APPENDIX

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Section A1. Empirical setting, alternate specifications, robustness checks

A1.1 Summary Statistics and Empirical Setting

Table A1. 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	8.386	20.895	4.931	14.951	1.010	3.396	1.003	3.381
Customer Share	0.053	0.115	0.031	0.073	0.039	0.081	0.022	0.049
Frontier Technology	7.653	19.541	4.158	13.038	0.860	2.918	0.850	2.906
Early Adoption	1.959	9.360	1.029	6.243	0.223	1.356	0.221	1.348
Multiple RF Bands	2.596	8.065	1.354	5.613	0.281	1.369	0.277	1.363
Multiple WiFi Standards	5.184	17.584	2.880	12.057	0.589	2.550	0.584	2.539
Max Relationship Duration	1.510	3.121	1.087	2.668	0.701	2.062	0.696	2.094
Average Relationship Duration	0.649	1.457	0.517	1.398	0.544	1.635	0.523	1.612
Firm age<5	0.165	0.371	0.151	0.359	0.142	0.349	0.144	0.351
Firm age>5 but <=10	0.241	0.428	0.215	0.411	0.212	0.409	0.213	0.410
Firm age>10	0.594	0.492	0.633	0.482	0.646	0.478	0.643	0.479
Observations	510		859		4099		4145	

Note. Observations at the firm-year level. **Customer share** measures bargaining power. Frontier Technology is the number of devices that implement the newest IEEE 802.11 standard at that time. Early Adoption is the number of devices that implement the newest standard in 1 year of its release. Multiple RF Bands counts the number of devices that support the 5GHz bandwidth. Multiple WiFi Standards counts the number of devices with 3 or more implemented standards.

Table A2. Correlation Matrix

Panel A: Suppliers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(110
(1) Device Count	1.000										
(2) Customer Share	0.815	1.000									
(3) Frontier Technology	0.989	0.806	1.000								
(4) Early Adoption	0.564	0.443	0.574	1.000							
(5) Multiple RF Bands	0.764	0.594	0.723	0.229	1.000						
(6) Multiple WiFi Standards	0.895	0.628	0.882	0.495	0.806	1.000					
(7) Max Relationship Duration	0.532	0.431	0.490	0.179	0.646	0.571	1.000				
(8) Average Relationship Duration	0.268	0.182	0.239	0.074	0.391	0.325	0.867	1.000			
(9) Assembler Age	-0.085	-0.117	-0.086	-0.061	-0.023	-0.039	-0.002	0.043	1.000		
(10) Supplier Age	0.000	-0.009	0.001	-0.011	0.013	0.004	0.010	0.013	0.007	1.000	
(11) HHI	0.068	0.168	0.059	0.043	0.123	0.118	0.140	0.144	0.034	0.009	1.000

Panel B: Assemblers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Device Count	1.000										
(2) Customer Share	0.685	1.000									
(3) Frontier Technology	0.977	0.689	1.000								
(4) Early Adoption	0.560	0.420	0.583	1.000							
(5) Multiple RF Bands	0.699	0.473	0.664	0.240	1.000						
(6) Multiple WiFi Standards	0.843	0.509	0.832	0.472	0.786	1.000					
(7) Max Relationship Duration	0.448	0.394	0.437	0.213	0.546	0.535	1.000				
(8) Average Relationship Duration	0.296	0.215	0.282	0.122	0.423	0.395	0.934	1.000			
(9) Assembler Age	0.031	0.015	0.021	-0.071	0.088	0.044	0.125	0.143	1.000		
(10) Supplier Age	-0.027	-0.009	-0.026	-0.034	-0.001	-0.006	0.113	0.106	0.134	1.000	
(11) HHI	-0.037	0.141	-0.071	-0.117	0.032	-0.103	0.025	0.049	0.061	-0.033	1.000

Note. Correlations between all the measures are calculated at the unit of observation, the firm-year level. **Sample sizes** are 317 for suppliers and 2320 for assemblers.

Table A3. Glossary

Term	Definition
CPU	The Central Processing Unit is typically the most important integrated circuit that performs calculations in a device.
FCC	Federal Communications Commission. A US federal agenda with regulatory authority over licensing all devices that use the electromagnetic spectrum – e.g., low-powered devices for wireless communications, such as Wi-Fi routers.
HotSpot	A hotspot is a data transmission medium, potentially mediated by a third party, for local use in a public space or on retail premises.
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.
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 communication between the operating system and device is released under an open-source license.
Router	A device that forwards data packets to the appropriate parts of a computer network.
Router assemblers	A firm that follows a design for a router and puts together machines using component parts.
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 the IEEE Committee 802.11
Wi-Fi chipset	A set of hardware memory circuits and communication microprocessors that enable wireless communication between devices.

Table A4. 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

Note. Total 63. 11 Wi-Fi only, 19 both, 33 CPU only. The most prominent assemblers include D-Link, TP-link, Netgear, and Asus.

A1.2 Robustness Checks

Table A5A. Are Device Counts associated with the change in Autonomy (Log outcomes)

DV: log(DeviceCounts+1)	(1) WLAN-Supplier	(2) CPU-Supplier	(3) WLAN-Assembler	(4) CPU-Assembler
Customer Share	7.046***	10.770***	6.252***	10.817***
	(1.209)	(1.016)	(0.296)	(0.662)
Max Relationship Duration	0.165**	0.124***	-0.021	-0.019
	(0.064)	(0.029)	(0.023)	(0.027)
Average Relationship Duration	-0.087	-0.058*	0.071***	0.082***
	(0.077)	(0.033)	(0.023)	(0.027)
Supplier age<5	-0.365**	-0.140	0.000	0.000
	(0.141)	(0.093)	(.)	(.)
Supplier age>5 but <=10	-0.109	0.088	0.000	0.000
	(0.121)	(0.081)	(.)	(.)
Constant	0.410***	0.266***	0.078***	0.078***
	(0.050)	(0.044)	(0.009)	(0.011)
Observations	510	859	4099	4145
Adjusted R^2	0.898	0.874	0.848	0.845

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 A6. Are Frontier Products associated with the change in Autonomy? (Log outcomes)

	(1) Log(Frontier Technology+1)	(2) Log(Early Adoption+1)	(3) Log(Multiple RF Bands+1)	(4) Log(Multiple Wi-Fi Standards+1)
Customer Share	6.201^{***}	2.807^{***}	2.353^{***}	2.753^{**}
	(1.015)	(0.677)	(0.839)	(1.164)
Max Relationship Duration	0.174^{**}	0.021	0.277^{***}	0.363^{***}
	(0.064)	(0.047)	(0.046)	(0.035)
Average Relationship Duration	-0.141	-0.058	-0.256^{***}	-0.315^{***}
	(0.092)	(0.081)	(0.072)	(0.052)
Supplier age<5	-0.248	-0.202	-0.011	-0.085
	(0.241)	(0.307)	(0.100)	(0.152)
Supplier age>5 but <=10	-0.030	0.184	0.084	-0.055
	(0.211)	(0.303)	(0.100)	(0.134)
Observations	199	199	510	510
Adjusted R^2	0.873	0.554	0.836	0.823

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 A7. Short-run effects of openness on innovation: Calendar time heterogeneity

