Open Devices and Slices: Evidence from Wi-Fi equipment.

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Abstract. Prior studies suggest that openness shapes the introduction of new products. This study collects novel data on all routers and subcomponents introduced between 2000 and 2018. We characterize each firm's position in a supply chain as upstream component providers or downstream router assemblers. We explore the quasi-natural experiments afforded by the staggered introduction of open-source drivers to estimate the impact of openness in supply chains on innovation. Following prior literature, we measure a firm's ability to negotiate with current and potential partners. We find evidence that the influence of openness depends on the firm's level of autonomy and restructuring. The most prominent component suppliers benefited from increased openness by expanding their opportunities to do business with others. In contrast, we see little evidence that openness induced entrants, small firms, or assemblers to introduce new products.

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1. Introduction

Does openness lead to more innovation in the form of new products? Many examples support the conventional intuition that openness plays a beneficial role in creating new products. Still, these examples also typically come with additional presumptions about modularity and the role of standardized interfaces in complex products. (Baldwin and Clark 2006, Henderson and Clark 1990).[2] The conventional intuition 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. That example captures attention because a large dominant firm introduced a modular and open design, enabling many complementary providers to enter. Openness raised the short-run market value of personal computers supplied by IBM and the importance of compatible components. The example also serves as a cautionary tale, as IBM's open modular design became imitated by clones. IBM lost market leadership in the long run as the system of compatible suppliers lived on (Bresnahan and Greenstein 1999).

Since then, many examples have been analyzed to understand the broader questions about openness and innovation. The meaning of open and closed varies in theory, and different market environments shape how firms bring products to market in practice. In addition, the literature entertains a variety of definitions for openness. In this study's post-millennial market for wireless routers, for example, openness has three distinct meanings. First, the standards committee that designs the protocols for routers is "open" because these new protocols are released without restrictions on who can learn about them and how they are used (Simcoe 2012, West 2007). Second, some router components are more "open" than others because no single party controls their development or usage (Boudreau 2010, West 2003). Third, by reputation, some component suppliers have been more "open" and willing to release open-source software voluntarily (Henkel 2006, Nagle 2018). For instance, CPU suppliers in this market have been more willing to support compatibility with open-source software, whereas Wi-Fi chip suppliers have not. In practice, we can observe the variance in the latter two factors and test for consequences.

Specifically, did the amount of innovative behavior, as measured by the number of product introductions, change after one firm, or one set of suppliers, became more open? Conventional reasoning does not provide a definitive prediction. Consider introducing open-source drivers, a software component (see Glossary in Table A3 for definitions). On the one hand, introducing openness decouples drivers from the other components and enables specialization (Arora and Bokhari 2007, Kretschmer et al. 2022, Kuan and West 2023, West and Wood 2014). The reduced barriers to obtaining information lower the cost of entry, and the increase in customer satisfaction could grow the market size in this segment. On the other hand, making some information non-proprietary gives firms fewer tools for protecting their margins and reduces the incentives to enter (Alexy et al. 2018, Alexy and Reitzig 2013, Bhaskarabhatla and Hegde

[2] Complex products tend to be made of more than one component. Components are usually made by different firms and traded in the market. To work well together, components need to share standard interfaces, and the role of a coordinator is important (Fontana and Greenstein 2021, Kuan and West 2023). Standardization and stability of interfaces over time favor specialization and division of labor between component suppliers and assemblers along the supply chain (Langlois and Robertson 1992), increase the flexibility of the relationships between them (Galunic and Eisenhardt 2001, Garud and Kumaraswamy 1995), reduce switching costs and risk of lock-in (Farrell et al. 1998). In addition, it increases the range of components assemblers can choose to design their final products and nurtures product differentiation and variety (Ethiraj and Levinthal 2004, Langlois and Robertson 1992).

2014, Henkel 2006, Nagaraj 2022). It is an empirical question about which effect is most important in practice.

Openness, defined as unrestricted access to information, matters because of its effects on a firm's bargaining position within a supply chain and final assembly (Hoetker 2005, Reitzig 2004, Teece 1986). Openness can shape the number of partners a firm chooses, the duration of the relationship, and, consequently, the number of new products. Openness can allow some firms to reshuffle their business relationships frequently to find better combinations while incentivizing others to retain longer relationships, concentrating on stabilizing their networks of suppliers and buyers. It also impacts how firms interact with business partners, and how they use their relationships with partners to support introducing innovative products.

This study contributes to the agenda of openness and innovation by measuring how a firm's position in a supply chain enables or hinders the introduction of new products. We analyze novel data on all routers built using IEEE 802.11 standards and on all the subcomponents in each supply chain introduced in the United States between 2002 and 2018 ad we ask the following questions: does the opening of software – i.e., eliminating restrictions on who has access to and controls the technical specifications – alter firms' introduction of new products? How does this depend on a firm's relationships with other component suppliers and final assemblers in a supply chain? The first router using 802.11, the Apple Airport, was introduced in 1999, so this data covers the entire history of all the supply chains in this market. We identify supplier-buyer relationships and identify every firm's upstream and downstream positions. This covers the experience of 255 assembler firms with 3,239 observations. There are also 63 component suppliers, 33 of which only build CPU chips, 11 of which only build Wi-Fi chips, and 19 that supply both (see the Glossary in Table A3 for definitions). On the supplier side, we see 541 Wi-Fi observations and 911 CPU observations. Each assembler and component supplier receives one observation each year.

The router is an ideal setting for researching new product introductions. First, this large and vital market has grown tremendously in its first two decades. Wi-Fi router equipment started from almost nothing at the turn of the millennia and grew into nearly 12.5 billion dollars market worldwide in 2020.[3] Demand grew as wireless routers grew in usage and popularity, and this was due, in no small part, to the actions of the 802.11 committees, which continued to release protocols that enabled improvements in the performance of products. Many firms responded to these conditions and entered with new designs, supporting a wide range of innovative products for many segments of users. In turn, those products were supported by both straightforward and complex supply chains involving many of the same suppliers and assemblers over time and hundreds of new entrants.

The structure of the market also makes these activities ideal for analysis. No firm has integrated into supplying the "entire stack." One set of companies provides CPUs, another Wi-Fi chipsets, while yet another group of companies assembles the products before distribution. This separation between the identities of upstream and downstream providers enables us to observe many configurations of upstream and downstream firms. Two different firms rarely interact with precisely the same suppliers and assemblers, so the structure varies widely across firms and changes over time. Moreover, growth in demand continued for almost two decades, generating various outcomes, which is ideal for statistical

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

analysis. Additionally, the documentation is unusually complete for product introductions. We can observe whether different configurations of supply result in more products in final goods markets – i.e., coming from assemblers – or inside the supply chain – i.e., coming from CPU and chip suppliers. Observing so much in a supply chain is rare.

Our research goals require measuring a firm's position in the value chain in several ways. Following prior analysis, we focus on a firm's abilities to negotiate with a partner it interacts with (Hoetker et al. 2007). We label these abilities as *current autonomy* and *potential autonomy*. For suppliers, increased autonomy – brought about by increasing openness – entails better opportunities to sell their components to more possible assemblers. For assemblers, increases in autonomy entail less reliance on a limited number of suppliers for their key components. That also can be interpreted as the result of strong negotiating positions. We expect to observe a positive correlation between increasing autonomy and new product introduction by suppliers and assemblers. We can directly test these predictions in our data.

We also measure a firm's ability to add or subtract from existing relationships (Khanna et al. 2022), which we call *restructuring*. Too much restructuring –adding or removing partners –should interfere with increasing new product introduction by creating coordination issues.[4] However, a moderate amount of restructuring would be expected with any new business initiative, such as introducing new products. The tension between these will likely lead to a non-linear relationship between device counts and restructuring, another prediction we can directly test in our data.

More crucial for our research goals, the supply chains for routers changed after the opening of the designs in some products due to the staggered release of open-source software. We exploit such events as quasi-natural experiments that changed market structure. Each release reduced the information barriers to technical knowledge and altered the conditions for entry. Introducing openness may shape the formation and dissolution of ties between suppliers and buyers in a supply chain. Moving from a closed to an open system allows suppliers to focus on manufacturing only one component with consequent gains in specialization and minor costs compared to when they produce for multiple segments. To examine these mechanisms, we adapt the measures of *autonomy* and *restructuring*, and, following the reasoning of prior research, we expect increases in openness to increase both and lead to more product introductions.[5] In contrast, the predictions for *potential autonomy* are ambiguous.[6]

[4] Though the links are not recognized, a similar intuition informs Burford et al. (2022), who studied the consequences on the performance of e-commerce startups of a misalignment in the web technologies with which websites were developed following an exogenous change in the regulatory framework that altered the interdependencies (i.e., the frequencies in which they are used together) among components. They find a negative correlation between the exogenous event and firms' performance, as measured by web traffic. Moreover, the negative effect is more substantial the higher the interdependence among components, suggesting that the quality of the ties and the type of complementarity matter.

[5] This concept of 'restructuring' has been recently employed in the trade literature to estimate the resilience of a value chain to exogenous shocks. Resilience in this context studies the more general issue of the impact of an external shock on the relationships between suppliers and buyers within the supply chain. For example, Khanna et al. (2022) analyze the effects of a supply chain disruption of an exogenous shock, the COVID-19 pandemic. While the source of surprises differs, we borrow his approach to measuring supply heterogeneity in response to the shock.

[6] Potential autonomy should positively correlate to new product introduction for suppliers and assemblers. High potential autonomy indicates the possibility of serving new buyers for suppliers and tapping into new sources of components for assemblers. However, the direction of the effect is likely to depend on the differential in the rate of entry upstream vis-à-vis downstream. For example, suppose the entry rate downstream is much higher than that upstream. In that case, the benefits from creating new ties will increase more for suppliers than for assemblers, who will compete for a constant or a slowly growing number of suppliers. In this case, the effect of potential autonomy on new product introduction will be negative.

We econometrically identify the importance of these factors in a fixed effect regression that exploits changes in firms' autonomy and restructuring over time. We also measure additional features that vary, such as the firm's age and experience, and the duration of its portfolio of relationships with other suppliers. After establishing the robustness of these relationships, we test for the effects of openness using a staggered differences-in-differences approach (Callaway and Sant'Anna 2021).

The estimates show that the position of a firm in the supply chain influences its ability to introduce new products. Specifically, we find that a firm's *autonomy* has a positive influence. Changes in the level of autonomy are associated with significant changes in the number of introduced devices. These findings hold for the different Wi-Fi, CPU, and assembler supply chains. For Wi-Fi and CPU suppliers, the effect is large. An increase of one standard deviation in current autonomy (6.4 and 3.9) translates into an increase of 17.0 and 7.6 devices, respectively. In contrast, the estimated coefficients for Wi-Fi router assemblers are small and imprecise. Also, contrasting prior research, we do not find that *potential autonomy* has much impact. Though we find a non-linear relationship for *restructuring,* the effect is small and does not influence a firm's behavior much.

We apply these findings to measure the effects of openness. We find that when suppliers provide open-source drivers and make information accessible, their autonomy and product introductions increase compared to never-open suppliers. We find that an increase in openness has a significant statistical effect on introducing new products through its change in autonomy. The numerical evidence is large. The average treatment effect on the treated (ATT) for autonomy is 4.851 (standard error 1.54), suggesting that firms that become more open experience a one standard deviation increase in autonomy. The ATT for the effect of openness on log device counts is 0.68 (standard error 0.228,) suggesting that it leads to a 97.4% increase in device counts. Openness also increased the average relationship duration by 0.97 years (standard error 0.365) while not significantly impacting restructuring. Consistent with different interpretations, we interpret it as a measure of the change in options influencing firms' negotiating position. We do not find evidence that openness worked through any other channel.

These estimates suggest that openness increased product introductions through a specific mechanism, enlarging the options available to component suppliers. Moreover, the mechanism did not work equally well for all suppliers. Larger suppliers and suppliers of both Wi-Fi and CPU chips experience the most significant benefits from openness, while smaller suppliers and assemblers experience little benefit. Differences between Wi-Fi and CPU suppliers do not arise, suggesting the Wi-Fi industry's reputation for closedness may be undeserved. The lack of effects from *potential autonomy* and *restructuring* further point to the benefits accruing to suppliers with many existing relationships at the time of openness. The evidence does not suggest that entrants could take advantage of the openness. The most prominent firms (e.g., Broadcom, Qualcomm, Ralink, and Realtek) benefited from openness by expanding their autonomy. In summary, this result is inconsistent with theories of openness that lead to dramatic rearrangements of business relationships that favor small firms and new entrants.

2. Related literature

This study is novel for research on market structure and product innovation. It places the nexus of analysis both at the feet of final assemblers and inside the supply chain, analyzing and measuring the entire history of a product market. It also identifies a mechanism for openness that has yet to receive attention from prior research.

