EMBEDDED IN TWO WORLDS:

HOW INCUMBENTS' BROKERAGE AFFECTS ADAPTATION WHEN OLD AND NEW SUPPLY NETWORKS COEXIST

Online Appendix

APPENDIX 1: MECHANISM TESTS VIA MEDIATION MODELS

We use mediation analysis to evaluate whether brokerage affects either the number of new technology models or model performance through the addition of two types of new technology suppliers (i.e., totally new suppliers or suppliers that previously produced ICE components for the focal OEM and were converted to making EV components) or model uniqueness. A significant indirect effect would support the proposition that brokerage in the ICE or EV network affects technological adaptation by mobilizing some manifestation of external integrative capabilities.

Parametric Bootstrap Estimation

We test indirect effects using Yzerbyt et al (2018)'s two-step framework. To claim a significant indirect effect, we first need to establish the joint significance of two component paths: (a) the path from brokerage (X) to the mediator (M), and (b) the path from the mediator (M) to the outcome (Y), with brokerage included in the equation. An indirect effect is inferred only when both paths are simultaneously significant. After establishing significance through the joint significance test, we estimate the magnitude of the indirect effect (a*b) as the product of the two path estimates and compute its standard error and confidence intervals using the Monte Carlo method (Preacher and Selig 2012).

Because our path models are non-linear (Poisson or beta regression), OLS-based joint significance testing could be inappropriate, and thus we instead assess the significance of individual paths using bootstrapped inference (Yzerbyt et al. 2018, footnote 2). Furthermore, because our data contains a very small number of clusters (G = 13 in the count models and 12 in the range models), conventional cluster-robust standard errors are unreliable[1]. Therefore, we apply the wild cluster bootstrap (Cameron et al. 2008) with Webb weights to calculate cluster-robust p-values for the individual paths, implemented via the boottest command in Stata (Roodman et al. 2019). Because the path models are estimated by maximum likelihood, boottest applies the score form of the wild cluster bootstrap (Kline and Santos 2012, Roodman et al. 2019). Following Yzerbyt et al.'s approach, we conclude that an indirect effect exists only if the two paths, (a) brokerage to mediator and (b) mediator to outcome, are simultaneously significant by these bootstrap p-values.

Monte Carlo method is a parametric bootstrap approach for computing the magnitude and precision of an indirect effect (Yzerbyt et al. 2018). For models with nonlinear outcomes, we did not find ready-made official or user-written commands in STATA. Instead, we used a tutorial from UCLA's Office of Advanced Research Computing (OARC)[2]. With Claude Opus 4.7, we wrote custom code to calculate Monte Carlo standard errors and confidence intervals to replicate

[1] With 12 or 13 clusters, conventional cluster-robust standard errors can understate uncertainty. This matters most for the mediation analysis, where the verdict depends on two paths being significant at once, so we use wild cluster bootstrap p-values for the individual paths.

[2] https://stats.oarc.ucla.edu/stata/faq/how-can-i-get-monte-carlo-standard-errors-for-indirect-effects/

OARC's calculations while accounting for the nonlinear nature of our dependent variables[3]. The intuition of the Monte Carlo method is that after fitting the path models (in our case, individual Poisson or beta regressions), we extract the estimated path coefficients (a) and (b) along with their variance-covariance matrix. Using the drawnorm command in Stata, we generate 20,000 coefficient sets drawn from a multivariate normal with those means, standard deviations, and correlations. For each draw, we compute the indirect effect (a*b), and the 2.5th and 97.5th percentiles of the resulting distribution give the 95% confidence interval. We verified this code by estimating indirect effects on the OARC dataset and also on two simulated datasets in which the true indirect effect was known[4].

Results

For the main paths, we report the point estimates, standard errors, and conventional cluster-robust p-values from GSEM, as in Table A1-1 (test of H1a), A1-2 (test of H1b), A1-3 (test of H2a), and A1-4 (test of H2b). The bootstrap p-values for paths (a) and (b), calculated with the boottest command in STATA with 9,999 replications (Roodman et al. 2019), are reported in Table A1-5.

The joint-significance tests that rely on these Webb-weighted score cluster bootstrap p-values are reported separately in Table A1-5 for each corresponding model.