	Device Count	Customer Share	Frontier Technology	Early Adoption	Multiple RF Bands	Multiple Wi-Fi Standards
CAverage	11.347*	0.056***	7.865	3.972	3.757	11.618*
	(6.399)	(0.019)	(5.934)	(3.197)	(2.612)	(6.618)
T2005	15.175***	0.128***	12.502***		0.011	
	(1.981)	(0.016)	(1.970)		(0.114)	
T2006	12.223*	0.071	9.926*	4.804	-3.147	4.804
	(7.003)	(0.047)	(5.400)	(3.912)	(2.851)	(3.912)
T2007	12.786**	0.052**	12.517***	6.761	-0.096	6.761
	(4.989)	(0.025)	(4.853)	(4.134)	(0.891)	(4.134)
T2008	16.117*	0.057	13.679*	17.377*	1.904*	16.877*
	(8.381)	(0.035)	(8.009)	(10.316)	(1.040)	(10.189)
T2009	22.688**	0.066	20.162**	26.332**	3.788**	25.707**
	(10.844)	(0.042)	(10.136)	(12.012)	(1.743)	(11.834)
T2010	18.181***	0.059*	14.598**	26.917***	2.159	26.917***
	(6.823)	(0.032)	(6.876)	(9.898)	(2.529)	(9.898)
T2011	27.304***	0.053**	25.802**	-3.993**	7.647***	31.756**
	(10.351)	(0.024)	(10.173)	(1.846)	(2.618)	(13.010)
T2012	26.418*	0.026	25.403	-0.135	14.259**	31.864**
	(15.942)	(0.042)	(15.528)	(2.522)	(6.385)	(15.670)
T2013	18.761	0.038	18.232	-0.387	7.069	18.579
	(20.272)	(0.051)	(19.574)	(1.134)	(8.314)	(19.258)
T2014	13.361	0.030	10.482	-5.982*	8.819	10.029
	(15.030)	(0.053)	(12.714)	(3.386)	(8.632)	(11.753)
T2015	5.588	0.055	-5.857	-14.000	6.740	5.810
	(11.396)	(0.049)	(10.017)	(.)	(4.200)	(9.813)
T2016	13.167	0.082	1.494	-14.000	14.424	11.389
	(17.260)	(0.065)	(14.698)	(.)	(9.924)	(15.031)
T2017	-6.630*	0.009	-14.500**		2.944	-5.685*
	(3.911)	(0.019)	(7.308)		(3.749)	(3.428)
T2018	-36.278*		-34.333*		-13.917***	-33.778*
	(19.367)		(17.914)		(4.223)	(18.307)

Note. This table reports calendar time treatment effects from the Callaway and Sant'Anna (2021) estimator.
Effects are shown by calendar year, representing the average treatment effect across all treated groups in each time period.
Standard errors clustered at the firm level are reported in parentheses.
The 'not-yet-treated' units are used as the control group.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8. Mechanisms for attracting firms: Calendar time heterogeneity

	Assembler Age (median)	Assembler is Entrant	Chinese Assembler
CAverage	-7.934***	0.831***	1.433*
	(2.285)	(0.205)	(0.849)
T2005	-12.152***	5.152***	3.721***
	(1.602)	(0.138)	(0.677)
T2006	-5.816	2.140	0.546
	(5.477)	(1.475)	(0.492)
T2007	-6.655	0.220	2.112**
	(5.386)	(0.512)	(1.050)
T2008	-3.855	0.437	3.695**
	(3.050)	(0.360)	(1.520)
T2009	-17.329	0.750**	3.454*
	(11.257)	(0.371)	(2.046)
T2010	-6.636	0.084	3.471**
	(6.623)	(0.224)	(1.540)
T2011	-19.009*	0.413*	3.212**
	(11.224)	(0.215)	(1.602)
T2012	-3.476	0.475	2.715
	(7.311)	(0.419)	(1.970)
T2013	-35.225**	0.450	1.454
	(14.620)	(0.436)	(2.105)
T2014	-5.025	-0.150	1.204
	(5.549)	(0.107)	(1.618)
T2015	-0.896	1.026	0.721
	(5.010)	(0.689)	(1.889)
T2016	-4.562	1.526	1.616
	(12.331)	(1.042)	(1.782)
T2017	17.500	1.056***	0.556
	(13.658)	(0.054)	(0.577)
T2018		-1.944***	-8.417*
		(0.054)	(4.577)

Note. This table reports calendar time treatment effects from the Callaway and Sant'Anna (2021) estimator. Effects are shown by calendar year, representing the average treatment effect across all treated groups in each time period. Standard errors clustered at the firm level are reported in parentheses.
The 'not-yet-treated' units are used as the control group.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9. Short-run effects of openness on innovation (Log outcomes)

Panel A: Simple Weighted Average ATT

	Device Count	Customer Share	Frontier Technology	Early Adoption	Multiple RF Bands	Multiple Wi-Fi Standards
ATT	0.426*	0.049***	0.154	0.139	0.533*	0.914**
	(0.233)	(0.018)	(0.248)	(0.697)	(0.274)	(0.399)

Panel B: Group-Specific ATT by Treatment Cohort

	Device Count	Customer Share	Frontier Technology	Early Adoption	Multiple RF Bands	Multiple Wi-Fi Standards
GAverage	0.282***	0.043***	0.019	0.147	0.402***	0.769***
	(0.097)	(0.007)	(0.189)	(0.287)	(0.099)	(0.137)
G2005	0.547***	0.047***	0.028	2.816***	-0.072	3.240***
	(0.199)	(0.017)	(0.381)	(0.319)	(0.114)	(0.104)
G2006	0.101	0.007	0.364	-0.633**	0.138	-0.175*
	(0.213)	(0.008)	(0.303)	(0.290)	(0.118)	(0.090)
G2007	1.001***	0.085***	0.417	0.644	1.487***	1.929***
	(0.194)	(0.016)	(0.313)	(0.519)	(0.261)	(0.364)
G2009	-0.049	-0.013	-0.278	-1.249***	-0.213**	-0.133
	(0.175)	(0.011)	(0.437)	(0.087)	(0.106)	(0.134)
G2011	1.309***	0.158***	0.196	-2.001***	1.149***	1.197***
	(0.132)	(0.008)	(0.269)	(0.064)	(0.103)	(0.105)
G2012	0.025	-0.008			-0.103	-0.125
	(0.127)	(0.008)			(0.113)	(0.095)
G2015	-1.116***	0.016***	-0.316		-0.504***	-1.079***
	(0.083)	(0.001)	(0.321)		(0.033)	(0.083)
G2017	-1.387***	-0.025***	-1.204**		-1.301***	-1.282***
	(0.058)	(0.003)	(0.490)		(0.054)	(0.058)

Note. All outcomes are +1 log-transformed. This table reports treatment effects from the Callaway and Sant'Anna (2021) estimator. Panel A shows simple weighted average treatment effects across all cohorts. Panel B shows group-specific average treatment effects by treatment cohort (year of OSS adoption). Standard errors clustered at the firm level are reported in parentheses. The 'not-yet-treated' units are used as the control group.

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

Table A10 Mechanisms for attracting firms (Log outcome variables)

Panel A: Simple Weighted Average ATT

	log(Assembler Age - median)	log(Chinese Assembler)	log(Assembler Foreign)
ATT	-0.349**	0.254**	0.199
	(0.174)	(0.111)	(0.190)

Panel B: Group-Specific ATT by Treatment Cohort

	log(Assembler Age - median)	log(Chinese Assembler)	log(Assembler Foreign)
GAverage	-0.134	0.217***	0.105
	(0.208)	(0.068)	(0.134)
G2005	-0.973***	0.307***	0.424
	(0.242)	(0.074)	(0.265)
G2006	-0.672***	0.155***	0.115
	(0.143)	(0.043)	(0.180)
G2007	-0.213	0.309*	0.227
	(0.259)	(0.169)	(0.272)
G2009	-0.471***	0.051	-0.045
	(0.179)	(0.097)	(0.308)
G2011	-0.654	0.817***	0.495*
	(0.466)	(0.031)	(0.271)
G2015	0.479	-0.165***	-0.212
	(0.455)	(0.036)	(0.199)
G2017	1.751		-0.549***
	(1.497)		(0.213)
G2012		-0.065	
		(0.052)	