We draw on several studies examining how openness alters final product innovativeness. Prior work stresses that openness can lead to innovations in complementary hardware (Boudreau 2010, Gawer and Henderson 2007). This can translate into benefits for the final customer. However, these benefits come at some costs for suppliers and buyers. Suppliers specializing in producing a single component must then depend on other components sold in the market. They may also forgo some benefits from economies of scope from the pre-existence of a "closed" system (Bresnahan et al., 2011). Thus, specialization and cost reduction gains must be compared with increased transaction costs and "lost" economies of scope. In addition to this, opening leads to imitation and increased upstream competition. More openness also can lead to increased competition in the downstream market. As assemblers are confronted with lower entry barriers,[7] entry increases, and so does competition. Extant studies have highlighted that competition is likely fiercer the more homogeneous the final demand for the product (Lee et al. 2015).[8] Further benefits from opening come from reducing information asymmetries between buyers and suppliers. We resemble these papers in our focus on complements, but our emphasis on the supply chain (in addition to assembly) is novel.

Focusing on restructuring a supply chain over long periods also draws on several distinct branches of the empirical literature. We draw on the study of Hoetker et al. (2007), which analyzes the population of carburetor and clutch suppliers in the U.S. auto industry from 1918 to 1942 and how their relationship with downstream automotive assemblers affects their performance. They focus on the supplier's current and potential autonomy – the option to act without depending on a single business partner. We also examine that factor in our setting.[9] Their findings suggest that suppliers that can operate independently (i.e., more 'autonomous') perform relatively better than those that cannot.[10] Another related study is de Figueiredo and Silverman (2012), which considers the evolution of the U.S. laser printer industry from 1984 through 1996 and studies the effect of competition among upstream suppliers of a core-specific component (i.e., the laser engine) on the performance of downstream firms. They find that the increasing number of upstream suppliers reduces the exit rate of downstream firms and that the effect is stronger for nonintegrated upstream suppliers than for fully integrated suppliers.[11] Our study differs in its focus on the number of product introductions as a measure of performance rather than the survival rate of firms. The

[7] The costs of accessing information decline, lowering the cost of acquiring and developing the competencies and skills needed to integrate the component into the focal device.

[8] Assemblers operating in specific segments would suffer less. Analogously, the level of complexity of the devices manufactured by the assemblers matters. More complex devices require better skills, and firms with such competencies will likely be less exposed to competition.

[9] In their original formulation, *current autonomy* reflects how a supplier (buyer) can act independently from its buyers (suppliers). The intuition is that a supplier (buyer) might be dependent on a buyer (suppliers) if it sells (buys) exclusively to (from) that buyer (supplier). Still, this dependence can be mitigated because the buyer (supplier) has few alternatives to buy from (supply to). *Potential autonomy* captures instead the opportunities to set up new relationships between suppliers and buyers. For suppliers, potential autonomy increases with the presence of potential buyers beyond those with whom they currently trade. For buyers, potential autonomy rises with the presence of potential suppliers beyond those with whom they currently trade.

[10] In their original formulation, the effect tends to be stronger for suppliers of high modular components than those of low modular components, which supports the idea that modularity provides information to buyers concerning how easily the component can be integrated into the design of the overall product.

[11] They explain these findings in terms of benefits from the increased variety and lower costs of inputs that more upstream competition can provide downstream buyers and argue that this applies to specific 'core' rather than 'generic' inputs used in various industries.

emphasis on openness is also novel, and we stress openness due to information access and limitations on usage, distinct from modularity in production, the focus of these prior studies.

We also resemble other studies of the role of openness in supply chains. Lee et al. (2015) study how the performance of 'satellite' Internet firms is affected by their relationships with 'portals.' To increase their exposure to potential customers, satellite firms compete to associate themselves with portals. Findings suggest that portals benefit satellite firms, but asymmetric dependence on one portal over another significantly increases their failure rates. The main reason for the asymmetry is that portals do not need to make any 'specific' investment to provide information to specific satellite firms. In contrast, satellite firms depend on them, thus becoming liable to opportunistic behavior. Ozcan (2018) provides a study of the U.S. wireless gaming market. She looks at the consequences for inter-firm ties of the changing levels of uncertainty and competition when an industry transitions from an early to a late stage of evolution. She finds that firms react to these changes differently depending on their position and prominence within the value chain. Prominent firms overwhelmed with too many partners may cut ties with partners with mediocre performance. Some new entrants may challenge major firms and attract entrepreneurial firms with high- and low-performing links to significant partners. Finally, existing partners may cut ties and become competitors after entering the market directly. We differ in focusing on routers, identifying a more extended period, and the mechanisms we highlight.

Despite its size and central place in networking activities, only a few studies have examined router markets. Our study partially draws on the analysis of Kim (2019), who examines the role of openness in the first decade of router markets. The results highlight two benefits of a reduction in information imperfections. First, in the case of software, to the extent that buyers can access the source code ex-ante, they can understand the characteristics of the components they need to buy and integrate into their systems. Second, open interfaces decrease search costs for final customers and allow buyers to (ex-post) monitor the sellers. Two key differences in this study are the length of the period studied and the focus on all supply chain activity, not only assemblers. These differences lead to the identification of previously unrecognized mechanisms.

Other related research on router markets is Fontana and Greenstein (2021), which examines how an innovative feature, wireless technologies, became embedded into laptops. Their analysis focuses on the role of Intel in restructuring its supply chain for notebooks and its consequences for component suppliers, such as laptop Wi-Fi card providers and early router suppliers. Similarly, our study examines whether a component firm's bargaining position in the supply chain influences innovative product introductions among router firms. However, the focal product differs (i.e., routers instead of laptops). The period in this study is much more extended, which contributes to identifying effects over time from the variance in supply chains, and that supports a very different set of insights. The focus of the prior study is on the IEEE 802.11 standard, which is a non-proprietary open standard. The emphasis on openness differs here, stressing the non-proprietary drivers that emerged and altered product introductions.

This study also benefits from extensive theoretical literature focused on links between the structure of supply chains and innovative outcomes in final goods. Much research focuses on identifying the characteristics of the market structure that define the best economic incentives for suppliers and buyers participating in the value chain and introducing new products.[12] However, only a tiny part of the existing literature analyzes supply chains comparable to those found in supply chains for routers, where upstream and downstream component suppliers interact in various relationships over time. Much less has focused on the empirical measurement of changes to these links over a long period and whether openness shapes the production introductions of component firms or assemblers, as this study does. Still, this study motivates further theoretical research about the optimal levels of autonomy and restructuring to encourage innovative product introductions.

3. Background information on industry and openness

Origins. We briefly review the events that led to the birth of router markets (Fontana and Greenstein 2021, Lemstra et al. 2010). Routers existed before the development of the standards from the IEEE Committee 802. However, these were based on proprietary definitions of the communications protocols. As a result, these products were only part of the next era of routers aimed at mass-market users.

Apple first pioneered the Wi-Fi router using 802.11b, the second design to come out of the IEEE 802.11 committee, which improved the first (and flawed) design released in 1997. The Apple Airport—the first mass-market Wi-Fi product—debuted in July 1999 at a MacWorld convention in New York. Famously, Jobs took out a hoop during the presentation to convince the audience that there were no wires. The Airport did something no prior wireless product had done: it was aimed at the mass market. The expansion card for the laptop had been priced at $99, and it came in a branded product from Apple. The base station was sold separately. Apple distributed the entire system.

That left a large part of the PC market uncovered at the time because most PCs used a Windows operating system from Microsoft. The IBM-compatible market was first addressed at Dell Computer, one of the largest PC providers in the world, by 1999. Making Wi-Fi compatible with Windows XP was the main challenge, and a new version was released in 2001. It supported IEEE 802.11b in a Windows-based system. At the time, some insiders forecasted that other laptop providers would include expansion slots in their designs and try to grow the use of wireless laptops.

Growth of Wi-Fi. Around the same time as the publication of 802.11b, firms that had helped pioneer the 802.11 standards formed the Wireless Ethernet Compatibility Alliance (WECA). WECA branded the new technology "Wi-Fi," a marketing ploy for the mass market. WECA's members believed that "802.11b" was a less appealing label. WECA also arranged to perform testing for conformance to the standard, such as certifying the interoperability of antennae and receivers made by different firms. In brief, while the IEEE committee designed the standard, an independent body (drawn from similar participating firms) performed conformance testing. Technical successes became publicized. Numerous businesses became early users of Wi-Fi and began directed experiments supporting what became known as *hot spots,* an

[12] Most early papers are theoretical and seek to explain scattered empirical evidence that was emerging from case studies of specific industries such as automotive (Ahmadjian and Lincoln 2001), aircraft engines (Bonaccorsi and Giuri 2001), garments and electronics (Kranton and Minehart 2000). See also Pepall and Norman (2001), who investigate the effects on the incentives of different organizational structures of the relationships between suppliers and buyers within a supply chain (i.e., fully decentralized relationships, upstream alliances, vertical integration, upstream consortia). Erkal (2007) studies the extent to which the flexibility of buyers in using the inputs of upstream suppliers may affect the structure of vertically related industries.

innovative business idea. A hot spot is a data transmission mediated, potentially by a third party, for local use in a public space or on retail premises.

In 2001, Intel's management thoroughly examined the supply chain for laptops and decided to consider changing priorities from desktops to laptops. Labeling this a “left turn,” the company considered how to support a Wi-Fi connection in all notebooks that used 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, usually supplied by a firm other than Intel and installed by users or OEMs. Intel ran into several unanticipated crises, such as insufficient parts for the preferred design, delays, and a trademark dispute over using its special symbol for the program. However, the most significant and crucial resistance came from the largest distributor of PCs, 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.

Router assemblers began to enter from the beginning of the deployment of the 802.11b design, initially under agreements with Apple and Dell and increasingly under their brands. With the standardization of the laptop, more firms chose to enter router assembly. The industry grew from there as routers became more popular in various settings. Responding to this growth in demand, the 802.11 committees continued to revise the standards over the subsequent years. These revisions improved error correction and data transmission rates and accommodated more users with less interference, among other design improvements, which user experiences as increased speed and improved reliability.

The supply chain for routers grew, eventually involving hundreds of companies producing 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 the Wi-Fi supply chain emerged as ‘horizontal’ with several companies specializing in different ‘slices’ of the industry. One set of companies provides CPUs, a smaller set provides Wi-Fi chips, and some suppliers provide both (Table A4 provides the entire list of 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 useful for analysis. It enables us to ask how the characteristics of the upstream and downstream structures of the supply chain shape the introduction of new devices by those in distinctly different slices.

Openness. The word “open” takes on a variety of meanings in markets for Wi-Fi routers. This study focuses on two, and each creates potential quasi-experiments. Therefore, we will investigate each with separate tests.

First, some software became open, potentially altering the conditions for bringing new products to market. Specifically, as the market grew, a small community of technical users resented the limitations of proprietary technologies. In 2004, they reverse-engineered the wireless drivers for the Linksys WRT54G, which led to the development of an open-source operating system for wireless routers (OpenWRT). Kim (2019) describes how, before this open-source alternative, assemblers relied on purchasing software licenses from proprietary software companies. Once the open-source alternative became available, suppliers began releasing more drivers as open-source software, effectively making the technical standards available for the 802.11 a/b/g/n segments of products. Kim (2019) found that the more open segment became more appealing to its customers.

Note that the variation explored in this paper is different from the variation explored in Kim (2019). We analyze open-source drivers that firms intentionally released, while Kim (2019) analyzes unintentional open-source drivers that were released by the community. Kim (2019) analyzes the effect of openness at the product level while we examine the effects at the firm level. Finally, our study focuses on the supply side effects of open source, while Kim (2019) analyzes its impact on demand.

Did the change in openness alter the comparative rate of product introductions after one segment became more open? This is not known. On the one hand, the reduced costs for obtaining information would lower the cost of entry, and the increase in customer satisfaction could grow the market size in this segment. On the other hand, making some information non-proprietary gives firms fewer tools for protecting their margins and reducing the incentives to enter. It is an empirical question about which effect is most important in practice.

Another distinct meaning of openness also arises in this setting. Generally, 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 incremental decisions for designs and distribution. It is thought that this difference demonstrates the ability of CPU suppliers to generate margins with branding and performance improvements, i.e., not suffering the downsides of openness nearly as much as 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 contrasts between these two types of firms offer another potential set of insights about the importance of openness in supply chains. On the one hand, the higher margins could incentivize CPU suppliers to be more willing to introduce new products. But on the other hand, it also enables them to exploit their negotiating position more than Wi-Fi chip suppliers. If this hypothesis holds, we should observe a substantial variance across suppliers regarding product entry following openness. We would capture these effects through our measures of autonomy, potential autonomy, and restructuring, as described below.