We classify the evidence for an indirect effect (a×b) in two tiers. When both paths' bootstrap p-values fall below 0.05, the joint significance criterion indicates a significant indirect effect. When both p-values fall below 0.1 but at least one lies between 0.05 and 0.1, we interpret the indirect effect as marginally significant. By these criteria, Models 1 and 4 in Table A1-5 show significant indirect effects, while Model 7 shows a marginally significant effect.

In Table A1-6, we summarize the indirect effect (a*b, which is literally a product of coefficients a and b) from Table A1-5, along with Monte Carlo standard errors and confidence intervals (Yzerbyt et al. 2018). As noted earlier, the underlying regressions are reported in Tables A1-1 to

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[3] Instead of estimating individual paths with suest command as in OARC that implemented OLS regressions, we ran Poisson or beta regressions when appropriate.

[4] Specifically, we downloaded hsbdemo dataset from OARC and calculated the indirect effects and MC confidence intervals using our custom code. Then compared them with those reported by OARC on their website. The differences between our estimates and OARC estimates in hsbdemo were very minimal (our a*b point estimate = 0.265 vs 0.265 OARC estimate, our MC CI is [0.166, 0.372] vs OARC MC CI assuming coefficients are uncorrelated [0.167, 0.371] and assuming correlated coefficients [0.164, 0.376]. Our MC standard error (SE) for (a*b) was 0.053. OARC SE assuming uncorrelated coefficients was equal to 0.052 or was equal to 0.054 assuming correlated coefficients. Then we simulated the first dataset with known parameters: path (a) = 0.5, path (b) = 0.4, direct path (c') = 0.2, and (a*b) = 0.2. This dataset had 20,000 simulated observations for 1,000 firms and 20 observations per firm. Our code recovered these effects both in terms of calculating "true" point estimates and calculating "true" Monte Carlo Standard Errors and Confidence Intervals (a= 0.493, b= 0.404, c' = 0.200, a*b = 0.199, a*b Monte Carlo SE=0.007, a*b Monte Carlo CI = [0.186, 0.213], which covers the true value of 0.2). The second simulated dataset had 14 firms with 8 observations per firm with the same known parameters. Our code again was able to recover these effects (a = 0.529, b = 0.447, c' = 0.203, a*b = 0.236, a*b SE = 0.042 and a*b CI = [0.161, 0.324], which again covers the true value of 0.2).

A1-4. Models 1, 4 and 7 are of particular interest. The mediator in Model 1 captures the number of new EV suppliers that the focal OEM has added in (t), which were also its ICE suppliers in the same year window (we call them *Shared ICE-EV Suppliers*), and the dependent variable is the *Number of EV models* in (t+2). Brokerage is captured in the old technology network. The positive indirect effect has $\beta = 0.011$, and its 95% confidence interval is [0.002, 0.022], which doesn't include zero (Model 1 in Table A1-6). Thus, we can say that ICE network brokerage's effect on the number of new EV models is mediated by the OEM's ability to convert its old technology suppliers into new-technology component suppliers.

The mediator in Model 4 captures the number of *Shared ICE-EV Suppliers*, and the dependent variable is the *Avg. Range of EV Models* in (t+2). Brokerage is captured in the old technology network. Both paths are individually significant, so the joint-significance criterion supports the mediation (Model 4 in Table A1-5). The positive indirect effect has $\beta = 0.004$, and its 95% confidence interval does not include zero (95% CI = [0.001, 0.009]; Model 4 in Table A1-6). Thus, we can say that the effect of *Brokerage in ICE Network* effect on the range of EV models is mediated by the OEM's ability to use shared suppliers from the ICE to EV network. In other words, this is evidence that old technology brokers convert their old technology suppliers into making new technology components.