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

Figure A1 Additional event study plots

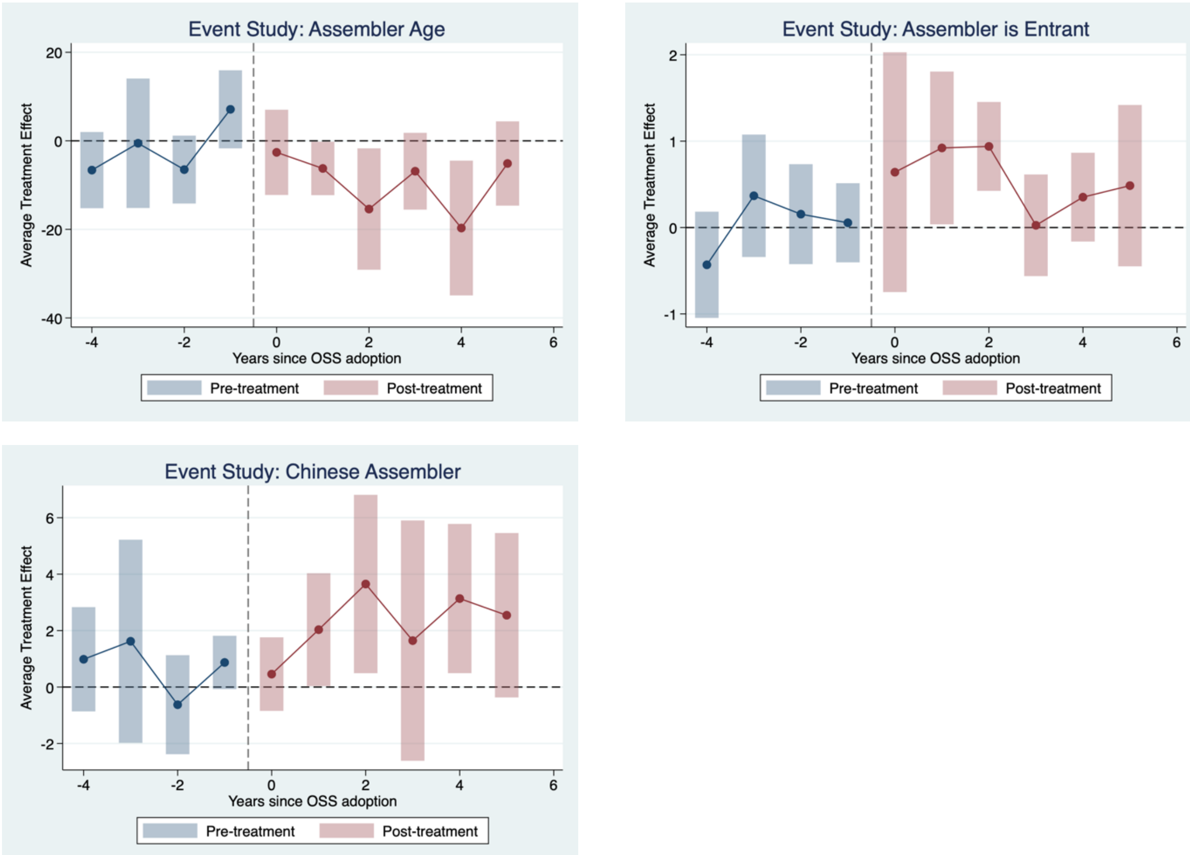
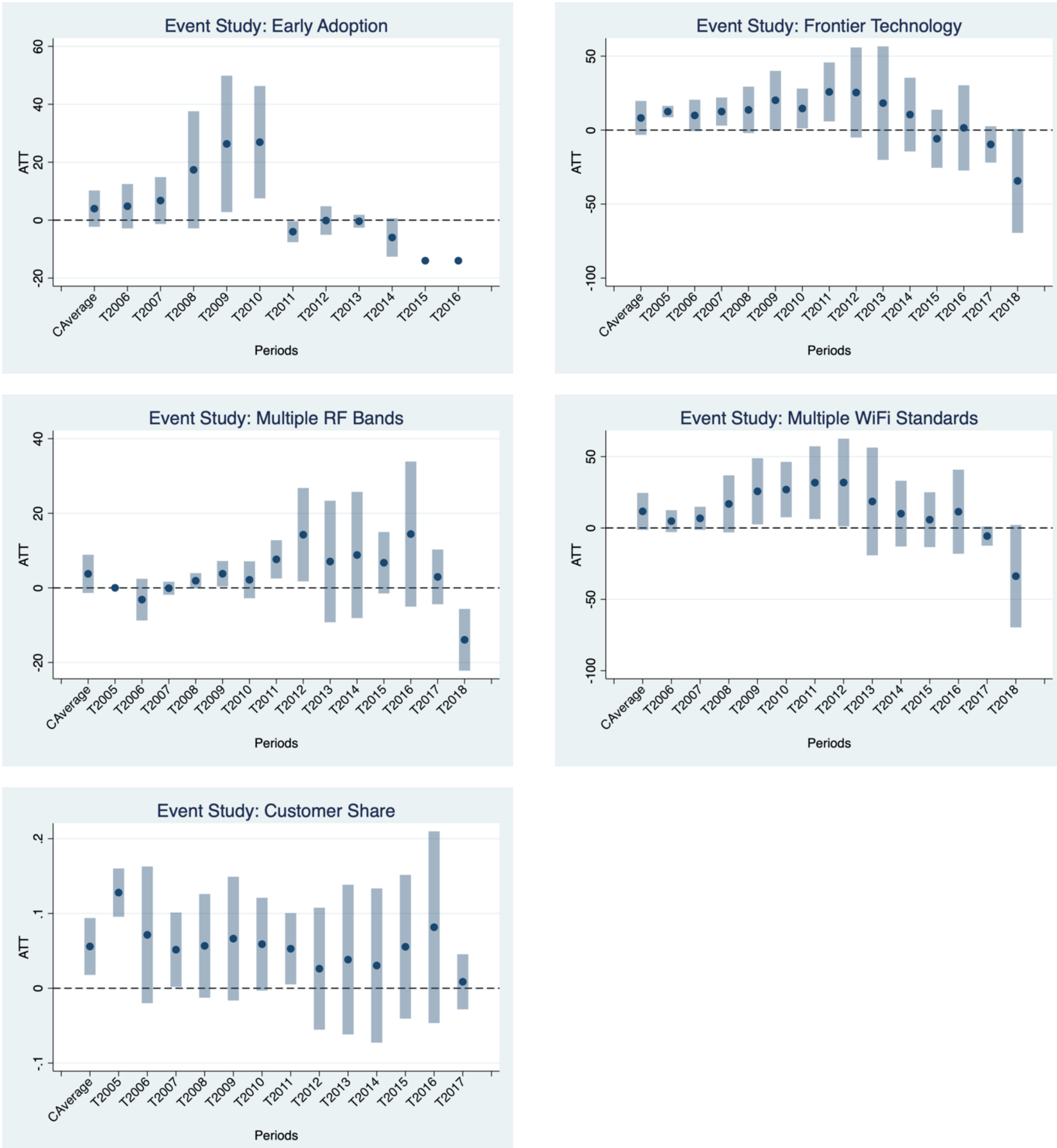


Figure A2 Calendar year effect plots



Section A2. Autonomy vs Customer Share

This section compares three different measures of "autonomy." A prior version of the draft followed Hoetker et. al. (2007) in calculating autonomy, or the "degree to which a supplier can act independently of its buyers (Burt 1992)." The measures were constructed to capture "(1) The more alternatives available to a firm, the less dependent it was on any given partner; and (2) the power of firm A over firm B depended on the difference between A's dependence on B and B's dependence on A." The authors define two measures of autonomy: current autonomy and potential autonomy.