We must acknowledge one meaning of openness that we cannot investigate. In particular, the deliberations and protocols of the IEEE 802.11 committee are "open" because these new protocols have become public. All firms have access to this published standard without restriction. Milestones after 802.11b included: 802.11g, released in 2003, 802.11n in 2008, 802.11ac in 2014, and 802ax in 2019. There is no observable variance in access to these protocols, so we expect all firms to react to them within a year. Therefore, while we *do* anticipate the open publication of protocols will generate the release of new designs for routers, we *do not* expect any *observable* change in the relationship between the supply chains for routers and the introduction of new products, nor do we expect the observable variance in that relationship to change due the publication of new protocols.

Despite the open standards, there is an unaddressed question of whether participation in the 802.11 committees gives some component suppliers and assemblers a privileged position. This is a challenging topic to address due to the endogeneity of participation and the extraordinarily detailed information required to measure differences in participation and product release dates of frontier attributes. It is beyond the scope of this paper and a topic for future work.

4. Data

4.1. The sample

We collect data for all routers sold in the U.S. between 2002 and 2018. This market is observable due to a quirk in 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 that use 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, we can extract information that enables us to observe firms' positions in a supply chain. For all intent and purposes, every assembler seeks FCC approval, so our data set covers virtually all routers made for global markets.

More specifically, our data comes from filings of all routers firms for authorization to use unlicensed spectrum. The FCC has maintained a database of all such products since 1980. We used the data after 2002, when the 802.11 standards came into use and standardized all routers.

To obtain information about the relationships between suppliers and assemblers, we supplement the data from the FCC with information from Wikidevi, a crowdsourced database for computer hardware. Wikidevi provides information about the hardware and software components of consumer electronic devices. In particular, Wikidevi includes information about routers' Wi-Fi and CPU chips, often with supporting links. Using the supplier information, we construct supplier-buyer relationships for CPU suppliers and assemblers and Wi-Fi chips suppliers and assemblers.

Finally, we obtain information about the openness of suppliers through their release of open-source drivers. The nature of open-source software development makes it clear when open-source suppliers source drivers. Specifically, we obtain the first dates at which firms wrote open-source drivers from the git commit histories of the Linux kernel, as well as data from the Linux Kernel Mailing List.

4.2. Dependent variable

Our dependent variable will be the number of devices a firm has released to the market in a given year. Firms take on different roles as assemblers of routers and suppliers of CPUs and Wi-Fi chips. As shown in the first row of Table 1, the average CPU firm offers 13 products for sale, while the average Wi-Fi supplier offers 22 products for sale. Figure 1 plots the distribution of products offered for sale each year. In both cases, there is enormous 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 enormous variance in the number of routers they offer for sale. Appendix Table A4 lists all the suppliers covered in our dataset, and the type of chip they supply.

[Insert Table 1 and 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 come from a few experienced firms. In our sample, more than half come from firms with ten or more years of experience. In contrast, routers come from many assemblers, both experienced and inexperienced firms, from a wide range of countries,. There is also considerable turnover among them. In our example, more than half are less than five years old.

Already, we begin to see a basic pattern. The CPU and Wi-Fi chip suppliers can negotiate with many different assemblers. In contrast, the assemblers have limited options among the suppliers they can negotiate. While this is a statement about the stability of the market structure, it is also relevant for econometric identification. We will be able to observe more variance in the options available to CPU and Wi-Fi chip suppliers than we will be able to observe among the options available to assemblers. The next set of figures will confirm this intuition.

4.3. Independent variables

This section outlines the main independent variables for our analysis. Specifically, we consider supplier and assembler autonomy (Hoetker et al., 2007) and supply chain restructuring (Khanna et al., 2022). The following discussion focuses on suppliers but applies to assemblers as well.

Autonomy and Potential Autonomy. Autonomy is "[…] the degree to which a supplier can act independently of its buyers" (Burt 1992). Suppliers can act independently if they have high bargaining power over their customers (and assemblers if they have power over their suppliers). Hoetker et al. (2007) call this type of autonomy *current autonomy*: the ratio of the number of assemblers to which it sold to the mean number of suppliers its customers had. In the following discussions, we denote the set of supplier i's customers in time t as A_{it}, and the set of assembler j's suppliers in time t as S_{jt}. Current autonomy is then calculated as follows:

$$CurrentAutonomy_{it} = \frac{\overbrace{\#(A_{it})}^{My\ Customers}}{\underbrace{\frac{1}{\#(A_{it})}\sum_{j\in A_{it}}\#(S_{jt})}_{My\ Customers'\ Suppliers}} \tag{1}$$

Alternatively, suppliers can act independently if it is easy to create new ties. Hoetker et al. (2007) call this *potential autonomy*: the ratio of the number of existing assemblers to which it did not sell to the mean number of existing suppliers from which its customers did not buy:

$$PotentialAutonomy_{it} = \# \frac{\overbrace{\#(A_{it}^{c})}^{My\ Potential\ Customers}}{\underbrace{\frac{1}{\#(A_{it})}\sum_{j\in A_{it}}\#(S_{jt}^{c})}_{My\ Customers'\ Potential\ Suppliers}} \tag{2}$$

Potential Autonomy captures "opportunities to form ties to new buyers […] relative to the buyers' opportunities to develop ties to new suppliers" (Hoetker et al., 2007, p.181), while Current Autonomy captures the "relative dependence of the supplier on its current buyers." (Hoetker et al., 2007, p.183)

Note that the potential autonomy of suppliers can change based on the total number of firms in the market. Specifically, the potential autonomy of suppliers increases if more assemblers enter the market or rival suppliers exit. On the contrary, the potential autonomy of assemblers increases if more suppliers enter the market or if assemblers exit. On the other hand, current autonomy only increases if a company expands its set of customers or if its current customers reduce their group of suppliers. Note also that autonomy is undefined when a firm does not produce any routers since the set of their partners is undefined.

Separation rate, Entry Rate, and Restructuring. Since we observe the creation and dissolution of supplier-buyer relationships over time, we can construct measures of supply chain resilience. We define *Restructuring* as the difference between *Separation Rates* and *Entry Rates*:

$$Restructuring_{i,t+1} = \overbrace{\frac{\overbrace{\#(A_{i,t}-A_{i,t+1})}^{Ties\ Broken}}{\frac{1}{2}\#(A_{i,t})+\frac{1}{2}\#(A_{i,t+1})}}^{SeparationRate_{i,t+1}} - \overbrace{\frac{\overbrace{\#(A_{i,t+1}-A_{i,t})}^{Ties\ Created}}{\frac{1}{2}\#(A_{i,t})+\frac{1}{2}\#(A_{i,t+1})}}^{EntryRate_{i,t+1}} \tag{3}$$

The *Separation Rate* measures the relative number of broken ties when moving from t-1 to t. At the same time, the *Entry Rate* measures the relative number of ties created. Thus, *Restructuring* is positive when more ties are broken than created and negative when more ties are created than broken. In the earliest periods of the market, almost by definition, most suppliers will have negative "restructuring" numbers as they build more ties than they break. A large positive "restructuring" indicates a consolidation of suppliers or a large loss.[13]

5. Results

5.1. Summary Statistics and Correlation Tables

First, we present some descriptive graphs of the market characteristics. Over a decade, the supplier market has become more concentrated, while the opposite seems to be true for downstream assemblers. Figure 2 shows the HHI, total number of firms, incumbents, and entrants over time. We see that 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 the supplier market.

[Insert Figure 2 about here]

Figure 3 presents how our main independent variables change over time for the supplier and assembler groups. Like Figure 2, Figure 3 suggests that suppliers' autonomy, and hence their bargaining power, is increasing over time. Each panel in Figure 3 is a binned scatter plot of our independent variables and

[13] This indicator is borrowed from Khanna et al. (2002) who call it 'net separation' and employs it to capture "how easy is for a firm to find alternative [buyers]". We prefer the label 'restructuring' to 'net separation' because it captures best the nature of the stability of the relationships in our context.

years. *Autonomy* is generally greater for suppliers than for assemblers. In particular, Wi-Fi chip suppliers have the greatest autonomy. Similarly, *potential autonomy* is greatest for suppliers and lowest for assemblers. In contrast, restructuring does not seem to vary much across the groups. *Restructuring* is slightly negative, suggesting that firms continue forming new relationships and making a denser network.

[Insert Figure 3 about here]

Further indications of the independent variables can be obtained by looking again at Table 1. As we saw above, suppliers' average current and potential autonomy is greater. In addition to differences in separation and entry rates across groups, restructuring is negative for all groups. This implies that more ties are being created than broken in this sample, and the supplier-buyer network is becoming denser.

Finally, in Table 2 we provide a correlation coefficients between our measures. Interestingly, *Potential Autonomy* and *Restructuring* are not positively correlated, despite both measures intending to capture the ease with which companies can create new ties.

[Insert Table 2 about here]

5.2. How do Autonomy/Restructuring relate to Device Counts?

To measure how supply chains impact firm performance, we test the relationship between their autonomy/potential autonomy and the number of devices they have released to the market. This section presents preliminary correlations.

Graphical overview. First, we plot the relationship between autonomy measures and device counts in Figure 4.

[Insert Figure 4 about here]

While autonomy is positively associated with the device counts of a company, potential autonomy is negatively associated, as can be seen from the trend lines. If we interpret potential autonomy as the relative ease with which suppliers can be switched, this evidence suggests that a firm's performance benefits more from stability. Alternatively, high levels of potential autonomy can also suggest many “potential” assemblers, for instance, and thus may indicate greater competition.

Figure 5 plots the relationship between restructuring and device counts.

[Insert Figure 5 about here]

Panel (a) of Figure 5 shows evidence that there might be a quadratic relationship between Restructuring and Device Counts. We double check this possibility by plotting a binned scatter plot in panel (b). We see a quadratic relationship, where firms near zero restructuring create the most devices. This indicates that the two most extreme situations – building many more ties than breaking and vice versa – predict little but moderate levels of positively contributing to firms' performance as measured by several devices.

Fixed Effect Regressions. We present regression tables from estimating ordinary least squares regressions using firm and year-fixed effects to formalize the visual analysis above. 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 measure the many factors that shift supply and demand conditions for all firms at the same time, such as macroeconomic fluctuations (e.g., the downturn of 2009) and the release of an upgrade in the protocols (e.g., 802.11n in 2008, and 802.11ac in 2014). Fixed effects also mean statistical identification comes from changes in a firm's situation over time. That also limits the set of controls. In each regression, we include controls for firm features that change over time, such as the maximum/average relationship duration, and dummies for firm age (the omitted category is age>10).

Because the dependent variable is skewed, we log transform the dependent variable in all specifications. Table A1 in the Appendix shows that we obtain similar results when estimating the same specification using Poisson pseudo-likelihood regressions using the raw device counts as the dependent variable. Results are reported in Table 3, separated by suppliers, columns (1) and (2), and assemblers (columns (3) and (4)).

[Insert Table 3 about here]

Current Autonomy is positively associated with device counts, especially for suppliers. Moreover, the estimates are precisely estimated. All in all, the estimated coefficients indicate that current autonomy shapes outcomes to a large degree. Consider Wi-Fi and CPU suppliers. A one-standard-deviation increase in current autonomy (6.4 and 3.9) increases the predicted number of logged devices by 0.77 and 0.58. Against a mean value of 22.1 and 13 devices, that would translate into an increase of 17.0 and 7.6 devices, respectively. These are large increases. In contrast, the estimated coefficients for Wi-Fi router assemblers are small and imprecise.

Interestingly, the coefficients for *potential autonomy* do not take on the expected sign. They are negative, implying that increased potential partners reduce new product introductions. However, all these effects are comparatively small and precisely estimated in only two cases: Wi-Fi suppliers and CPU assemblers, when a one standard deviation increase results in less than a 0.1 decline in potential autonomy. This result may be interpreted as new potential partners working with competitors and introducing products. This would proxy for the evolution of the market structure toward a more competitive situation, even though treating all potential partners alike could exaggerate the importance of potential partnerships with young entrants. We test for these possibilities below.

The coefficients for *restructuring* are precisely estimated, with one exception. The sign on the first coefficient is negative, and the sign of the second coefficient is also negative, centering the estimate at the restructuring of zero. In other words, with controls, the estimates take on an inverted U-shape, as indicated above in Figure 5 without controls. In all cases, the average values for restructuring are positive, and the standard deviations are high, reflecting both negative and positive values, as indicated in the previous figures.

To understand the magnitudes of the effects of restructuring, consider that the standard deviations are 0.43 and 0.47 for Wi-Fi and CPU suppliers, respectively, and that the magnitude of the impact depends on the direction of the change. Consider a movement of restructuring from -1 to -0.5 to 0 for Wi-Fi (and CPU) suppliers. The estimated effect goes from -0.46 (and -0.57) to -0.15 (and -0.19), to zero.[14] These are moderate changes in the range of -0.5 to 0.5 from a baseline of 22 and 13 for Wi-Fi and CPU devices, respectively. They are larger at the extremes. This evidence suggests that potential autonomy is a more important factor, with rare exceptions.