Mediator in Model 7 is also *Shared ICE-EV Suppliers* while the dependent variable is the *Number EV Models* (t+2). Brokerage is captured in the new technology network. The b-path is statistically significant ($p < 0.001$), whereas the a-path is only marginally significant ($p = 0.083$). Accordingly, the joint-significance criterion provides only marginal support for mediation (Model 7 in Table A1-5). The positive indirect effect has $\beta = 0.006$, and its 95% confidence interval marginally includes zero (-0.001, 0.016). These results are consistent with the EV-network brokerage effect on the number of EV models operating, in part, through the OEM's ability to convert its established ICE suppliers into makers of new EV components. This latter model is interesting because we don't really see the significant effect of *Brokerage in EV Network* on OEM ability to make EV models in the main analysis (Model 5 in Table 3). The incorporation of a mediator in the form of *Shared ICE-EV Suppliers* helps us identify a positive path from EV brokerage to the number of EV models. However, a separate negative effect of EV brokerage on the number of EV models cancels this effect in a simple regression model that doesn't have the mediator.

We don't observe even marginally significant indirect effects in any of the other models. Specifically, Model 2 (Table A1-1) tests the mediation path *Brokerage in ICE Network* → *New non-ICE EV Suppliers* → *Number of EV models in (t+2).* Model 5 tests the mediation path *Brokerage in ICE Network*→ *New non-ICE EV Suppliers* → *Avg. Range of EV Models* in (t+2). All models with *Avg. Range of EV Models* in (t+2) as a dependent variable are estimated on a reduced sample (N = 63) where range takes nonzero values to reflect the fact that zero in a range model reflects the absence of the EV. The lack of significance for the indirect effect in these

models indicates that firms' ability to attract entirely new suppliers is not a meaningful mechanism through which *Brokerage in ICE Network* translates into adaptation.

Models 3 and 6 test the mediating effect of component uniqueness. None of the indirect effects are significant; therefore, this mechanism does not operate in our sample. We also note that all equations with *Component Uniqueness* as an outcome are estimated using beta regression (Ferrari and Cribari-Neto 2004), which is appropriate when the dependent variable is bound by 1 and 0.

Models 8-12 examine the effects of *Brokerage in EV Network* on the outcomes via the same mediators. None of the indirect effects are significant.

Conclusions

Taken together, these results indicate that old technology network brokerage affects firm adaptation through a specific facet of external integrative capabilities: the ability to identify which existing old technology suppliers can convert to producing new technology components (Models 1 and 4). This channel is the only mediation mechanism receiving consistent support, as neither the recruitment of entirely new suppliers nor component uniqueness transmit brokerage effects in our sample. New technology brokerage operates through the same channel, but with offsetting pathways. Without the mediator, *Brokerage in EV Network* shows no significant effect on the *Number of EV Models* (Table 3, Model 5). Introducing Shared ICE–EV Suppliers yields a positive indirect effect that is only marginally supported. The direct effect is negative and imprecisely estimated ($\beta = -0.018$, 95% CI = [−0.045, 0.009]; Model 7.2 in Table A1-3). One interpretation is that EV brokerage benefits from shared suppliers, but coordination costs from managing a sparse, unstable supplier base offset these gains. This may reflect costs of managing unique suppliers in the new technology market. Old technology brokerage thus emerges as the more reliable enabler of adaptation: its indirect effect is unambiguous and is not undermined by offsetting direct costs.

Table A1-1. GSEM Estimates for the Mediation Model (Hypothesis 1a)