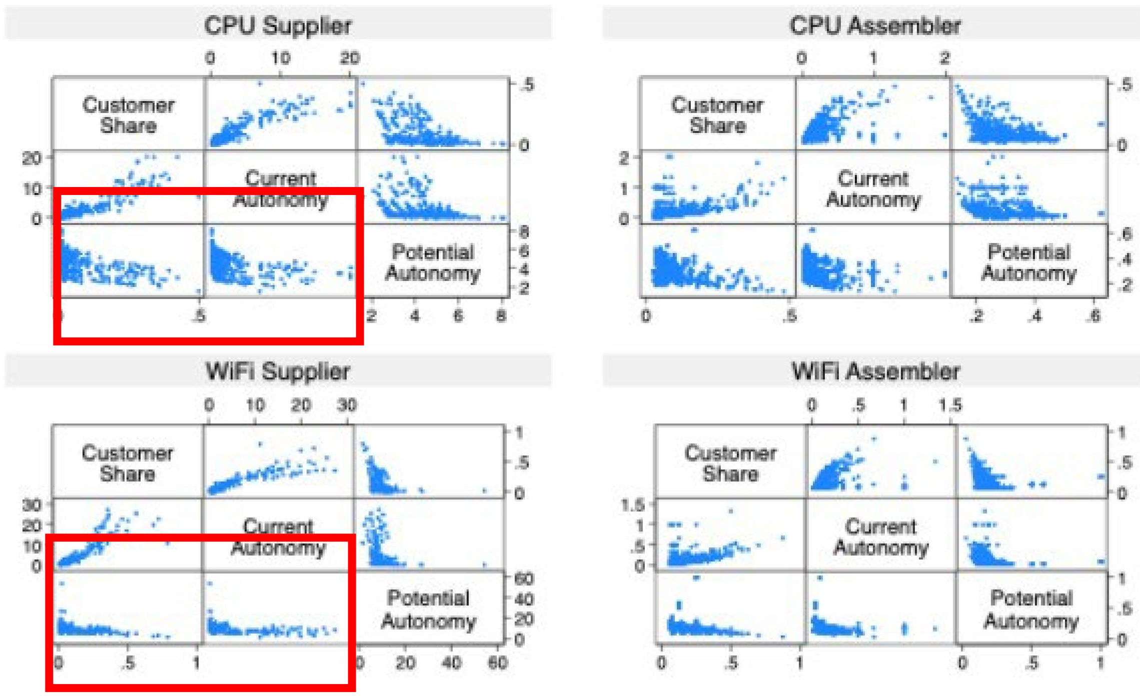
The current study, alternatively, defines "customer share" as a Porterian measure of autonomy (e.g., Porter 1985). The customer share measure builds on insights from the bargaining power of suppliers and more carefully captures the context of the the wireless router industry where the supplier market is concentrated, and switching costs between suppliers exist thus limiting the ability of firms in an industry to capture value.

A mechanical comparison of the three measures is provided below. Denote suppliers with subscripts i and assemblers with a subscript j. A_{it} denotes the customers of the chip supplier i at time t, while A_t denotes the set of all active assemblers at time t. Similarly, S_{jt} denotes the chip suppliers of the assembler j at time t, and S_t the set of all active suppliers at time t. The complement of the sets A_{it}, S_{jt} are denoted A_{it}^c, S_{jt}^c, and are defined as $A_{it}^c = A_t - A_{it}$ and $S_{jt}^c = S_t - S_{jt}$.

Customer Share	Current Autonomy	Potential Autonomy
$\dfrac{\overbrace{\#(A_{it})}^{My\ Customers}}{\underbrace{\#(A_t)}_{All\ Customers}}$	$\dfrac{\overbrace{\#(A_{it})}^{My\ Customers}}{\underbrace{\frac{1}{\#(A_{it})}\sum_{j\in A_{it}}\#(S_{jt})}_{Avg.\#Suppliers\ of\ My\ Customers}}$	$\dfrac{\overbrace{\#(A_{it}^c)}^{My\ Potential\ Customers}}{\underbrace{\frac{1}{\#(A_{it})}\sum_{j\in A_{it}}\#(S_{jt}^c)}_{Avg.\#Potential\ Suppliers\ of\ My\ Customers}}$

The primary simplification from autonomy to customer share involves using all customers (both potential and realized) in the denominator, rather than weighting each customer by the number of suppliers they have. Below is a plot of the relationship between the three measures.

Figure A3 Scatterplot visualization of autonomy measures



As can be seen above (red boxes), customer share most closely tracks current autonomy, particularly for suppliers. This is confirmed in the correlation tables below. For suppliers, the correlation between autonomy and customer share is approximately 0.9, indicating a strong similarity between the two measures.

Table A11 Correlation tables across autonomy measures

Wi-Fi Supplier

	Customer Share	Current Autonomy	Potential Autonomy
Customer Share	1.0000		
Current Autonomy	0.8970	1.0000	
Potential Autonomy	-0.4008	-0.3058	1.0000

N = 541

CPU Supplier

	Customer Share	Current Autonomy	Potential Autonomy
Customer Share	1.0000		
Current Autonomy	0.8987	1.0000	
Potential Autonomy	-0.4771	-0.3577	1.0000

N = 911

Wi-Fi Assembler

	Customer Share	Current Autonomy	Potential Autonomy
Customer Share	1.0000		
Current Autonomy	0.4836	1.0000	
Potential Autonomy	-0.1156	-0.1623	1.0000

N = 4351

CPU Assembler

	Customer Share	Current Autonomy	Potential Autonomy
Customer Share	1.0000		
Current Autonomy	0.4062	1.0000	
Potential Autonomy	-0.2505	-0.2124	1.0000

N = 4401

Finally, the table below replicates the results from Tables 2 and 3 in the main body of the text using current autonomy instead of customer share.

Table A12 ***Are Device Counts associated with the change in Autonomy? (Current autonomy)***

	(1) WLAN-Supplier	(2) CPU-Supplier	(3) WLAN-Assembler	(4) CPU-Assembler
Current Autonomy	0.101^{***}	0.105^{***}	0.787^{**}	0.428^{***}
	(0.010)	(0.013)	(0.346)	(0.153)
Max Relationship Duration	0.208^{***}	0.174^{***}	0.122^{***}	0.187^{***}
	(0.041)	(0.026)	(0.033)	(0.021)
Average Relationship Duration	-0.147^{***}	-0.079^{*}	-0.124^{***}	-0.142^{***}
	(0.037)	(0.044)	(0.029)	(0.023)
Supplier age<5	-0.356	-0.426^{**}	-0.204	-0.169
	(0.287)	(0.211)	(0.165)	(0.151)
Supplier age>5 but <=10	-0.284	-0.072	-0.124	-0.135
	(0.236)	(0.161)	(0.127)	(0.108)
Constant	1.478^{***}	1.635^{***}	1.536^{***}	1.236^{***}
	(0.136)	(0.156)	(0.082)	(0.082)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Log-Likelihood	-620.67	-834.54	-1950.83	-1965.92
Observations	199	334	1142	1180

Standard errors in parentheses, clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A13 Are Frontier Products associated with the change in Autonomy? (Current Autonomy)

	(1) Frontier Technology	(2) Multiple RF Bands	(3) Multiple WiFi Standards
Current Autonomy	0.058^{***}	0.054^{***}	0.089^{***}
	(0.017)	(0.020)	(0.012)
Max Relationship Duration	0.421^{***}	0.270^{***}	0.344^{***}
	(0.147)	(0.066)	(0.094)
Average Relationship Duration	-0.504^{***}	-0.118	-0.110^{***}
	(0.161)	(0.088)	(0.023)
Supplier age<5	1.551	0.347	-1.037^{*}
	(0.943)	(0.381)	(0.596)
Supplier age>5 but <=10	0.096	0.582	-0.091
	(0.300)	(0.373)	(0.277)
Constant	0.863	0.124	-0.029
	(0.756)	(0.495)	(0.767)
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Log-Likelihood	-186.60	-369.55	-359.24
Observations	95	164	109

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Section A3. Identification framework

A3.1. Potential outcomes framework and target parameters

We use a potential outcomes framework. We define $Y_{i,t}(g)$ as firm i's potential outcome at time t if it (potentially) released open-source device drivers at time g. We use G_i to denote treatment times (the time at which firm i actually released open source device drivers), and $\mathcal{G}$ to denote the set of all treatment times. Finally, if a firm never releases open source device drivers, we set $g = \infty$ and denote that firm's potential outcomes as $Y_{i,t}(\infty)$. We only observe outcomes for whether firms do or do not open, therefore we observe $Y_{i,t}$:

$$Y_{i,t} = \sum_{g \in \mathcal{G}} Y_{i,t}(g) 1\{G_i = g\}$$

Ideally, we would like to observe both the treated and untreated potential outcomes and take their differences to estimate the effect of open source drivers (i.e., $Y_{i,t}(1) - Y_{i,t}(0)$). In the absence of this, we must approximate the counterfactual outcomes.