For assemblers, the range of the estimates is small. The standard deviations are 0.37 and 0.39 for Wi-Fi and CPU assemblers. Consider a movement of restructuring from -1 to -0.5 to 0 for Wi-Fi (and CPU) assemblers. The estimated effect goes from -0.19 (and -0.16) to -0.07 (and -0.06) to zero. In other words, even a change of more than one standard deviation does not change the number of devices by more than 10% and often less. However, this is still a larger statistically significant effect for current autonomy. It reflects the relative stability of the supply faced by assemblers, as noted above.

The estimate for maximum duration has the expected sign 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 a device. That is small against the mean number of devices. In the case of Wi-Fi and CPU assemblers, holding on to an established relationship for four years also results in the introduction of half a device, which is moderate against the mean level of devices.

In contrast, average duration is not statistically significant for Wi-Fi and CPU suppliers, while it is for assemblers. In the latter case, the effect goes in the negative direction. Lower average duration leads to more devices, reflecting how recently established relationships lead to expanding capacity. The effect is comparatively small, however. A one standard deviation increase yields a third of a new device.

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. Even in this case, it matters only moderately.

All in all, these estimates confirm the importance of autonomy as the most critical factor shaping the introduction of new devices. Other measures of a firm's position in the supply chain have moderate or no effect, and their effects are smaller than those of current autonomy. Because the devices embody innovation in new designs, these findings suggest that the structure of the supply chain greatly influences the rate at which innovation reaches consumers.

5.3. Are the effects of autonomy/restructuring different across subgroups?

[14] Symmetrically, moving from 0, to 0.5, to 1 the simulations are similar.

Thus far, we have seen that *Current Autonomy* is positively associated with device counts for Suppliers and that there is an inverted U-shape relationship between *Restructuring* and device counts. This section explores whether these effects vary across upstream suppliers/downstream assemblers.

To test for heterogeneity, we estimate the following equation separately for suppliers and assemblers.

$$\begin{aligned} Y_{it} = \phi_i + \lambda_t + \beta_0 WiFi_{it} & \\ & \times \left(Autonomy_{it} + PotentialAutonomy_{it} + Restructuring_{it}\right. \\ & \left. + Restructuring_{it}{}^2\right) + \beta_1 Autonomy_{it} + \beta_2 PotentialAutonomy_{it} \\ & + \beta_3 Restructuring_{it} + \beta_4 Restructuring_{it}{}^2 + \epsilon_{it} \end{aligned} \tag{4}$$

The coefficient of interest will be the β_0 coefficient on the interaction terms. A positive β_0 coefficient on the interaction term with autonomy, for instance, will indicate that high autonomy is correlated with greater device counts for Wi-Fi chips. A negative coefficient, on the other hand, would suggest that autonomy is less critical in determining Wi-Fi chips and, consequently, more critical for CPU device counts. Note that the same firm may appear in two different component technologies if it sells CPU and Wi-Fi chips. We present the results in Table 4 below.

[Insert Table 4 about here]

First, in column 1, we see again that current autonomy is positively associated with supplier device counts. Interestingly, the coefficients on the interaction terms between Wi-Fi and current autonomy are negative and precisely estimated, suggesting autonomy is a less important determinant of device counts in the Wi-Fi chips market. This is consistent with the findings in Hoetker et al. (2007) that more modular products such as CPUs, stand to benefit more from autonomy. In column 2, we estimate the same equation on the sample of router assemblers. We find that for assemblers, neither of the Wi-Fi interaction terms are significant, suggesting modularity is less important here. However, potential autonomy has a negative coefficient, which potentially reflects increased competition outweighs the benefits from potentially sourcing from more diverse chip suppliers.

Similarly, we can see whether the impact of autonomy/restructuring is different across upstream/downstream layers in the supply chain by estimating the following equation separately for the sample of CPU and Wi-Fi chip components:

$$\begin{aligned} & Y_{it} = \phi_i + \lambda_t + \beta_0 Assembler_i \times \left(Autonomy_{it} + PotentialAutonomy_{it} + \right. \\ & \left. Restructuring_{it} + Restructuring_{it}{}^2\right) + \beta_1 Autonomy_{it} + \beta_2 PotentialAutonomy_{it} + \\ & \beta_3 Restructuring_{it} + \beta_4 Restructuring_{it}{}^2 + \epsilon_{it} \end{aligned} \tag{5}$$

The coefficients of interest are the β_0 interaction terms, which indicate whether there are significant differences in the effect of autonomy for assemblers compared to suppliers. A negative coefficient, for instance, on the interaction term between the assembler indicator and potential autonomy would imply that potential autonomy has stronger negative associations with device counts for assemblers than suppliers. That is, an increase in potential suppliers has a greater negative effect on device counts for assemblers than an increase in potential assemblers has on device counts for suppliers. Table 5 presents the results.

[Insert Table 5 about here]

Again, in all specifications, the estimated coefficient for current autonomy is positive and significantly associated with device counts. Note that since we include interaction terms with indicators for assemblers, the coefficients capture the effect on device counts of the dependence of assemblers on component suppliers. Similarly, the coefficient for potential autonomy is negative in all specifications, but they are precisely estimated only for the CPU supplier market.

Interestingly, the interaction term between the assembler indicator and potential autonomy measure is negative for Wi-Fi chips. This implies that increases in potential suppliers are negatively associated with assembler device counts. For assemblers, an increase in the potential Wi-Fi suppliers is bad news. This is not true in the case of an increase in the number of potential CPU suppliers.

5.4. The impact of the release of open-source Wi-Fi drivers

The introduction of open-source Wi-Fi drivers was a significant change in the wireless router market. Beginning in the early 2000s and in response to the increasing popularity of an open-source operating system (OpenWRT), firms began supporting the development of open-source drivers for Wi-Fi chips. Support for open source would have significantly reduced the cost of producing new devices, as assemblers no longer needed to license operating systems for routers.

To test whether the release of open-source drivers affected device counts, we can estimate the following specification with triple interaction terms for the sample of component suppliers.

$$\begin{aligned} Y_{it} = \phi_i + \lambda_t + \alpha_0 Post_{it} \times WiFi_i \times Autonomy_{it} + \alpha_1 Post_{it} \times WiFi_i \\ + \alpha_2 Post_{it} \times Autonomy_{it} \\ + \alpha_3 WiFi_i \times Autonomy_{it} + \alpha_4 Post_{it} + \alpha_5 WiFi_i + \alpha_6 Autonomy_{it} + \epsilon_{it} \end{aligned} \tag{6}$$

The coefficient of interest in the specification above is α_0 which measures how openness moderated the effect of autonomy in the market for Wi-Fi chips. A positive α_0 coefficient suggests supplier autonomy became more critical in determining device counts after introducing open-source software. A positive coefficient would thus be consistent with open-source software enhancing the returns to bargaining power. A negative coefficient would instead indicate a weaker effect of autonomy on device counts after the development of open-source drivers. Table 6 presents some preliminary evidence on whether the importance of autonomy changed.

[Insert Table 6 about here]

Columns 1 reports the results for suppliers, while Columns 2 reports results for assemblers. Our Post variable indicates time periods in which the open-source operating system for routers existed. We see from both columns that the association between autonomy and device counts grew stronger for both suppliers and assemblers. Both columns show that, after the release of OpenWRT and when open-source software became more readily available, this difference between CPUs and Wi-Fi chips increased (positive coefficient on the triple interaction term), suggesting that autonomy became more important for both markets. The negative coefficients on Wi-Fi x Current Autonomy compared to the relationship between autonomy and device count in CPUs, autonomy had a smaller effect on device counts in the Wi-Fi chip market ().

5.5. Understanding the impact of the release of open-source Wi-Fi drivers on product count: An event study approach

In the previous section, we have shown that the release of open-source drivers changed the effect of autonomy on device counts. Indeed, open-source drivers make suppliers' components more 'open' by lowering assemblers' development costs and facilitating software access. However, openness also led to lower entry barriers, increased competition, and imitation. The net effect of increased openness on firms' performance, as captured by device counts, will depend on the combination of these effects. In this section, we provide evidence of various mechanisms through which increased openness impacted device count: an increase in autonomy, an increase in the average duration of partnerships, and an increase in the number of partnerships with both new entrants and established firms.

We carry out our analysis by estimating a staggered difference-in-difference specification. We focus on Wi-Fi suppliers because there is no variation in which CPUs are compatible with the Linux kernel as all are compatible. Specifically, we employ yearly panel data for suppliers of Wi-Fi chips and compare supplier-buyer relationships before and after the release of open-source drivers. Thus, we exploit variance from the differential timing of firms' decision to open. The literature has frequently employed the following two-way fixed effect (TWFE) regression to estimate the causal impact of such staggered differences in differences:

$$Y_{it} = \beta Post_t * Treated_i + \eta_i + \lambda_t + \epsilon_{it} \qquad (7)$$

Recent work, however, suggests that this TWFE estimator is biased and does not recover the treatment effect of interest (Borusyak et al. 2022, Callaway and Sant'Anna 2021, Goodman-Bacon 2021). Thus, we follow Callaway and Sant'Anna (2021) in plotting the average treatment at specific periods for cohorts treated at different times and aggregate those average treatment effects to the appropriate levels. Our empirical strategy involves using a "never-treated" group of firms (i.e., those that never provided open-source drivers) as the control group and using cohorts of firms that released open-source drivers around the same time. The initial dates at which firms contributed open-source drivers are obtained via the Linux kernel git commit history and their historical context (Tourrilhes, 2003). In calculating the effect sizes, we trim observations to 6 years of pre-post firms releasing open-source drivers to minimize the effect of outliers.

Figure 6 below presents our timing-based estimates, which trace the effect of the release of an open-source driver on product innovations of the Wi-Fi chip supplier. Each coefficient plots the average difference in log device counts for suppliers that open-sourced a driver versus those that did not for a given time period since opening. We see that before the opening of drivers, there was no significant difference between firms that eventually became open. However, after opening, open firms released more products than their closed counterparts. The ATT for the effect of openness on log device counts is 0.590 (standard error 0.253,) suggesting that opening up leads to an 80.4% increase in device counts. The large coefficient is partly driven by the prevalence of firm-year observations with zero devices in our dataset.

[Insert Figure 6 about here]

In Figure 7, we show the impact of openness on our independent variables, as well as the relationship duration. Again, we see that before the release of open-source drivers, there is no significant difference in our variables for open and closed firms, suggesting no pre-trends. However, firms' current autonomy increases significantly once open, consistent with our hypotheses. The effect declines after about 3 years, suggesting the effects on current autonomy are short lived. Potential autonomy, on the other hand, initially decreases but then increases for the rest of our sample period. The average treatment effect on the treated (ATT) for autonomy is 4.011 (standard error 1.73), suggesting that firms that become more open experience a one standard deviation increase in autonomy. The ATT on potential autonomy and restructuring are noisier, and in the 6-year time window, the effect sizes are -1.064 (standard error 1.737) for potential autonomy and 0.210 (standard error 0.184) for restructuring, suggesting that openness reduces potential autonomy. Finally, the average relationship duration also increased by 0.824 years for open firms (standard error 0.307), showing that openness allows for longer supplier-buyer relationships.

[Insert Figure 7 about here]

5.6. Heterogeneity in the effect of openness across firms

We also check for heterogeneity across firm types. Table 7 presents the breakdown of effects by cohorts of companies that released open-source software in the same year. We see that the positive effects on Autonomy are strongest for the 2011 cohort (entry by Qualcomm), followed by the 2007 (entry by Broadcom, Celeno, Ralink, Realtek), and 2005 (entry by Atheros) cohorts. Notably, these cohorts contain exactly the most prolific companies, jointly producing 74.6% of devices, suggesting that the benefit of openness is concentrated in larger companies. Those cohorts also have the largest increases in autonomy (Column 2) and show signs of decreased potential autonomy (Column 3) and minimal changes in restructuring (Column 4).

[Insert Table 7 about here]

Table 7 also shows that late openers do not benefit much from openness. In column 1, the ATT of openness on device counts is positive for early cohorts but negative for the 2015 and 2017 cohorts. Interestingly, those cohorts see decreases in autonomy as well. Note that Table 7 aggregates the treatment effects for the first 6 years after releasing open source drivers. In the Appendix, Table A5, we include all time periods beyond the 6-year window and find that while the 2011 cohort still benefits the most from openness, the effect for the 2005 cohort flips. This suggests that the long-run effects of openness may be negative, as more open competitors enter.

Next, we ask whether the effect of openness is different for Wi-Fi and CPU suppliers. To the extent that a supplier provides both Wi-Fi chips and CPUs, openness in one segment may enhance outcomes in other segments as well. For instance, bundling an open Wi-Fi chip with a CPU may increase demand for both. We test whether this is the case.

