator.
Panel A shows simple weighted average treatment effects across all cohorts.
Panel B shows group-specific average treatment effects by treatment cohort (year of OSS adoption).
Standard errors clustered at the firm level are reported in parentheses.
The 'not-yet-treated' units are used as the control group.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Mechanisms for attracting firms.

Panel A: Simple Weighted Average ATT

	(1)	(2)	(3)
	Assembler Age	Assembler is Entrant	Chinese Assembler
ATT	-8.927***	0.549**	2.196**
	(3.079)	(0.216)	(1.048)

Panel B: Group-Specific ATT by Treatment Cohort

	Assembler Age	Assembler is Entrant	Chinese Assembler
GAverage	-5.358*	0.466***	1.840***
	(3.041)	(0.115)	(0.430)
G2005	-14.655***	1.404***	2.577***
	(3.372)	(0.115)	(0.639)
G2006	-9.981**	0.221***	-0.247
	(4.550)	(0.062)	(0.194)
G2007	-7.846	0.545*	5.266***
	(4.777)	(0.281)	(1.135)
G2009	-13.740***	0.050	-0.267
	(4.855)	(0.153)	(0.466)
G2011	-13.007*	1.530***	4.931***
	(7.269)	(0.059)	(0.423)
G2012		-0.117	-0.502
		(0.098)	(0.381)
G2015	3.028	-0.196***	-4.183***
	(8.009)	(0.053)	(0.063)
G2017	24.500		-1.028***
	(19.644)		(0.083)

Note. This table reports treatment effects from the Callaway and Sant'Anna (2021) estimator.
Panel A shows simple weighted average treatment effects across all cohorts.
Panel B shows group-specific average treatment effects by treatment cohort (year of OSS adoption).
Standard errors clustered at the firm level are reported in parentheses.
The 'not-yet-treated' units are used as the control group.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Large vs small firms

Panel A: Simple Weighted Average ATT (Large Suppliers)

			Technological Frontier		Product Complexity	
	Device Count	Customer Share	Frontier Technology	Early Adoption	Multiple RF Bands	Multiple Wi-Fi Standards
ATT	29.646***	0.077***	28.304***	16.833**	6.991**	34.308***
	(8.406)	(0.028)	(8.430)	(8.231)	(2.931)	(10.161)

Panel B: Simple Weighted Average ATT (Small Suppliers)

	Device Count	Customer Share	Frontier Technology	Early Adoption	Multiple RF Bands	Multiple Wi-Fi Standards
ATT	7.162	0.031**	5.023*	20.410**	0.667	10.714
	(4.427)	(0.015)	(2.763)	(9.133)	(1.310)	(7.432)

Note. This table reports treatment effects from the Callaway and Sant'Anna (2021) estimator.
Panel A shows simple weighted average treatment effects for Large suppliers (more than 6000 employees, or $2B in revenue).
Panel B shows simple weighted average treatment effects for Small suppliers (less than 6000 employees, or $2B in revenue).
Standard errors clustered at the firm level are reported in parentheses.
The 'not-yet-treated' units are used as the control group.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$