Before the empirical construction of our estimator, we first define the parameter of interest. As in Callaway and Sant'Anna (2021), our parameter of interest is $ATT(g,t)$, or the average treatment effect on treated units in g at time t. This measures the average (among units that actually released open drivers at some time g) treatment effect (at time t) of releasing open-source device drivers at time g relative to never starting it. Formally, for some set of weights ω, the parameter of interest is defined as:

$$ATT(g,t) = E_{\omega}\left[Y_{i,t}(g) - Y_{i,t}(\infty)\right]$$

The $ATT(g,t)$ "building blocks" measure the weighted average treatment effect for all treated units i in year t compared to their untreated potential outcomes. Weights are calculated by the proportion of the sample for group g.

A3.2. Identification assumptions

For our staggered difference in difference results, we require two assumptions.

Our first assumption is **parallel trends based on not-yet treated groups (PT-NYT)**. For all years t, firms i who eventually release open source device drivers in year g (i.e., treatment group g), and firms in not-yet treated groups g'

$$E_{\omega}\left[Y_{i,t}(\infty) - Y_{i,t-1}(\infty) \middle| G_i = g\right] = E_{\omega}\left[Y_{i,t}(\infty) - Y_{i,t-1}(\infty) \middle| G_i = g'\right]$$

This assumption states that, if firms had never released open-source drivers, the potential outcome trends (i.e., the change in outcomes over time, $Y_{i,t}(\infty) - Y_{i,t-1}(\infty)$) evolve similarly for firms that eventually release open-source device drivers and those that have not yet released them.
Violations of PT-NYT tend to depend on how firms select into releasing open-source device drivers.

On the one extreme, if firms have full information about their untreated potential outcomes across time (i.e., $Y_{i,t}(\infty)$ for all t), they can choose the optimal time (i.e., g) to release open-source device drivers to maximize profits. In this case, Ghanem et al. (2025) show that PT-NYT holds only if $Y_{i,t}(\infty) - Y_{i,t-t}(\infty)$ is constant for all i, t. On the other extreme, if firms choose to release open-source device drivers at random, then PT-NYT holds. We discuss the cases in between in Section A3.4.

Our second assumption is **no anticipation with staggered timing (NA-S)**. Formally, for all pre-treatment years t, and all firms i that are eventually treated,

$$Y_{i,t}(g) = Y_{i,t}(\infty)$$

should hold. This assumption states that the decision to release open-source drivers does not affect innovation outcomes before the drivers are actually released.

Violations of NA-S can occur if there is a difference between our definition of the treatment time (i.e., the release date of open source device drivers) and the actual time it affects outcomes. In many cases, the "announcement" of policies can affect equilibrium outcomes before the policies are actually implemented. We discuss the plausibility of this assumption in Section A3.5.

A3.3. Estimation method

Under the assumptions of no anticipation (NA-S) and parallel trends (CPT-GT-NYT), Callaway and Sant'Anna (2021) show that we can estimate $ATT(g,t)$ as follows:

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

And we can estimate population means using sample averages:

$$\widehat{ATT}_{nyt}(g,t) = \frac{\sum_{i=1}^{n} 1\{G_i = g\}\left(Y_{i,t} - Y_{i,t=g-1}\right)}{\sum_{i=1}^{n} 1\{G_i = g\}} - \frac{\sum_{i=1}^{n} 1\{G_i > t\}\left(Y_{i,t} - Y_{i,t=g-1}\right)}{\sum_{i=1}^{n} 1\{G_i > g\}}$$

For our summary parameters, we present three different aggregations: 1) event study analysis, 2) short-run effects, and 3) calendar year analysis.

Event study parameters summarize the treatment effect dynamics in terms of event time:

$$\begin{aligned} ATT_{es}(e) &= E_\omega[ATT(G, G+e)|G+e \in [1,T], G \leq T] \\ &= \sum_{g<\infty} w_{\omega,g,e}^{es} ATT(g, g+e) \end{aligned}$$

Where the weights $w_{\omega,g,e}^{es}$ gives the share of group $G = g$ among treated units that have been exposed to treatment for exactly e periods, and is formally defined as:

$$w_{\omega,g,e}^{es} = 1\{g + e \leq T\} P_\omega(G = g|G + e \leq T, G \leq T)$$

Next, we estimate short-run effects by aggregating the $ATT(g,t)$ estimates for the first five years of treatment:

$$ATT_{st}(g) = \sum_{e\leq 5}\sum_{g<\infty} w^{es}_{\omega,g,e} ATT(g, g+e)$$

The weights are defined identically as in the previous section.

A3.4. Heterogeneity and Additional Assumptions

A3.4.1 Heterogeneity variable construction

Prior work suggests that to profit from implementation, firms need complementary assets (Teece 1986, Gans and Stern 2003). We collect information about suppliers that illustrate whether they have complementary assets. In this context, technology suppliers' reputation and size are important complementary assets.

For each firm, we create an indicator for the firm's scale, as well as their reputation. For scale, we obtain the number of employees or the revenue at the point in time they released open source software. If they never release open source software, we use [∞] as the date.

Firms in our sample may be: Large/Small, or Established/Nascent. Suppliers are categorized as Large if they have 6000 or more employees, or their revenue is above $2B. Similarly, suppliers are categorized as Established if they were founded in 1991 or earlier, when the first wireless networking protocols were written. Firms are categorized as Nascent if they are founded after 1992. Below, we list the information for each supplier.

Table A14 Cohorts of companies that released open-source drivers in the same year

Open Year	Company	Founded	Established vs. Nascent	Employees	Revenue	Categorization
2001	Agere	2000	Nascent	18,400[1]	4.7B[2]	Large
2005	Atheros	1998	Nascent	260[3]	183.5M[4]	Small
2006	ZyDAS	2000	Nascent	70+[5]	N/A	Small
2007	Broadcom	1991	Established	3,700[6]	3.78B[7]	Large
	Celeno	2005	Nascent	N/A	N/A	Small
	Ralink	2001		N/A	230M[8]	Small

[1] https://www.mcall.com/2001/12/06/agere-will-slice-950-more-jobs-about-570-of-them-will-be-in-breinigsville-allentown-and-reading/
[2] https://www.encyclopedia.com/books/politics-and-business-magazines/agere-systems-inc
[3] https://www.sec.gov/Archives/edgar/data/1140486/000119312511031110/d10k.htm
[4] https://www.sec.gov/Archives/edgar/data/1140486/000119312506015129/dex991.htm
[5] https://www.lightreading.com/business-management/atheros-acquires-zydas
[6] https://stockanalysis.com/stocks/avgo/employees/
[7] https://investors.broadcom.com/static-files/fd02838e-e55f-4a21-bd1b-261913b279a2
[8] https://www.eetimes.com/ralink-trendchip-merge-to-form-wireless-broadband-ic-player/