[Insert Figure 8 about here]

Figure 8 plots the effect of openness for suppliers who produce both CPU and Wi-Fi chips. Blue lines denote the impact on the number of new devices using a firm's CPUs, while red lines denote the impact on the number of new devices using a firm's Wi-Fi chips. Panel A shows that Wi-Fi openness increased supplier autonomy even in the CPU market. The red lines show a significant increase in autonomy for the first 5-6 years, which subsequently taper off to zero. However, Panel B shows that such increases did not have a significant impact on new product introductions. Similarly, Panels C and D show that openness in the Wi-Fi market did not affect potential autonomy or restructuring for the same suppliers in the CPU market. Overall, these graphs suggest that openness in one market can have spillovers onto other markets, but those effects tend to be limited.

5.6 Causal Impact of Autonomy on New Product Innovations

Our goal in this section is to isolate the impact of autonomy on new product innovations using the release of open-source device drivers. To the extent that open-source device drivers only affect new product innovation through autonomy, we can estimate the impact of autonomy on new product innovation through a fuzzy-did approach. The idea is to use the release of open-source device drivers as an instrument for the increase in new products, and weight the increase in new products by the increase in autonomy.

In traditional diff-in-diff settings with a "continuous" treatment, various methods exist to estimate a "fuzzy" diff-in-diff, or a Wald-did as the treatment group is differentially more likely to receive treatment than the control group. de Chaisemartin and D'HaultfŒuille (2018) provide assumptions under which this simple weighting approach recovers the LATE, as well as propose an alternate estimator. However, in staggered diff-in-diff settings (e.g., Callaway and Sant'Anna, 2021), no such estimator exists.

Given how there exist no established processes for estimating a fuzzy diff-in-diff with staggered treatment, we adopt a bootstrapped approach to the Wald-did type estimator. Our approach is to estimate the following Wald-type estimator using block bootstrapping with replacement:

$$\gamma = \frac{E[Y_{it}|Treatment_{it} = 1] - E[Y_{it}|Treatment_{it} = 0]}{E[Autonomy_{it}|Treatment_{it} = 1] - E[Autonomy_{it}|Treatment_{it} = 0]} \tag{8}$$

Where Y_{it} measures the number of products by supplier i in year t, $Treatment_{it}$ is an indicator for years t in which supplier i had open-source device drivers, and $Autonomy_{it}$ measures supplier $i's$ autonomy in year t. We obtain the estimate γ by choosing a random sample (with replacement) of firms, estimating a diff-in-diff for Y_{it} and $Autonomy_{it}$, then dividing the diff-in-diff coefficient for new products by the diff-in-diff coefficient for autonomy. We repeat this process 1,000 times and report the mean, as well as the exact 95% confidence intervals.

In traditional diff-in-diff settings, additional assumptions are required to interpret the parameter of interest γ as the causal impact of autonomy on new device counts. de Chaisemartin and D'HaultfŒuille (2018) show that for γ to be identified, one needs to assume that 1) the effect of the treatment is stable over time, and 2) the effect of the treatment is the same in the treatment and control groups. In our setting, assumption 1) states that the impact of autonomy on new product innovations is constant across time, and assumption 2) states that the effect is constant for switchers (e.g., firms who do not open-source drivers but still get increased autonomy).

We find that a one-unit increase in autonomy increases new product innovations for Wi-Fi suppliers by 15.9% (bootstrapped 95% CI [0.008, 0.513]), or about 1.26 devices. Similarly, in bootstrapped results using log-transformed autonomy, a 1% increase in autonomy increases new product innovations by about 1.71%. In our sample, the firm with the largest average autonomy is MediaTek (average autonomy of 11.71), followed by Broadcom (average autonomy of 9.84) and Realtek (average autonomy of 9.419). Firms with the lowest autonomy are Agere (0.40), ZyDAS (0.52), and AMIT (0.56).

6. Conclusion

This study examined how openness alters the relationship between a firm's position in the supply chain and its introduction of new devices. We find evidence of an association between the role of a firm in the supply chain and its ability to introduce new products. Specifically, we find that a firm's *autonomy* has a positive influence. We also find that a firm's ability to alter its supply chain, as measured by *restructuring*, has less impact. These findings hold for different supply chains for suppliers of Wi-Fi chips and CPUs and less so for the assembly of routers. In contrast to prior research, we do not find that *potential autonomy* influences a firm's behavior. These findings contribute to understanding how openness shapes product introductions within a supply chain.

Specifically, we find that when suppliers provide open-source drivers and share information, their autonomy and product introductions increase compared to never-open suppliers. We find that an increase in openness has a significant statistical effect on introducing new products through its change in autonomy. The numerical evidence is large. We interpret it as a measure of the change in options influencing a firm's negotiating position. The absence of evidence for other effects is also interesting. We interpret these findings to mean that a tendency to be open is either persistent (and, thus, unobserved as part of a firm fixed effect) or the position in a supply chain overwhelms it in importance.

These estimates provide evidence that openness increased product introductions by enlarging the number of options available to component suppliers. However, the mechanism did not work equally well for all suppliers. Larger suppliers and suppliers of both Wi-Fi and CPUs experience the biggest benefits, while no evidence suggests smaller suppliers and assemblers experience much of a benefit. Differences between Wi-Fi and CPU suppliers do not arise, as expected. Large suppliers with many existing relationships at the time of openness benefit the most.

These results pertain to one industry with specific participants and market opportunities and where an industry group determined a standard at an early moment in the growth of products and continued to improve it over time. Investigating whether the insights hold in other markets that display these "horizontal" features over the long term would be worthwhile. It also would be interesting to learn whether standards emerge long after establishing product markets instead of at the beginning. The results also indirectly raise questions about vertically organized production, which potentially loses these benefits from not being able to benefit from openness. Further research could investigate the opportunity costs of missed opportunities.

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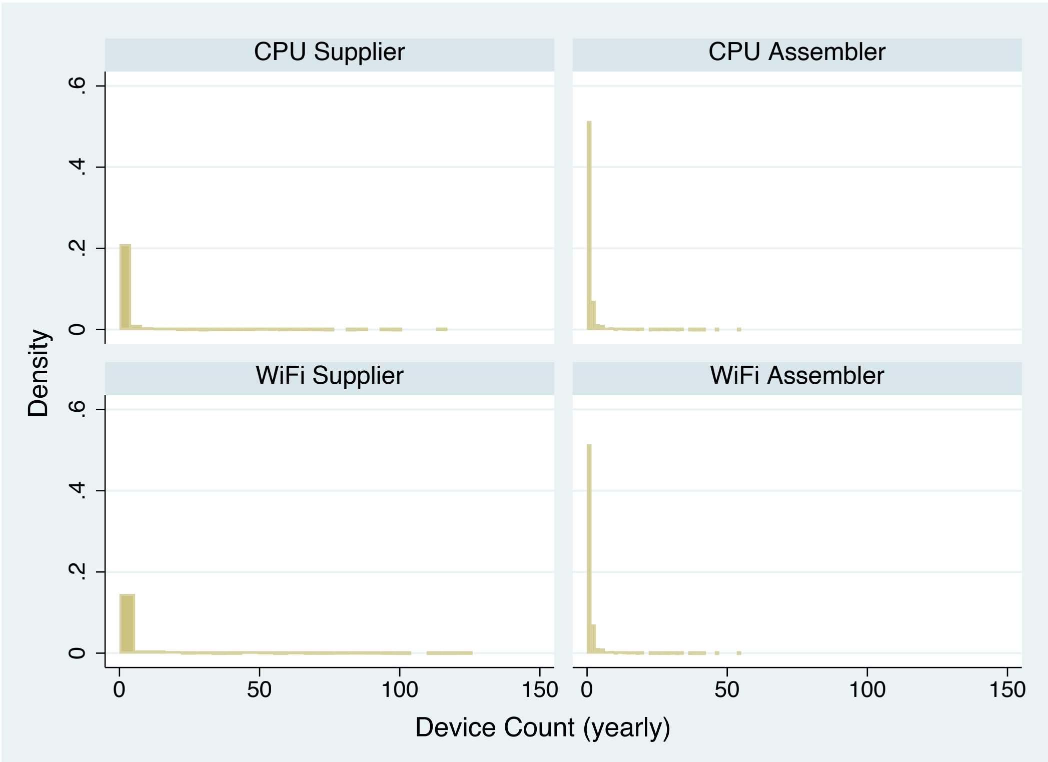
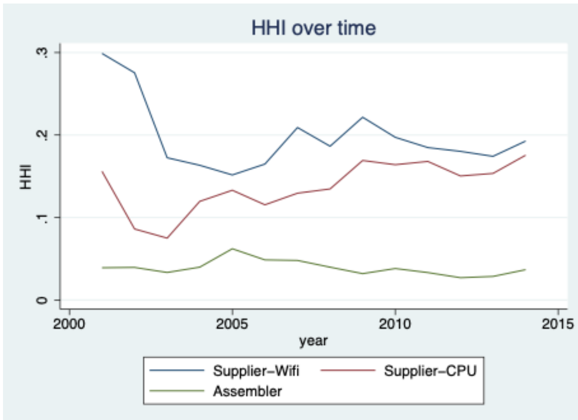
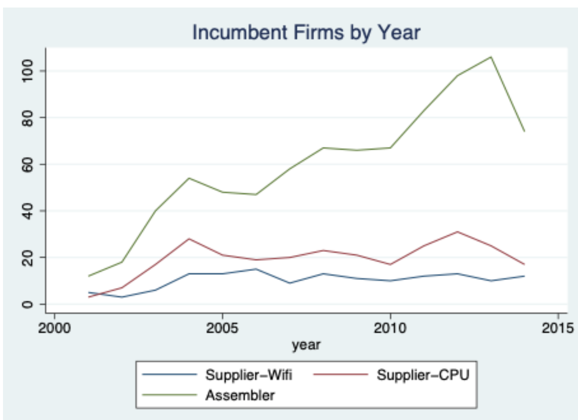


Figure 1. Distribution of product counts
Histograms of the number of new devices released by suppliers in a given year. Each bar denotes the fraction of firm-years with 0 devices, 1 device, and so forth.

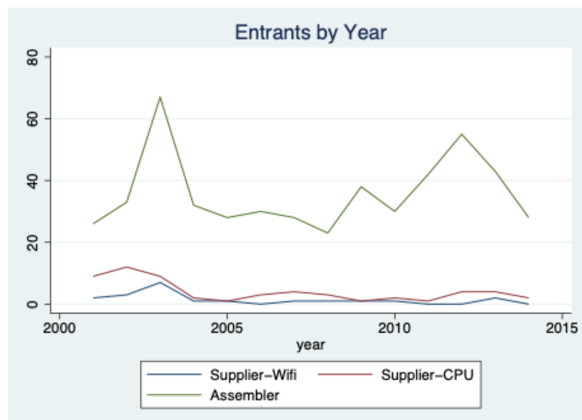


(a) HHI

(b) Total Firms



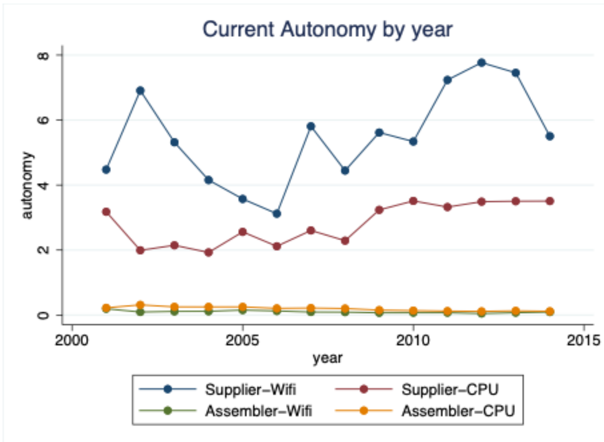
(c) Incumbent Firms



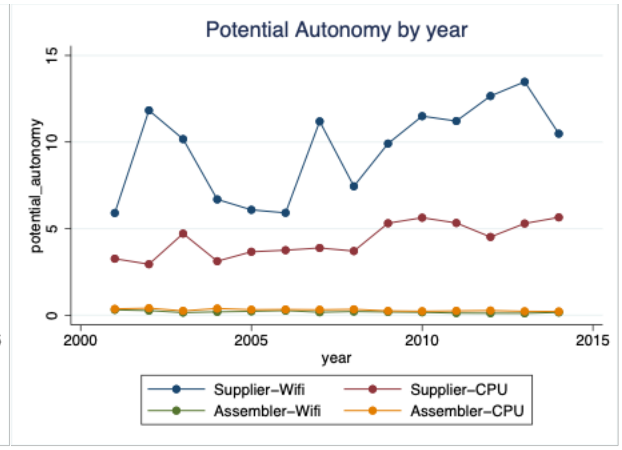
(d) Entrants

Figure 2. Market Characteristics Over Time

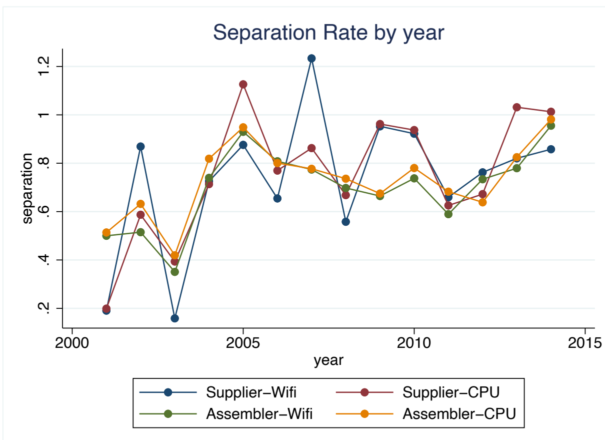
Plots of the HHI (Panel A), Total number of firms (Panel B), Incumbent firms (Panel C), and Entrants (Panel D) over time for suppliers and assemblers. Incumbents are firms that released new products in that year who were not entrants.