	Model 1		Model 2		Model 3	
	Model 1.1 Shared ICE-EV Suppliers	Model 1.2 Num. of EV Models (t+2)	Model 2.1 New non-ICE EV Suppliers	Model 2.2 Num. of EV Models (t+2)	Model 3.1 Uniqueness of EV Components	Model 3.2 Num. of EV Models (t+2)
Shared ICE-EV Suppliers		0.304				
		(0.063)				
		[0.181,0.427]				
		$p = 0.000$				
New non-ICE EV Suppliers				-0.006		
				(0.242)		
				[-0.479,0.468]		
				$p = 0.981$		
Uniqueness of EV Components						1.026
						(2.150)
						[-3.187,5.239]
						$p = 0.633$
Brokerage in ICE Network	0.035	0.005	-0.111	0.041	-0.031	0.045
	(0.013)	(0.023)	(0.076)	(0.025)	(0.018)	(0.019)
	[0.009,0.062]	[-0.039,0.050]	[-0.261,0.039]	[-0.007,0.089]	[-0.065,0.004]	[0.007,0.083]
	$p = 0.009$	$p = 0.810$	$p = 0.147$	$p = 0.095$	$p = 0.080$	$p = 0.021$
Proportion of Advanced Battery Chemistry	0.647	0.869	-0.184	1.216	0.395	1.144
	(0.432)	(0.608)	(1.214)	(0.586)	(0.159)	(0.530)
	[-0.199,1.494]	[-0.322,2.060]	[-2.563,2.196]	[0.067,2.364]	[0.083,0.707]	[0.106,2.183]
	$p = 0.134$	$p = 0.153$	$p = 0.880$	$p = 0.038$	$p = 0.013$	$p = 0.031$
Return on Assets	-6.002	3.770	-15.097	-1.261	-2.664	-0.827
	(1.790)	(4.857)	(6.935)	(5.005)	(1.218)	(5.443)
	[-9.510,-2.494]	[-5.751,13.290]	[-28.690,-1.505]	[-11.071,8.550]	[-5.050,-0.277]	[-11.495,9.841]
	$p = 0.001$	$p = 0.438$	$p = 0.029$	$p = 0.801$	$p = 0.029$	$p = 0.879$
Num. of ICE Models	-0.004	-0.008	0.082	-0.009	0.006	-0.009
	(0.010)	(0.020)	(0.042)	(0.023)	(0.009)	(0.023)
	[-0.024,0.016]	[-0.047,0.032]	[-0.001,0.165]	[-0.055,0.036]	[-0.010,0.023]	[-0.053,0.036]
	$p = 0.694$	$p = 0.706$	$p = 0.052$	$p = 0.686$	$p = 0.455$	$p = 0.704$
ICE Suppliers Network Density	-2.041	1.802	51.160	0.580	6.951	-0.447
	(3.173)	(6.086)	(20.006)	(5.360)	(2.907)	(5.730)
	[-8.259,4.177]	[-10.127,13.731]	[11.949,90.370]	[-9.926,11.086]	[1.254,12.649]	[-11.676,10.783]
	$p = 0.520$	$p = 0.767$	$p = 0.011$	$p = 0.914$	$p = 0.017$	$p = 0.938$
EV Suppliers Network Density	-1.452	3.024	-11.429	2.983	-0.541	2.984
	(1.365)	(1.903)	(4.906)	(2.963)	(1.048)	(2.805)
	[-4.128,1.224]	[-0.706,6.754]	[-21.044,-1.813]	[-2.824,8.790]	[-2.595,1.513]	[-2.514,8.482]
	$p = 0.287$	$p = 0.112$	$p = 0.020$	$p = 0.314$	$p = 0.606$	$p = 0.288$
World Green Car Candidate	-0.391	-0.207	-0.297	-0.273	0.050	-0.280
	(0.325)	(0.260)	(0.529)	(0.241)	(0.120)	(0.193)
	[-1.027,0.246]	[-0.717,0.303]	[-1.334,0.739]	[-0.745,0.200]	[-0.185,0.285]	[-0.659,0.099]
	$p = 0.229$	$p = 0.426$	$p = 0.574$	$p = 0.258$	$p = 0.677$	$p = 0.147$
Avg. MPGe of EV Models	-0.004	-0.004	0.002	-0.006	-0.001	-0.006
	(0.003)	(0.006)	(0.005)	(0.006)	(0.001)	(0.005)
	[-0.009,0.001]	[-0.015,0.008]	[-0.008,0.011]	[-0.017,0.005]	[-0.003,0.001]	[-0.017,0.005]
	$p = 0.149$	$p = 0.557$	$p = 0.727$	$p = 0.295$	$p = 0.174$	$p = 0.286$
Num. of New ICE Suppliers	0.365	-0.232	-0.402	-0.004	-0.214	0.034
	(0.072)	(0.135)	(0.255)	(0.120)	(0.050)	(0.126)
	[0.224,0.506]	[-0.497,0.033]	[-0.902,0.098]	[-0.240,0.232]	[-0.312,-0.116]	[-0.214,0.281]
	$p = 0.000$	$p = 0.086$	$p = 0.115$	$p = 0.972$	$p = 0.000$	$p = 0.788$
Num. of ICE Suppliers	0.017	0.045	0.171	0.033	0.037	0.027
	(0.021)	(0.063)	(0.121)	(0.066)	(0.015)	(0.069)
	[-0.024,0.057]	[-0.078,0.168]	[-0.066,0.409]	[-0.096,0.161]	[0.007,0.067]	[-0.108,0.162]
	$p = 0.416$	$p = 0.476$	$p = 0.157$	$p = 0.618$	$p = 0.017$	$p = 0.697$
Num. of Dual Purpose Factories	-0.064	0.160	-0.742	0.156	0.137	0.143
	(0.087)	(0.149)	(0.175)	(0.140)	(0.069)	(0.125)
	[-0.235,0.107]	[-0.131,0.452]	[-1.085,-0.400]	[-0.120,0.431]	[0.002,0.272]	[-0.103,0.388]
	$p = 0.463$	$p = 0.282$	$p = 0.000$	$p = 0.268$	$p = 0.047$	$p = 0.254$
Num. of In-house Components	0.076	0.010	0.160	0.067	0.063	0.059
	(0.061)	(0.050)	(0.198)	(0.077)	(0.042)	(0.056)
	[-0.044,0.196]	[-0.088,0.108]	[-0.228,0.547]	[-0.084,0.218]	[-0.019,0.146]	[-0.051,0.169]
	$p = 0.215$	$p = 0.845$	$p = 0.419$	$p = 0.383$	$p = 0.131$	$p = 0.295$
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91	91	91	91	91	91