	Realtek	1987	Nascent Established	N/A	3.9B[9]	Large
2009	Atmel	1984	Established	5,600[10]	1.217B	Small
	Marvell	1995	Nascent	5,552[11]	2.95B[12]	Large
2011	Qualcomm	1985	Established	21,200[13]	14.957B	Large
2012	Texas Instruments	1951	Established	34,151[14]	12.825B	Large
2015	MediaTek	1997	Nascent	15,204[15]	7B[16]	Large
2017	Quantenna	2006	Nascent	400[17]	175M	Small
∞	AMD	1969	Established	28,000[18]	29.6B[34]	Large
	AMIT	1998	Nascent	~500[19]	23.9M[35]	Small
	Airgo	2001	Nascent	23[20]	N/A	Small
	BridgeCo	2000	Nascent	100[21]	7.2M	Small
	Cisco	1984	Established	90,400[22]	57B	Large
	Conexant	1999	Nascent	312[23]	104M	Small
	Espressif	2008	Nascent	840[24]	282M[36]	Small
	G2Microsystems	2004	Nascent	50[25]	N/A	Small
	GainSpan	2006	Nascent	90+[26]	N/A	Small
	Infineon	1999	Nascent	58,065[27]	17B	Large
	Inprocomm	2002	Nascent	N/A	N/A	Small
	Lantiq	2009	Nascent	1,000[28]	N/A	Small
	Lucent	1996	Nascent	30,500[29]	9.44B	Large
	OzmoDevices	2004	Nascent		N/A	Small

[9] https://companiesmarketcap.com/realtek/revenue/
[10] https://www.sec.gov/Archives/edgar/data/872448/000095012310018576/f55057e10vk.htm
[11] https://stockanalysis.com/stocks/mrvl/employees/
[12] https://www.marvell.com/company/newsroom/marvell-technology-reports-fiscal-fourth-quarter-and-fiscal-2009-results.html
[13] https://www.sec.gov/Archives/edgar/data/804328/000123445211000360/qcom10-k2011.htm
[14] https://www.sec.gov/Archives/edgar/data/97476/000009747613000009/txn-12312012x10xk.htm
[15] https://cdn-www.mediatek.com/page/2015_Annual_Report_en.pdf
[16] https://www.forbes.com/companies/mediatek/
[17] https://www.cleartosend.net/quantenna-wifi-chipset-company/
[18] https://www.macrotrends.net/stocks/charts/AMD/amd/number-of-employees
[19] https://brandfetch.com/amitwireless.com
[20] https://rocketreach.co/airgo-networks-management_b4475c49fae592fd
[21] https://www.kroll.com/en/transactions/smsc-acquires-bridgeco
[22] https://www.cisco.com/c/dam/en_us/about/annual-report/cisco-annual-report-2023.pdf
[23] https://investor.synaptics.com/news-releases/news-release-details/synaptics-accelerates-consumer-iot-strategy-acquisitions
[24] https://www.espressif.com/sites/default/files/financial/688018_20250322_Espressif%20Systems%202024%20Annual%20Report.pdf
[25] https://www.bizjournals.com/sanjose/stories/2010/03/22/daily25.html
[26] https://www.telit.com/press/telit-adds-wi-fi-and-low-power-solutions-for-iot-with-acquisition-of-gainspan-to-extend-end-to-end-iot-solutions-reach
[27] https://www.infineon.com/assets/row/public/documents/corporate/investors/annual-reports/2024/2024-infineon-financial-data-2020-2024-v01-00-en.pdf
[28] https://www.cbinsights.com/company/lantiq
[29] https://thebhc.org/rise-and-demise-lucent-technologies
[34] https://finance.yahoo.com/quote/AMD/financials/
[35] https://rocketreach.co/amit-wireless-inc-profile_b5d16f58f42e43a4
[36] https://www.espressif.com/sites/default/files/financial/688018_%E4%B9%90%E9%91%AB%E7%A7%91%E6%8A%80_2025-08-30_%E4%B9%90%E9%91%AB%E7%A7%91%E6%8A%80%EF%BC%9AEspressifSystems2025Q2_Half-YearReport.pdf

RDC	1986	Established	50[30]	9.6M	Small
VLSI	1979	Established	93[31]	719.92M	Small
Xilinx	1984	Established	2,738[32] 4,890[33]	3.15B	Small

A3.4.2 Heterogeneity analysis assumptions

For our heterogeneity analysis results, we require two additional assumptions. Conditional parallel trends based on not-yet treated groups and strong overlap with staggered adoption.

Conditional parallel trends based on not-yet treated groups (CPT) is similar to the parallel trends assumption above, but conditional on covariates. For all years t and eventually treated groups g, and covariate value X_i:

$$E_\omega\left[Y_{i,t}(\infty) - Y_{i,t-1}(\infty) \middle| G_i = g, X_i\right] = E_\omega\left[Y_{i,t}(\infty) - Y_{i,t-1}(\infty) \middle| G_i = g', X_i\right]$$

This assumption states that the PT-NYT assumption holds for each value of X_i.

Finally, the **strong overlap with staggered adoption (SO)** condition states that for each value of X_i there is variation in treatment status. For every group $g \in \mathcal{G}$ there exists some $\epsilon > 0$ such that:

$\epsilon < P_\omega(G_i = g|X_i) < 1 - \epsilon.$

Note that to satisfy both the SO condition, we must focus on years in which at least two suppliers opened. This is because we need $P_\omega(G_i = g) > 0$ for all g within X_i. This implies that we are not able to use many treatment groups. For example, using the large vs small split, conditional on $X_i = Large$, $P_\omega(G_i = 2005) = 0$, violating the Strong overlap assumption. Therefore, we focus on years for which both large and small firms exist. This includes firms that never opened, or opened in 2007 or 2009.

A3.4.3 Heterogeneity analysis and results

Our target parameters are the ATTs for large vs small, and established vs nascent. We define $Large_i, Small_i, Established_i, Nascent_i$ as above and estimate the following quantity:

$$ATT_{X_i}(g,t) = E_\omega\left[Y_{i,t} - Y_{i,t=g-1} \middle| G_i = g, X_i = 1\right] - E_\omega\left[Y_{i,t} - Y_{i,t=g-1} \middle| G_i > \max\{g,t\}, X_i = 1\right]$$

Then, we aggregate to the 5-year short-term effect level as above.

[30] https://pitchbook.com/profiles/company/43039-18
[31] https://www.investing.com/pro/TPEX:3228/explorer/total_rev
[32] https://www.company-histories.com/VLSI-Technology-Inc-Company-History.html
[33] https://pitchbook.com/profiles/company/14186-62

Table A15 Established vs nascent firms

Panel A: Simple Weighted Average ATT (Established Suppliers)

	Assembler Age (median)	Assembler is Entrant	Chinese Assembler
ATT	-17.767***	0.750***	5.204***
	(3.825)	(0.226)	(1.327)

Panel B: Simple Weighted Average ATT (Nascent Suppliers)

	Assembler Age (median)	Assembler is Entrant	Chinese Assembler
ATT	-4.829	0.869**	1.114
	(7.350)	(0.405)	(0.722)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The mechanisms operate similarly, with openness allowing suppliers to attract younger and foreign assemblers.

A3.5. Threats to identification

In this section, we revisit the identification assumptions from Section 3 and discuss their plausibility. We first discuss the no-anticipation assumption and potential violations. Next, we discuss the parallel trends assumption and potential violations, as well as their remedies. Finally, we provide evidence from the literature that is consistent with parallel trends holding in our context.

A3.5.1 Violations of no anticipation: Announcement effects

As stated above, no anticipation (NA) assumes that the treatment effect is zero in all pre-treatment periods. This could be violated if the announcement of a treatment, rather than the treatment itself, affects outcomes. For example, announcements of regulatory changes might affect firm behaviors even before the regulations are put in place.

First, suppliers' announcement of support for open source is unlikely to affect relationships with their assemblers. Assemblers benefit from open source device drivers because it lowers costs of development, and they can go to the community for help instead of having to go directly to the suppliers. Furthermore, announcements may have an impact at the supplier selection stage, but it is unlikely to be reflected in product innovation outcomes.