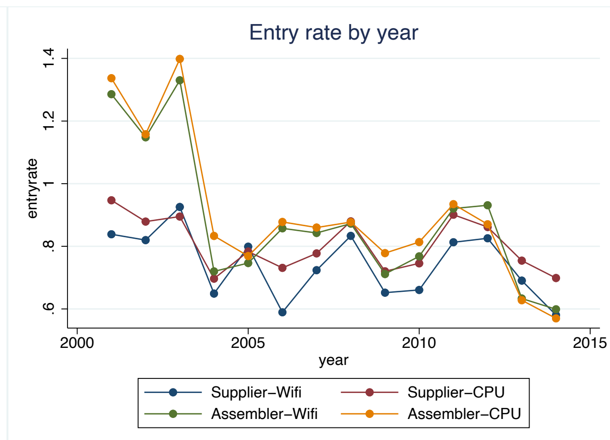
(a) Current Autonomy



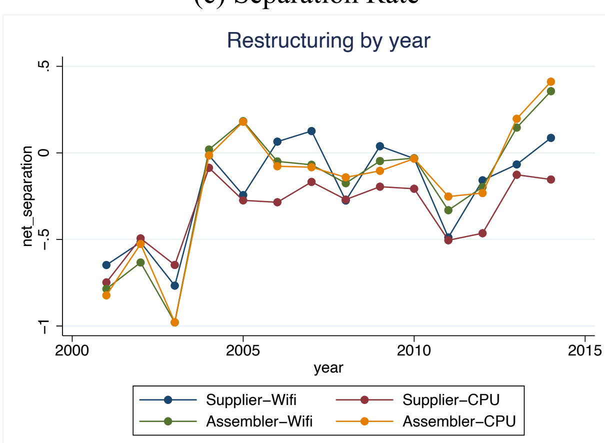
(b) Potential Autonomy



(c) Separation Rate



(d) Entry Rate



(e) Restructuring

Figure 4. Binned Scatterplots of Independent Variables Over Time

Binned scatterplots using the "binscatter" command in STATA. Panels present current autonomy (Panel A), Potential Autonomy (Panel B), Separation Rate (Panel C), and Entry Rate (Panel D) over time for assemblers and suppliers. Each point on the graph is the average value of the independent variable across all firms that released a product in that year.

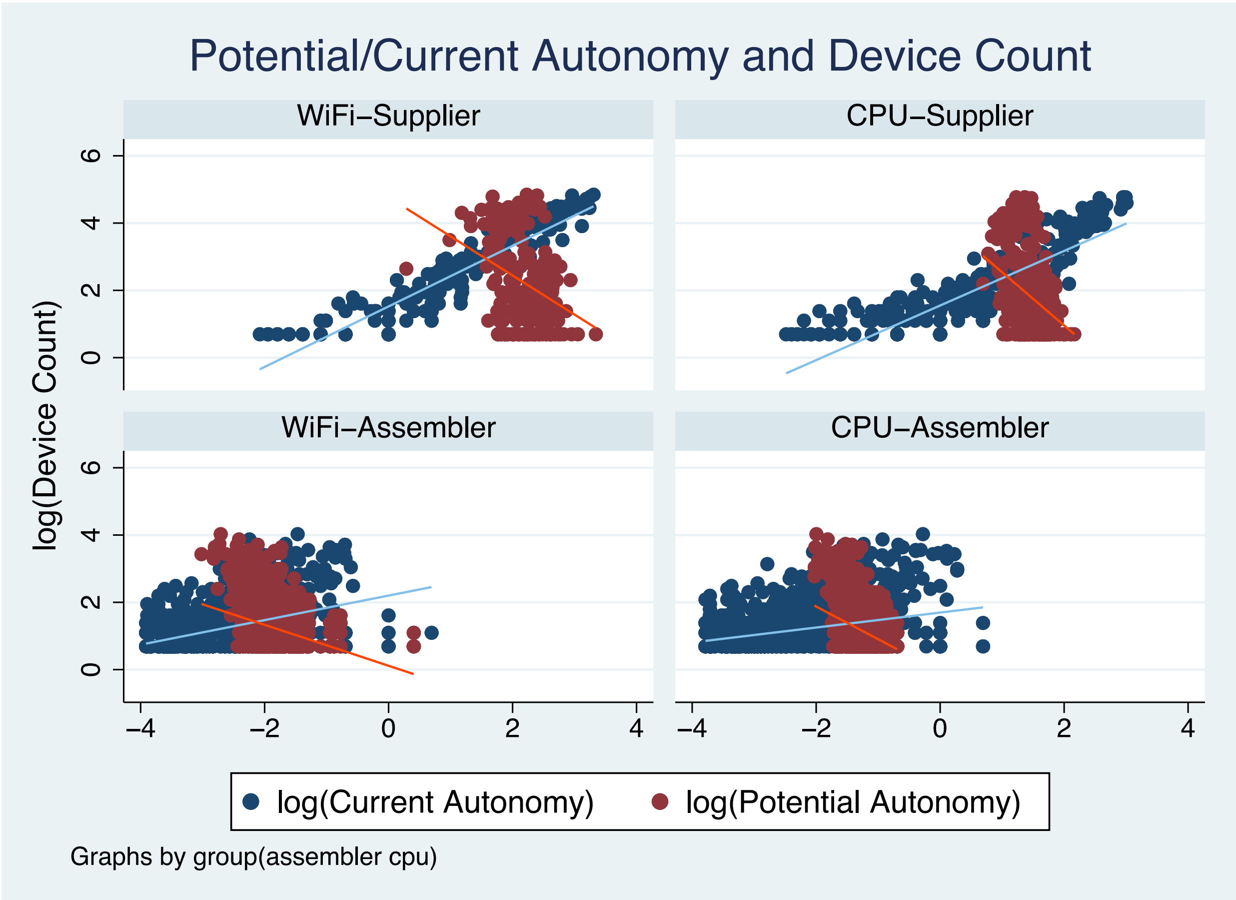
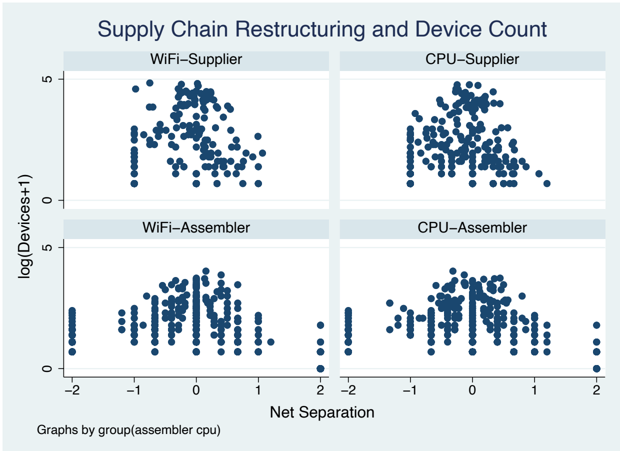
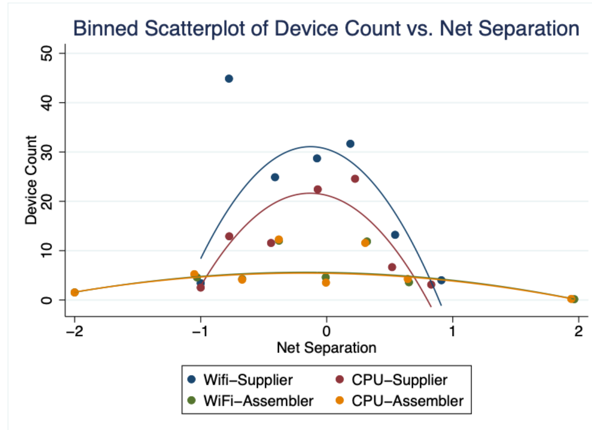


Figure 4. Device Count vs. Autonomy/Potential Autonomy
Each panel shows scatterplots of device counts against autonomy and potential autonomy for different groups of suppliers/assemblers and Wi-Fi/CPU chips. Lines plot the linear prediction of device count from autonomy and potential autonomy.



(a) Scatterplots of raw data



(b) Binned scatterplots

Figure 5. Device Count and Supply Chain Restructuring
Panel (a) shows scatterplots of device counts against entry rate, separation rate, and restructuring for different groups of suppliers/assemblers and Wi-Fi/CPU chips. Panel (b) shows binned scatterplots using STATA's "binscatter" command and quadratic fit. The restructuring rate measures tie dissolution, and the restructuring rate measures tie creation. Restructuring measures the net dissolution of ties or the ease with which firms can find alternative suppliers/buyers (separation rate – entry rate).

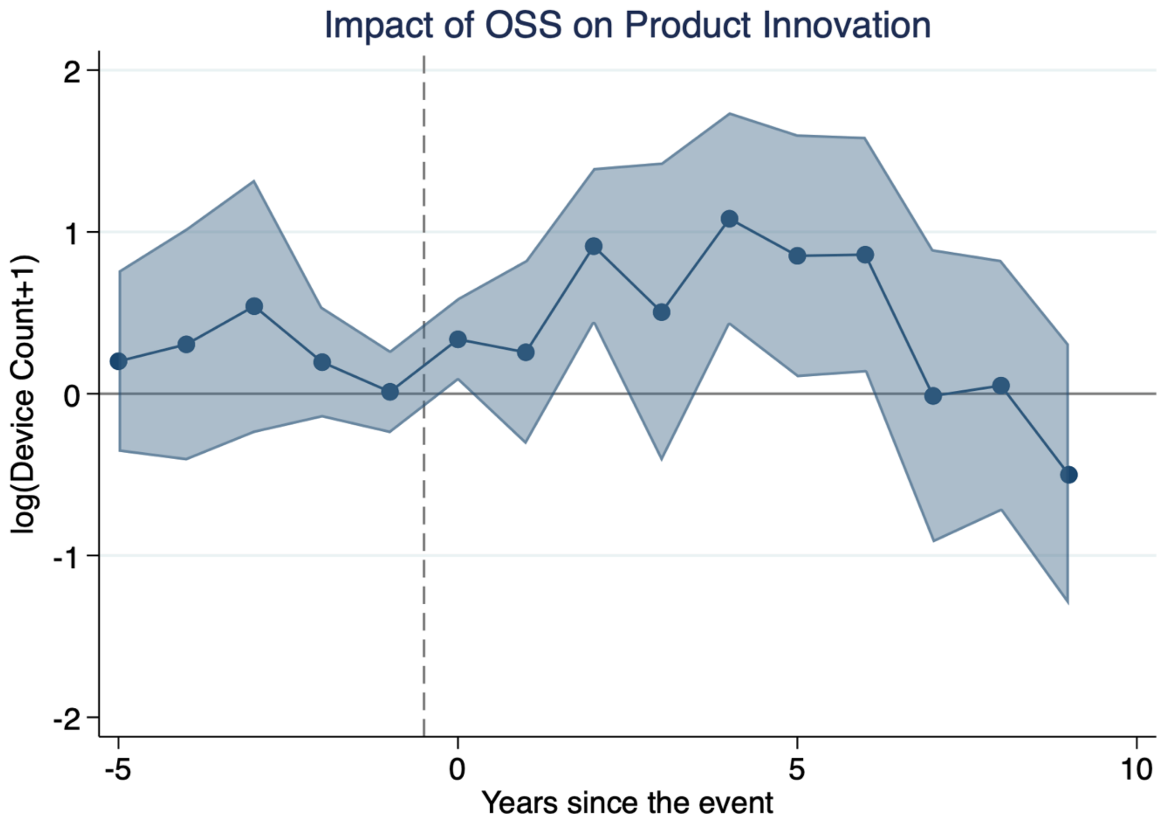
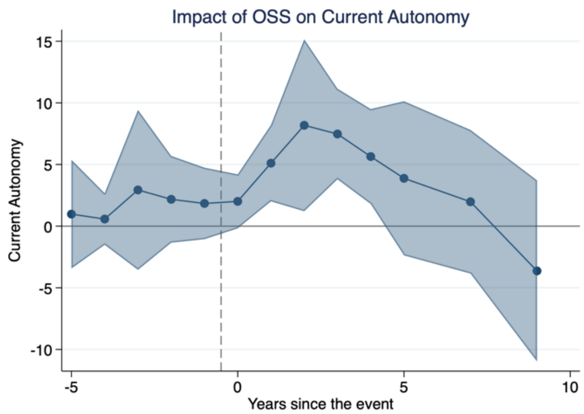
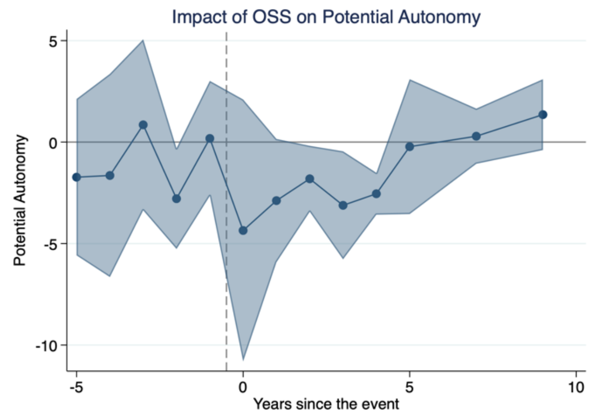