Column k.1 = mediator equation (X -> M); column k.2 = outcome equation (M -> Y, X -> Y).

GSEM estimates; standard errors in parentheses, clustered at the OEM level; 95% confidence intervals in brackets.

Mediator equations: Poisson for the two supplier-count mediators, beta regression (logit link) for Uniqueness of EV Components; outcome equations: Poisson.

Table A1-2. GSEM Estimates for the Mediation Model (Hypothesis 1b)

	Model 4		Model 5		Model 6	
	Model 4.1 Shared ICE-EV Suppliers	Model 4.2 Avg. Range of EV Models (t+2), rounded	Model 5.1 New non-ICE EV Suppliers	Model 5.2 Avg. Range of EV Models (t+2), rounded	Model 6.1 Uniqueness of EV Components	Model 6.2 Avg. Range of EV Models (t+2), rounded
Shared ICE-EV Suppliers		0.103				
		(0.031)				
		[0.042,0.164]				
		$p = 0.001$				
New non-ICE EV Suppliers				0.116		
				(0.061)		
				[-0.004,0.236]		
				$p = 0.058$		
Uniqueness of EV Components						0.283
						(0.300)
						[-0.304,0.871]
						$p = 0.345$
Brokerage in ICE Network	0.043	0.024	-0.003	0.036	0.012	0.033
	(0.013)	(0.006)	(0.119)	(0.006)	(0.009)	(0.005)
	[0.018,0.068]	[0.012,0.036]	[-0.236,0.229]	[0.024,0.047]	[-0.006,0.030]	[0.023,0.043]
	$p = 0.001$	$p = 0.000$	$p = 0.977$	$p = 0.000$	$p = 0.186$	$p = 0.000$
Proportion of Advanced Battery Chemistry	-0.258	0.220	1.610	0.146	0.135	0.210
	(0.675)	(0.358)	(2.270)	(0.442)	(0.218)	(0.445)
	[-1.581,1.064]	[-0.482,0.922]	[-2.839,6.059]	[-0.719,1.012]	[-0.294,0.563]	[-0.661,1.081]
	$p = 0.702$	$p = 0.539$	$p = 0.478$	$p = 0.740$	$p = 0.538$	$p = 0.637$
Return on Assets	-13.936	-1.693	-27.327	-3.421	-1.967	-2.931
	(5.701)	(2.886)	(32.767)	(3.182)	(2.101)	(3.226)
	[-25.110,-2.762]	[-7.349,3.963]	[-91.549,36.895]	[-9.658,2.816]	[-6.085,2.151]	[-9.255,3.393]
	$p = 0.015$	$p = 0.557$	$p = 0.404$	$p = 0.282$	$p = 0.349$	$p = 0.364$
Num. of ICE Models	-0.003	0.011	-0.102	0.009	0.006	0.008
	(0.016)	(0.004)	(0.078)	(0.007)	(0.007)	(0.007)
	[-0.035,0.028]	[0.002,0.020]	[-0.256,0.051]	[-0.005,0.023]	[-0.008,0.019]	[-0.005,0.022]
	$p = 0.835$	$p = 0.012$	$p = 0.192$	$p = 0.206$	$p = 0.408$	$p = 0.223$
ICE Suppliers Network Density	-3.097	4.499	171.356	3.573	5.291	4.117
	(5.830)	(2.027)	(80.673)	(1.934)	(2.024)	(2.498)