Second, we show that in the case of wireless routers, there is minimal time difference between supplier announcement of open source support and actual driver release. For each supplier in our dataset, we search for the earliest press articles mentioning the firm releasing open source device drivers and compare with the actual driver open date.

Table A16 Supplier announcement dates vs open dates

Company	Driver name(s)	Open Date	Earliest News Article Date	Announced – Open Difference	Notes
Agere	wavelan2_cs.o	2001/04/27	2000/11/25	< 1 year	
Atheros	ath(4)	2005/02/09	2008/07/27		OpenBSD date (i.e., "open")
ZyDAS	zd1201 zd1211rw	2005/03/07 2006/06/02	2005/01/18	< 1 year	Zd1201 was earlier but supported only wireless dongles (less applicable for routers)
Broadcom	b43	2007/09/18	2010/09/09		Reverse engineered driver
Celeno	rt2x00	2007/09/25	2022/05/24		Rebranded Ralink chips
Ralink	rt2x00	2007/09/25	2005/03/17	2 years	
Realtek	rtl8187	2007/05/24	2019/05/29		
Atmel	atmel at76c50x-usb	2003/06/05 2009/02/07	2002/08/05	< 1 year	"atmel" was a binary blob
Marvell	mwl8k	2009/03/16	2009/06/09		
Qualcomm	ar5523	2012/10/29	2012/03/29	< 1 year	
Texas Instruments	wl18xx	2012/06/05	2011/04/12	1 year	
MediaTek	mt76	2015/05/28	2015/12/03		
Quantenna	quantenna	2017/05/24	2017/05/11		

We see that of the 13 open companies, 6 make their announcements before the actual driver release date, and only one company makes the announcement more than 1 year in advance. This suggests that, to the extent that announcement effects exist, they may affect only one company.

A3.5.2 Violations of parallel trends: Selection into treatment

Generally, parallel trends are violated when the untreated potential outcome trends are different for treatment and control groups. In our setting, parallel trends would hold if for some year, the change in outcome variables for open suppliers would have been the same as the change for closed ones, had they not opened. In simple terms, there should be no reason to believe that open and not-yet open firms' potential outcomes were on different trajectories. Fundamentally, the parallel trends assumption restricts unobservable potential outcomes and thus is not empirically testable. As a result, we focus on providing contextual details to support parallel trends. Particularly since our setting has staggered treatment adoption, we focus on explaining issues related to treatment timing, and whether there is selection into treatment.

Recent literature finds that when selection into treatment exists, researchers should consider firms' information sets in the pre-treatment period and how it affects the credibility of the parallel trends assumption (Marx et al. 2024, Ghanem et al. 2025, Baker et al. 2025). On the one extreme, if firms have *perfect information* about untreated potential outcome trends, they could choose the optimal point in time to release open-source drivers. Parallel trends would be difficult to justify in this case. On the other extreme, firms may have *no information* about untreated potential outcomes and therefore choose to release open-source device drivers randomly. Both extremes are unlikely in our setting. The early days of the wireless router market had uncertainty surrounding assemblers' demand for open device drivers, and examples of successful open source business models were limited, suggesting perfect information is unlikely. However, the same suppliers are profit maximizing firms, active participants in standard setting committees, making the no information situation also unlikely.

One takeaway from this literature is that distinguishing between time-varying and time-invariant factors within firms' information sets is helpful. Roughly, when firms select into treatment based on time-invariant factors, parallel trends can hold. In the next subsections, we outline the drivers of openness and discuss whether they pose a threat to our identification.

A3.5.2.1 Time-invariant drivers of openness

In the context of wireless routers, we argue that parallel trends hold because in the time frame of our study, firms release open-source device drivers primarily based on *time-invariant determinants* of the untreated potential outcomes, not short-run shocks that also move innovation outcomes. For example, a time-invariant component could involve firm-specific attitudes towards open source software, while an example of a time varying factor could be demand-shocks (e.g., poor sales performance in the previous year led to a firm opening). In this section, we show evidence suggesting three primary time-invariant drivers: legal requirements, company culture and ideology, and product architecture. Each is plausibly difficult to change within our study window.

Legal Requirements. Legal concerns are an important factor in determining whether firms open. For open source software, copyleft licenses such as the GPL require that firms using open source software must release the corresponding source code. The academic literature supports this notion. In a survey of hardware manufacturers, Henkel (2006) finds that the primary reason to release open source drivers is because "the GPL requires it" with close to 80% of survey respondents agreeing with the statement. In the wireless router setting, the issue was complicated by FCC regulations. For instance, in an interview with Sam Leffler, he says "I arranged a deal with [Atheros] where […] I would provide open source software that supported their hardware, and I would protect the interfaces to their hardware, which they needed to control because of regulatory requirements. They couldn't release documentation or software that programmed their radios because people could then train them to bands that were illegal or raise the transmit power and so forth." Thus, for many companies, releasing open source device drivers was less of a strategic decision, but a legal requirement.

Company Culture/Ideology. Another significant factor in releasing open source drivers is the company culture. In the same survey, Henkel (2006) finds that the second most-agreed upon reason for releasing open source is because they want to "appear as a good player in the open source community." Henkel (2009) also shows that individual developers have a strong say in firms' release of open source software, and developers who identify with the OSS community can act as a "champion of revealing." Similarly, Daniel et al. (2018) find that both individual and firm ideology matter for open source contributions.

Product architecture. Product architecture can be an important driver of a firm's performance, providing firms with a useful strategic lever that impacts their products' quality and variety (Ulrich 1995). The literature suggests that firms' decisions to reveal open source drivers is based on long-term product architecture decisions, rather than short-term fluctuations. While firms have control over product architecture, changing it can pose significant challenges to firms, as small changes to the product architecture can make firms' architectural knowledge obsolete, hurting incumbent performance (Henderson and Clark 1990). Furthermore, changing product architecture is a difficult process because of the variety of industry participants (MacDuffie 2013). Thus, at the firm level, they align their intellectual property strategy with their product architecture in order to capture value (Henkel et al. 2013).

Taken together, the literature suggests that firms' decisions to release device drivers are primarily tied to time-invariant factors. In the next section, we outline potential time-varying drivers that might impact our setting.

A3.5.2.2 Time-varying drivers of openness

Parallel trends can fail if there exist time-varying factors that drive firms' decisions to open. As discussed in the previous section, we believe that the primary drivers of openness are time-invariant. In this section, we outline an important time-varying factor that shapes firms' choices to open: Learning. We outline why such factors may exist, and propose a robustness check that should mitigate the impact of this time-varying factor on our estimates.

The literature suggests that firms can learn about the impacts of open source over time in several ways. First, firms can learn from their customers. Henkel et al. (2014) finds that firms that open see an initial demand pull that eventually leads to a positive feedback loop. Second, firms can learn from the community. A large literature shows that firms benefit from their open source contributions because they benefit from community contributions, as well as contributing to the community (Nagle 2018). Finally, firms can learn from their competitors decisions to open, and their ensuing performance.

Our estimates may contain not only the effect of opening, but also the effect of learning. For example, firms that open relatively late may have chosen to do so after observing the effect of openness on their competitors' innovation outcomes. Thus, firms that open late have more information than firms that move early about the effects of openness and its impacts on innovation.

To mitigate these concerns, we re-evaluate the effect of openness using companies that opened before 2011, when Qualcomm, the largest supplier of WiFi chips, announced support for open source.