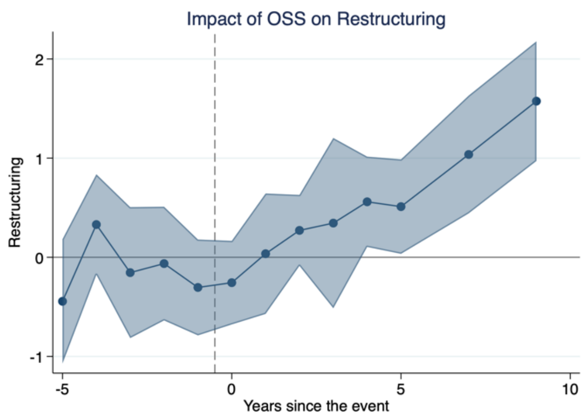
Figure 6. Effect of releasing open-source drivers on product innovation
Event study plot using Callaway Sant'Anna (2022) coefficients on the average treatment effect of releasing open-source drivers. Treatment group firms released open-source drivers in year t=0, while control firms never released open source drivers. Plots for t=1 onward plot the difference in treatment and control based on the t-1 period. Plots for t=0 and before plot the difference in treatment and control based on t-1.



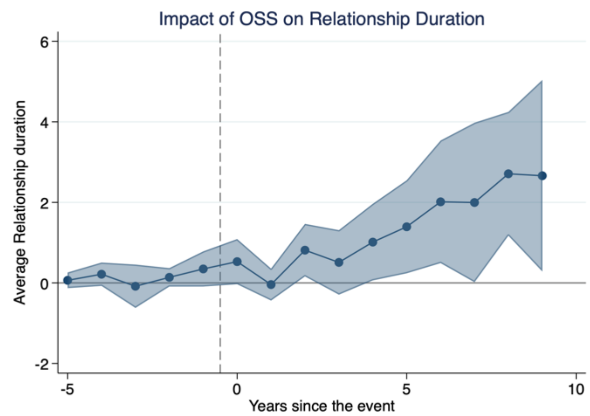
Panel A



Panel B



Panel C



Panel D

Figure 7. Impact of open-source drivers on device count and relationship duration
Event study plot using Callaway Sant'Anna (2022) coefficients on the average treatment effect of releasing open-source drivers. Treatment group firms released open-source drivers in year t=0, while control firms never released open source drivers. Plots for t=1 onward plot the difference in treatment and control based on the t-1 period. Plots for t=0 and before plot the difference in treatment and control based on t-1.

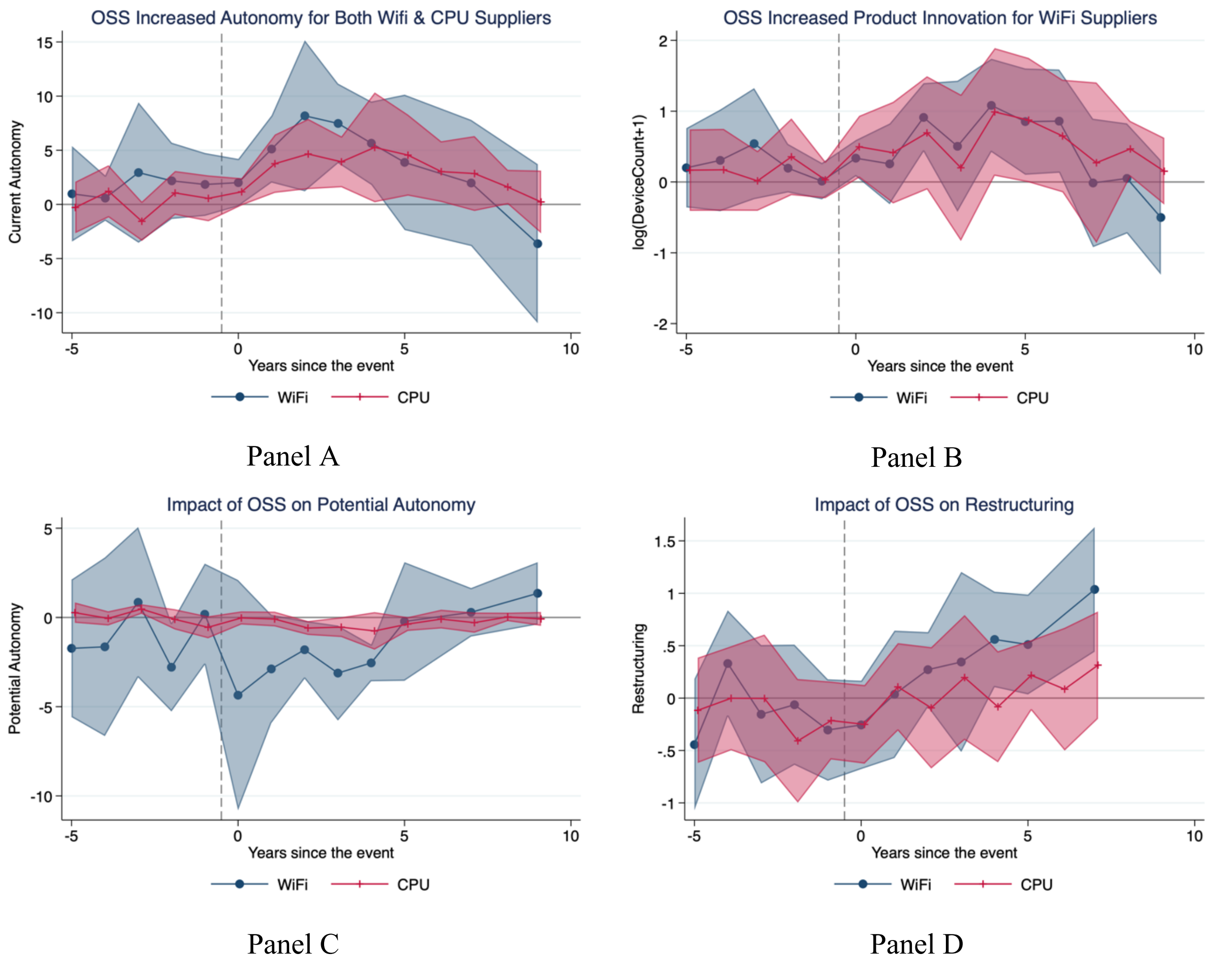


Figure 8. Impact of open-source Drivers on the CPU Market
Event study plot using Callaway Sant'Anna (2022) coefficients on the average treatment effect of releasing open-source drivers. Treatment group firms released open-source drivers in year t=0, while control firms never released open source drivers. Plots for t=1 onward plot the difference in treatment and control based on the t-1 period. Plots for t=0 and before plot the difference in treatment and control based on t-1. Blue lines denote the impact on the number of new devices using a firm's CPUs, while red lines denote the impact on the number of new devices using a firm's Wi-Fi chips.

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Table 1. Summary Statistics by Group

	(1)		(2)		(3)		(4)	
	Suppliers				**Assemblers**			
	Wi-Fi		CPU		Wi-Fi		CPU	
	mean	sd	mean	sd	mean	sd	mean	sd
Device Count	22.088	29.617	13.028	22.218	3.595	5.767	3.522	5.687
Current Autonomy	5.270	6.401	2.868	3.882	0.093	0.114	0.178	0.247
Potential Autonomy	9.243	3.577	4.428	1.123	0.177	0.069	0.305	0.073
Separation Rate	0.567	0.430	0.491	0.472	0.225	0.371	0.258	0.396
Entry Rate	0.730	0.275	0.798	0.263	1.152	0.844	1.162	0.832
Restructuring	-0.163	0.550	-0.306	0.562	-0.927	1.041	-0.903	1.054
HHI	0.189	0.033	0.147	0.036	0.040	0.011	0.040	0.012
Max Relationship Duration	3.979	4.045	2.951	3.785	2.526	3.239	2.478	3.335
Average Relationship Duration	1.738	1.975	1.380	1.971	1.952	2.559	1.859	2.589
Supplier age<5	0.108	0.311	0.092	0.290	0.562	0.496	0.570	0.495
Supplier age>5 but <=10	0.320	0.468	0.264	0.441	0.312	0.464	0.303	0.460
Supplier age>10	0.572	0.496	0.644	0.479	0.126	0.332	0.127	0.333
Observations	194		326		1125		1165	

Note: **Current Autonomy** measures bargaining power; **Potential Autonomy** measures the relative ease with which links can be created. **Separation Rate** measures the decrease in ties, and **Entry Rate** measures the increase in ties. **Restructuring** is the Separation Rate minus the Entry Rate and measures how many links were broken, net of new links created. Negative restructuring implies that the supplier-assembler network is becoming denser over time.

Table 2. Correlation table

Panel A: Suppliers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Device Count	1.000									
(2) Current Autonomy	0.939	1.000								
(3) Potential Autonomy	-0.063	-0.077	1.000							
(4) Separation Rate	-0.008	0.003	0.064	1.000						
(5) Entry Rate	-0.333	-0.279	-0.003	-0.133	1.000					
(6) Restructuring	0.153	0.136	0.054	0.880	-0.588	1.000				
(7) Max Relationship Duration	0.489	0.447	0.050	0.166	-0.451	0.352	1.000			
(8) Average Relationship Duration	0.250	0.192	0.067	0.134	-0.416	0.309	0.864	1.000		
(9) Supplier Age	-0.002	-0.016	0.113	-0.047	0.024	-0.050	0.006	0.007	1.000	
(10) HHI	0.116	0.177	0.435	0.062	-0.085	0.091	0.215	0.219	0.023	1.000

Panel B: Assemblers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Device Count	1.000									
(2) Current Autonomy	0.264	1.000								
(3) Potential Autonomy	-0.242	-0.063	1.000							
(4) Separation Rate	0.054	0.015	0.018	1.000						
(5) Entry Rate	-0.324	-0.007	0.110	-0.385	1.000					
(6) Restructuring	0.279	0.011	-0.082	0.675	-0.941	1.000				
(7) Max Relationship Duration	0.449	0.042	-0.249	0.022	-0.383	0.315	1.000			
(8) Average Relationship Duration	0.294	-0.039	-0.194	0.008	-0.342	0.277	0.932	1.000		
(9) Supplier Age	0.310	0.008	-0.256	0.161	-0.304	0.302	0.717	0.659	1.000	
(10) HHI	-0.027	0.108	0.276	0.005	-0.010	0.010	0.043	0.066	0.035	1.000

Note: Correlations between all our measures, the unit of observations at the firm-year level. **Sample sizes** are 317 for suppliers and 2320 for assemblers. While **Net Separation** and **Potential Autonomy** theoretically measure how easy it is to create new ties, they are weakly negatively correlated here.

Table 3. Are Device Counts associated with the change in Autonomy/Restructuring?