	[-14.524,8.330]	[0.526,8.473]	[13.239,329.472]	[-0.217,7.364]	[1.323,9.258]	[-0.780,9.013]
	$p = 0.595$	$p = 0.026$	$p = 0.034$	$p = 0.065$	$p = 0.009$	$p = 0.099$
EV Suppliers Network Density	-2.190	1.938	-13.429	1.852	0.827	1.546
	(1.925)	(0.908)	(9.292)	(0.782)	(1.212)	(0.887)
	[-5.963,1.584]	[0.158,3.717]	[-31.640,4.783]	[0.319,3.384]	[-1.548,3.202]	[-0.193,3.286]
	$p = 0.255$	$p = 0.033$	$p = 0.148$	$p = 0.018$	$p = 0.495$	$p = 0.082$
World Green Car Candidate	0.035	-0.297	-0.154	-0.360	0.081	-0.318
	(0.191)	(0.168)	(0.624)	(0.156)	(0.140)	(0.181)
	[-0.340,0.410]	[-0.626,0.032]	[-1.377,1.068]	[-0.665,-0.054]	[-0.194,0.356]	[-0.672,0.036]
	$p = 0.855$	$p = 0.077$	$p = 0.804$	$p = 0.021$	$p = 0.563$	$p = 0.079$
Avg. MPGe of EV Models	-0.001	-0.002	0.012	-0.002	-0.001	-0.002
	(0.002)	(0.002)	(0.012)	(0.002)	(0.001)	(0.002)
	[-0.006,0.003]	[-0.005,0.001]	[-0.011,0.035]	[-0.006,0.001]	[-0.003,0.001]	[-0.006,0.001]
	$p = 0.536$	$p = 0.212$	$p = 0.312$	$p = 0.204$	$p = 0.394$	$p = 0.202$
Num. of New ICE Suppliers	0.221	-0.028	-1.243	0.036	-0.166	0.027
	(0.077)	(0.041)	(0.693)	(0.043)	(0.030)	(0.042)
	[0.071,0.371]	[-0.107,0.051]	[-2.602,0.116]	[-0.049,0.120]	[-0.226,-0.106]	[-0.055,0.108]
	$p = 0.004$	$p = 0.489$	$p = 0.073$	$p = 0.407$	$p = 0.000$	$p = 0.525$
Num. of ICE Suppliers	0.028	0.031	0.066	0.032	0.013	0.032
	(0.033)	(0.018)	(0.126)	(0.021)	(0.014)	(0.021)
	[-0.037,0.092]	[-0.005,0.067]	[-0.182,0.314]	[-0.009,0.073]	[-0.015,0.041]	[-0.009,0.074]
	$p = 0.407$	$p = 0.094$	$p = 0.601$	$p = 0.127$	$p = 0.354$	$p = 0.122$
Num. of Dual Purpose Factories	0.011	0.034	-0.474	0.030	0.044	0.032
	(0.055)	(0.020)	(0.237)	(0.024)	(0.045)	(0.026)
	[-0.097,0.118]	[-0.006,0.074]	[-0.939,-0.009]	[-0.017,0.077]	[-0.045,0.133]	[-0.019,0.083]
	$p = 0.844$	$p = 0.099$	$p = 0.046$	$p = 0.212$	$p = 0.330$	$p = 0.219$
Num. of In-house Components	0.116	-0.023	0.185	-0.011	0.033	-0.004
	(0.032)	(0.028)	(0.146)	(0.028)	(0.040)	(0.033)
	[0.053,0.179]	[-0.078,0.032]	[-0.101,0.471]	[-0.066,0.045]	[-0.046,0.112]	[-0.069,0.060]
	$p = 0.000$	$p = 0.405$	$p = 0.204$	$p = 0.710$	$p = 0.412$	$p = 0.892$
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63	63	63	63	63	63

Column k.1 = mediator equation (X -> M); column k.2 = outcome equation (M -> Y, X -> Y).