Table A17 ***Short-run effects of openness on innovation (Pre-2011 suppliers)***

	Device Count	Customer Share	Frontier Technology	Early Adoption	Multiple RF Bands	Multiple Wi-Fi Standards
ATT	18.737***	0.053***	16.945***	12.982**	3.823**	22.249***
	(6.031)	(0.017)	(5.880)	(5.716)	(1.851)	(7.644)

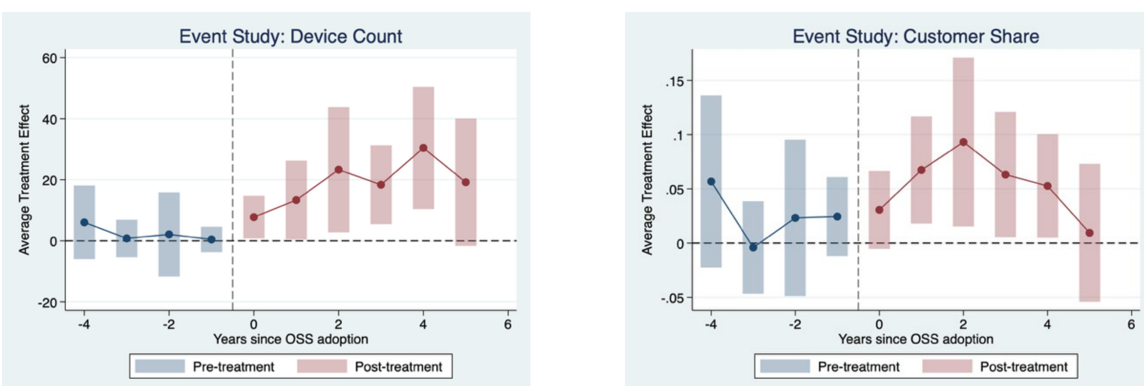
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 18 Mechanisms for attracting firms (Pre-2011 suppliers)

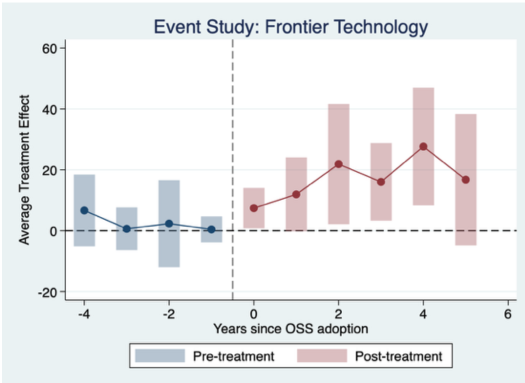
	Assembler Age (median)	Assembler is Entrant	Chinese Assembler
ATT	-10.345***	0.662***	3.118***
	(3.908)	(0.199)	(1.038)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

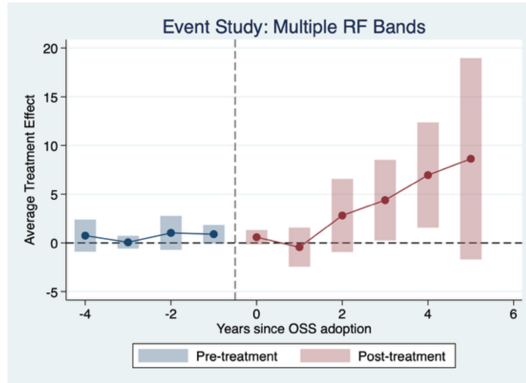
Figure A4 Event study graph excluding 2011-2017 cohorts



(a) Device Count (b) Customer Share



(c) Frontier Technology



(d) Multiple RF Bands

Section A4. Do assemblers change Wi-Fi suppliers more often than CPU suppliers?

We measure changes in buyer-supplier relationships in several different ways. First, we utilize Entry Rate and Separation Rate. Entry Rate captures the rate at which assemblers form new supplier relationships from year t-1 to t. We define Entry Rate as:

$$EntryRate = \frac{\#Relationships\ Created\ from\ t-1\ to\ t}{Average\ \#\ relationships\ in\ t, t-1}$$

Similarly, Separation Rate measures the rate at which assemblers terminate their supplier relationships:

$$SeparationRate = \frac{\#Relationships\ Ended\ from\ t-1\ to\ t}{Average\ \#\ relationships\ in\ t, t-1}$$

Below, we plot the average separation and entry rates for assemblers' choice of Wi-Fi and CPU suppliers.

Figure A5 Patterns of switching Wi-Fi vs CPU suppliers

Graphically, there is no significant difference for a given year. To estimate whether assemblers switch Wi-Fi suppliers or CPU suppliers more frequently, we estimate the following regression equation using assembler-year level observations of supplier-assembler relationships:

$$Y_{it} = \beta WiFi_i + \eta_i + \xi_t + \epsilon_{it}$$

Here, Y_{it} measures the Entry Rate and Separation Rate of firm i's suppliers in year t. $WiFi_i$ is an indicator for observations for the Wi-Fi suppliers of firm i. We include assembler fixed effects η_i to control for assembler-level characteristics affecting supplier-assembler relations, and year fixed effects ξ_t to control for year-level unobservables.

Table A19 Assemblers are less likely to switch Wi-Fi suppliers

	(1) Entry Rate	(2) Separation Rate
Wi-Fi Supplier	-0.014**	-0.023***
	(0.007)	(0.007)
Constant	0.822***	0.785***
	(0.003)	(0.004)
Assembler FE	Yes	Yes
Year FE	Yes	Yes
Wi-Fi Mean	0.7889	0.7954
CPU Mean	0.8001	0.8138
Observations	3284	3284

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Overall, we see that assemblers are less likely to switch Wi-Fi suppliers. The negative coefficient on Entry Rate for assembler-Wi-Fi supplier relationships suggests that assemblers are about 1.8% less likely to create new ties with Wi-Fi suppliers than with CPU suppliers. Similarly, assemblers are 2.9% less likely to break existing ties with Wi-Fi suppliers compared to CPU suppliers.

Section A5. Mediating effects of autonomy on innovation

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 and proposes an alternate estimator. However, no such estimator exists in staggered diff-in-diff settings (e.g., Callaway and Sant'Anna, 2021).

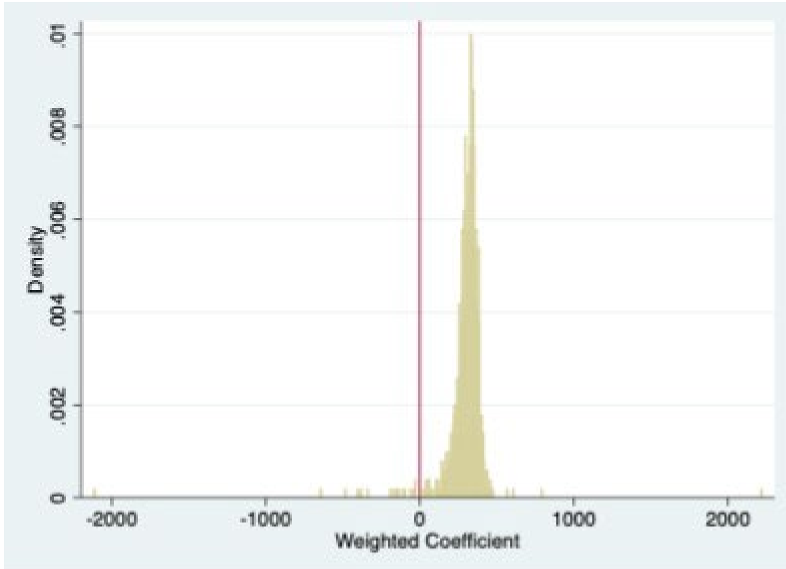
Given that no established processes exist for estimating a fuzzy diff-in-diff with staggered treatment, we adopt a bootstrapped approach to the Wald-did type estimator. Our approach is to estimate the following Wald-type estimator using block bootstrapping with replacement:

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

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 and 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).

Figure A6 Bootstrapped coefficient distribution



Above, we plot the distribution of the bootstrapped coefficients. The results show that increasing autonomy from the median to the 75th percentile (an increase of 0.0329) increases new product innovations for Wi-Fi suppliers by 10.55 devices (beta = 320.59, bootstrapped 95% CI [166.17, 790.41]), or about 30.58% compared to the pre-treatment period device counts. This is slightly larger than our results from the Poisson pseudo-likelihood estimates in Table 2.