	(1)	(2)	(3)	(4)
	Suppliers		Assemblers	
DV: log(DeviceCounts+1)	Wi-Fi	CPU	Wi-Fi	CPU
Current Autonomy	0.120^{***}	0.149^{***}	0.098	0.005
	(0.015)	(0.020)	(0.216)	(0.084)
Restructuring	-0.142	-0.184^{***}	-0.108^{**}	-0.090^{**}
	(0.097)	(0.049)	(0.043)	(0.040)
Restructuring Sq.	-0.324^{**}	-0.385^{***}	-0.081^{***}	-0.068^{***}
	(0.126)	(0.064)	(0.023)	(0.021)
Potential Autonomy	-0.023^{**}	-0.055	-0.076	-1.031^{**}
	(0.010)	(0.064)	(0.406)	(0.430)
Max Relationship Duration	0.110^{**}	0.103^{***}	0.137^{***}	0.157^{***}
	(0.043)	(0.029)	(0.021)	(0.022)
Av. Relationship Duration	-0.068	-0.075	-0.134^{***}	-0.145^{***}
	(0.049)	(0.046)	(0.023)	(0.024)
Supplier age<5	-0.296	-0.109	-0.060	-0.071
	(0.206)	(0.218)	(0.085)	(0.085)
5< Supplier age <=10	-0.106	0.176	0.055	0.081
	(0.204)	(0.129)	(0.068)	(0.066)
Constant	1.710^{***}	1.509^{***}	1.192^{***}	1.445^{***}
	(0.143)	(0.315)	(0.115)	(0.181)
Adjusted R^2	0.898	0.881	0.734	0.739
Observations	191	326	1123	1163

Note: Estimates from OLS regressions, standard errors in parentheses, clustered at the firm level. All specifications include firm and year-fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Effect of Autonomy by Degrees of Openness: Stronger Effects for CPU Chips

DV: log(DeviceCounts+1)	(1) Suppliers	(2) Assemblers
Wi-Fi # Current Autonomy	-0.026**	0.046
	(0.010)	(0.124)
Wi-Fi # Potential Autonomy	-0.004	0.212
	(0.036)	(0.131)
Wi-Fi # Restructuring	0.022	0.010
	(0.079)	(0.026)
Wi-Fi # Restructuring Sq.	0.068	0.001
	(0.127)	(0.015)
Current Autonomy	0.145***	0.031
	(0.015)	(0.060)
Potential Autonomy	-0.015	-0.425**
	(0.038)	(0.209)
Restructuring	-0.178***	-0.109***
	(0.048)	(0.036)
Restructuring Sq.	-0.383***	-0.077***
	(0.066)	(0.020)
Wi-Fi	0.001	-0.063
	(0.197)	(0.040)
Max Relationship Duration	0.108***	0.141***
	(0.030)	(0.020)
Average Relationship Duration	-0.085*	-0.136***
	(0.043)	(0.021)
Supplier age<5	-0.198	-0.072
	(0.159)	(0.083)
5< Supplier age <=10	0.054	0.063
	(0.125)	(0.065)
Constant	1.478***	1.277***
	(0.199)	(0.108)
Adjusted R2	0.892	0.765
N	518	2290

Note: Estimates from OLS regressions, standard errors in parentheses, clustered at the firm level. All specifications include firm and year-fixed effects. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5. Effect of Potential Autonomy Across the Supply Chain: Potential Autonomy is More Negative Downstream

DV: log(DeviceCounts+1)	(1) Wi-Fi	(2) CPU
Assembler # Current Autonomy	-0.135	-0.033
	(0.089)	(0.206)
Assembler # Potential Autonomy	-1.135**	-0.127
	(0.510)	(0.375)
Assembler # Restructuring	0.094	0.043
	(0.065)	(0.093)
Assembler # Restructuring Sq.	0.292***	0.174
	(0.076)	(0.122)
Current Autonomy	0.145***	0.117***
	(0.020)	(0.013)
Potential Autonomy	-0.028	-0.029**
	(0.040)	(0.012)
Restructuring	-0.200***	-0.164**
	(0.051)	(0.077)
Restructuring Sq.	-0.374***	-0.271**
	(0.074)	(0.118)
Assembler	-0.011	-0.249
	(0.339)	(0.342)
Max Relationship Duration	0.135***	0.119***
	(0.017)	(0.020)
Average Relationship Duration	-0.117***	-0.112***
	(0.021)	(0.022)
Supplier age<5	-0.180**	-0.268***
	(0.078)	(0.085)
5< Supplier age <=10	0.052	-0.030
	(0.057)	(0.062)
Constant	1.521***	1.643***
	(0.225)	(0.284)
Adjusted R2	0.817	0.829
N	1489	1314

Note: Estimates from OLS regressions, standard errors in parentheses, clustered at the firm level. All specifications include firm and year-fixed effects.
$^{*}p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$

Table 6. Open Source Software Changed the Impact of Current Autonomy

	(1) Suppliers	(2) Assemblers
Post x Wi-Fi x Current Autonomy	0.112*	0.515**
	(0.066)	(0.223)
Post x Wi-Fi x Potential Autonomy	-0.086	-0.368
	(0.078)	(0.361)
Post x Wi-Fi x Restructuring	1.789**	0.005
	(0.855)	(0.138)
Post x Wi-Fi x Restructuring Sq.	1.953**	0.007
	(0.947)	(0.079)
Post x Wi-Fi	0.030	-0.068
	(0.603)	(0.123)
Post x Current Autonomy	-0.092	-0.143
	(0.063)	(0.130)
Post x Potential Autonomy	0.067	-0.516
	(0.077)	(0.648)
Post x Restructuring	-0.514*	-0.093
	(0.292)	(0.169)
Post x Restructuring Sq.	-0.559	-0.070
	(0.483)	(0.088)
WiFi	0.091	0.012
	(0.608)	(0.124)
WiFi x Current Autonomy	-0.137**	-0.358*
	(0.068)	(0.205)
WiFi x Potential Autonomy	0.058	0.332
	(0.074)	(0.351)
WiFi x Restructuring	-1.732**	0.008
	(0.853)	(0.131)
WiFi x Restructuring Sq.	-1.883*	-0.003
	(0.962)	(0.073)
Current Autonomy	0.237***	0.150
	(0.066)	(0.150)
Potential Autonomy	-0.061	-0.107
	(0.070)	(0.652)
Restructuring	0.317	-0.024
	(0.280)	(0.166)
Restructuring Sq.	0.183	-0.015
	(0.467)	(0.087)
Max Relationship Duration	0.107***	0.134***
	(0.032)	(0.020)
Average Relationship Duration	-0.088*	-0.130***
	(0.046)	(0.021)
Supplier age<5	-0.152	-0.059

	(0.158)	(0.083)
Supplier age>5 but <=10	0.054	0.065
	(0.129)	(0.065)
Constant	1.382***	1.313***
	(0.214)	(0.106)
R2	0.914	0.797
N	518.000	2290.000

Note: Estimates from OLS regressions, standard errors in parentheses, clustered at the firm level. All specifications include firm and year-fixed effects. Post is defined as 1 if open-source operating systems were available in that time period (i.e., indicator for the year 2004 and onwards, when OpenWRT was created).

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

Table 7. Heterogeneity in effect sizes across firms

	(1) log(Device Counts+1)	(2) Current Autonomy	(3) Potential Autonomy	(4) Restructuring
Average	0.413***	3.039***	-0.777	0.151
	(0.122)	(0.956)	(0.543)	(0.105)
2005 Cohort	0.454**	3.625**	-2.060***	0.417
	(0.212)	(1.753)	(0.562)	(0.263)
2006 Cohort	0.122	1.078**	-3.450***	-0.478**
	(0.187)	(0.483)	(0.773)	(0.230)
2007 Cohort	1.265***	5.006**	-1.064	0.388**
	(0.267)	(2.197)	(1.045)	(0.194)
2009 Cohort	0.180	-0.382	0.107	-0.514**
	(0.189)	(1.301)	(0.916)	(0.224)
2011 Cohort	1.383***	10.164***	-1.981	0.663
	(0.134)	(1.207)	(1.646)	(0.450)
2015 Cohort	-1.075***	-1.188**	3.392**	-0.073
	(0.084)	(0.476)	(1.618)	(0.405)
2017 Cohort	-1.387***	-1.671***	0.293	0.100
	(0.058)	(0.088)	(1.453)	(0.354)
2012 Cohort	0.039			
	(0.109)			
Observations				

Note: Cohort treatment effect estimates (ATTGT's) from Callaway and Sant'Anna (2022). Sample uses only time periods 6 years prior to and 6 years after firms release open-source drivers, thus reports the 6-year effect of treatment. Standard errors in parentheses

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

APPENDIX

Table A1. Poisson pseudo-likelihood regressions

	(1) Device Count	(2) Device Count	(3) Device Count	(4) Device Count
Current Autonomy	0.075	0.052	0.481	0.005
Potential Autonomy	-0.090	-0.414	-0.527	-3.315
Restructuring	-0.032	-0.235	-0.046	-0.016
Restructuring Sq.	-0.516	-0.571	-0.074	-0.052
Max Relationship Duration	0.196	0.151	0.120	0.167
Average Relationship Duration	-0.062	-0.013	-0.119	-0.130
Supplier age<5	-0.421	-0.086	-0.231	-0.195
Supplier age>5 but <=10	-0.163	-0.008	0.038	0.105
Constant	2.519	3.749	1.761	2.313
Log likelihood	-560	-785	-1883	-1901
N	191	326	1123	1163

Note: Estimates from Poisson pseudo-maximum likelihood regressions with fixed effects, standard errors in parentheses, clustered at the firm level. All specifications include firm and year-fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2. Glossary

Term	Definition
Supply chain	A logistics system that converts parts into finished products, which are later distributed.
Wi-Fi	A feature allowing computers, smartphones, or other devices to connect to the internet or communicate with one another wirelessly within a particular area, defined by IEEE Committee 802.11
IEEE	Institute of Electronics and Electrical Engineers. A not-for-profit industry organization that organizes standard-setting committees.
IEEE Committee 802.11	A committee that defines a set of standards and protocols that define data communication for wireless local area networks.
Router	A device that forwards data packets to the appropriate parts of a computer network.
CPU	The Central Processing Unit is typically the most important integrated circuit that performs calculations in a device.
Open Source	Software in which the source code is released with a license that makes the code freely available without restriction on who may examine the code and may be redistributed and modified, potentially with limitations on commercial activity and obligations for sharing further additions.
Open-source driver	The software enabling the operating system and device communication is released under an open-source license.
Wi-Fi chipset	A set of hardware memory circuits and communications microprocessors that allows wireless communications between devices.
Router assemblers	A firm that follows a design for a router and puts together machines using component parts.
FCC	Federal Communications Commission. A US federal agenda with regulatory authority over licensing all devices that use electromagnetic spectrum – e.g., low-powered devices for wireless communications, such as Wi-Fi routers.

Table A3. List of Suppliers

Wi-Fi only	Both Wi-Fi and CPUs	CPU only
AGERE	AMD	2Wire
Airgo	AMIT	ADMtek
Atheros	Atmel	AMCC
Cisco	BridgeCo	Allwinner
G2Microsystems	Broadcom	Ambarella
GainSpan	Celeno	Amlogic
Inprocomm	Conexant	Annapurna Labs
Lucent	Espressif	Apple
RDC	Infineon	Brecis
VLSI	Lantiq	Cavium
Xilinx	Marvell	Cortina Systems
	MediaTek	Freescale (NXP)
	Qualcomm	Globespan Virata
	Quantenna	Grain Media
	OzmoDevices	HiSilicon
	Ralink	IDT
	Realtek	Ikanos
	Texas Instruments	Intel
	ZyDAS	Intellon
		Intersil
		Micrel
		Microchip
		Mindspeed
		Motorola
		PLX Technology
		Renesas
		Rockchip
		STMicroelectronics
		Samsung
		Sigma Designs
		Star
		TrendChip
		NVIDIA

Table A4. Cohorts of companies that released open-source drivers in the same year

Year	Company
2001	Agere
2005	Atheros
2006	ZyDAS
2007	Broadcom
	Celeno
	Ralink
	Realtek
2009	Atmel
	Marvell
2011	Qualcomm
2012	Texas Instruments
2015	MediaTek
2017	Quantenna

Table A5. Long term effect of Openness on the entire sample

	(1) Current Autonomy	(2) Potential Autonomy	(3) Restructuring	(4) log(Device Counts+1)
Gaverage	1.611*	-0.299	0.205	0.014
	(0.911)	(0.539)	(0.134)	(0.160)
G2005	-2.801	-0.307	0.755***	-0.853***
	(1.865)	(0.495)	(0.266)	(0.213)
G2006	1.344***	-3.512***	-0.423**	-0.036
	(0.416)	(0.763)	(0.206)	(0.212)
G2007	2.965	-0.763	0.502**	0.597
	(1.997)	(0.929)	(0.212)	(0.393)
G2009	-0.487	0.394	-0.526**	0.085
	(1.014)	(0.961)	(0.207)	(0.159)
G2011	10.090***	-0.552	0.448	0.917***
	(1.198)	(1.784)	(0.447)	(0.112)
G2015	-1.188**	3.392**	-0.073	-1.075***
	(0.476)	(1.618)	(0.405)	(0.084)
G2017	-1.671***	0.293	0.100	-1.387***
	(0.088)	(1.453)	(0.354)	(0.058)
G2012				0.039
				(0.109)
Observations				

Note: Cohort treatment effect estimates (ATTGT's) from Callaway and Sant'Anna (2022). Sample uses all time periods in our sample. Standard errors in parentheses

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