GSEM estimates; standard errors in parentheses, clustered at the OEM level; 95% confidence intervals in brackets.

Mediator equations: Poisson for the two supplier-count mediators, beta regression (logit link) for Uniqueness of EV Components; outcome equations: Poisson.

Table A1-3. GSEM Estimates for the Mediation Model (Hypothesis 2a)

	Model 7		Model 8		Model 9	
	Model 7.1 Shared ICE-EV Suppliers	Model 7.2 Num. of EV Models (t+2)	Model 8.1 New non-ICE EV Suppliers	Model 8.2 Num. of EV Models (t+2)	Model 9.1 Uniqueness of EV Components	Model 9.2 Num. of EV Models (t+2)
Shared ICE-EV Suppliers		0.343				
		(0.068)				
		[0.210,0.475]				
		$p = 0.000$				
New non-ICE EV Suppliers				-0.088		
				(0.226)		
				[-0.530,0.354]		
				$p = 0.697$		
Uniqueness of EV Components						0.836
						(2.676)
						[-4.408,6.081]
						$p = 0.755$
Brokerage in EV Network	0.017	-0.018	-0.004	-0.002	-0.038	0.004
	(0.010)	(0.014)	(0.031)	(0.014)	(0.007)	(0.021)
	[-0.003,0.037]	[-0.045,0.009]	[-0.064,0.057]	[-0.028,0.025]	[-0.052,-0.023]	[-0.036,0.045]
	$p = 0.094$	$p = 0.186$	$p = 0.905$	$p = 0.902$	$p = 0.000$	$p = 0.836$
Proportion of Advanced Battery Chemistry	0.873	0.842	-0.181	1.418	0.242	1.377
	(0.364)	(0.579)	(0.777)	(0.585)	(0.175)	(0.545)
	[0.159,1.586]	[-0.292,1.976]	[-1.704,1.342]	[0.271,2.565]	[-0.102,0.585]	[0.310,2.444]
	$p = 0.016$	$p = 0.146$	$p = 0.816$	$p = 0.015$	$p = 0.168$	$p = 0.011$
Return on Assets	-6.067	4.582	-14.542	-1.755	-2.076	-1.279
	(1.843)	(5.315)	(7.340)	(5.178)	(1.156)	(5.568)
	[-9.680,-2.454]	[-5.834,14.999]	[-28.928,-0.157]	[-11.903,8.394]	[-4.341,0.190]	[-12.193,9.635]
	$p = 0.001$	$p = 0.389$	$p = 0.048$	$p = 0.735$	$p = 0.073$	$p = 0.818$
Num. of ICE Models	-0.009	-0.010	0.070	-0.013	0.005	-0.012
	(0.011)	(0.020)	(0.040)	(0.023)	(0.009)	(0.022)
	[-0.030,0.013]	[-0.049,0.029]	[-0.007,0.148]	[-0.058,0.031]	[-0.012,0.022]	[-0.055,0.031]
	$p = 0.423$	$p = 0.625$	$p = 0.076$	$p = 0.554$	$p = 0.586$	$p = 0.589$
ICE Suppliers Network Density	-1.275	1.592	44.582	0.974	6.484	-0.047
	(3.433)	(6.818)	(21.892)	(6.145)	(1.594)	(6.479)
	[-8.003,5.453]	[-11.770,14.955]	[1.674,87.491]	[-11.069,13.018]	[3.359,9.609]	[-12.746,12.653]
	$p = 0.710$	$p = 0.815$	$p = 0.042$	$p = 0.874$	$p = 0.000$	$p = 0.994$
EV Suppliers Network Density	-2.139	4.079	-9.868	2.769	1.102	2.625
	(1.386)	(2.231)	(5.417)	(3.089)	(0.712)	(2.804)
	[-4.856,0.578]	[-0.294,8.452]	[-20.485,0.750]	[-3.286,8.823]	[-0.293,2.498]	[-2.871,8.121]
	$p = 0.123$	$p = 0.068$	$p = 0.069$	$p = 0.370$	$p = 0.122$	$p = 0.349$
World Green Car Candidate	-0.372	-0.183	-0.268	-0.232	0.181	-0.276
	(0.261)	(0.246)	(0.618)	(0.248)	(0.107)	(0.220)
	[-0.884,0.140]	[-0.665,0.300]	[-1.479,0.943]	[-0.718,0.254]	[-0.027,0.390]	[-0.707,0.154]
	$p = 0.155$	$p = 0.458$	$p = 0.664$	$p = 0.349$	$p = 0.089$	$p = 0.208$
Avg. MPGe of EV Models	-0.004	-0.004	0.004	-0.007	-0.002	-0.007
	(0.003)	(0.006)	(0.004)	(0.006)	(0.001)	(0.005)
	[-0.010,0.001]	[-0.016,0.007]	[-0.003,0.011]	[-0.019,0.004]	[-0.003,-0.001]	[-0.018,0.003]
	$p = 0.116$	$p = 0.472$	$p = 0.234$	$p = 0.195$	$p = 0.003$	$p = 0.175$
Num. of New ICE Suppliers	0.293	-0.223	-0.240	-0.073	-0.136	-0.047
	(0.089)	(0.133)	(0.165)	(0.130)	(0.045)	(0.121)
	[0.120,0.467]	[-0.483,0.037]	[-0.563,0.084]	[-0.328,0.182]	[-0.224,-0.048]	[-0.284,0.190]
	$p = 0.001$	$p = 0.093$	$p = 0.147$	$p = 0.576$	$p = 0.002$	$p = 0.697$
Num. of ICE Suppliers	0.046	0.039	0.083	0.065	0.001	0.066
	(0.024)	(0.067)	(0.067)	(0.077)	(0.008)	(0.076)
	[-0.001,0.094]	[-0.091,0.170]	[-0.049,0.214]	[-0.086,0.216]	[-0.014,0.016]	[-0.083,0.215]
	$p = 0.056$	$p = 0.554$	$p = 0.217$	$p = 0.400$	$p = 0.917$	$p = 0.385$
Num. of Dual Purpose Factories	-0.044	0.154	-0.705	0.204	0.088	0.201
	(0.092)	(0.133)	(0.140)	(0.155)	(0.038)	(0.136)
	[-0.225,0.137]	[-0.107,0.415]	[-0.979,-0.430]	[-0.100,0.508]	[0.013,0.162]	[-0.064,0.467]
	$p = 0.632$	$p = 0.246$	$p = 0.000$	$p = 0.189$	$p = 0.021$	$p = 0.138$
Num. of In-house Components	0.090	0.036	0.094	0.094	0.119	0.073
	(0.067)	(0.050)	(0.215)	(0.080)	(0.024)	(0.067)
	[-0.040,0.221]	[-0.062,0.134]	[-0.327,0.515]	[-0.063,0.252]	[0.072,0.167]	[-0.060,0.205]
	$p = 0.175$	$p = 0.470$	$p = 0.662$	$p = 0.238$	$p = 0.000$	$p = 0.282$
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91	91	91	91	91	91

Column k.1 = mediator equation (X -> M); column k.2 = outcome equation (M -> Y, X -> Y).

GSEM estimates; standard errors in parentheses, clustered at the OEM level; 95% confidence intervals in brackets.

Mediator equations: Poisson for the two supplier-count mediators, beta regression (logit link) for Uniqueness of EV Components; outcome equations: Poisson.

Table A1-4. GSEM Estimates for the Mediation Model (Hypothesis 2b)

	Model 10		Model 11		Model 12	
	Model 10.1 Shared ICE-EV Suppliers	Model 10.2 Avg. Range of EV Models (t+2), rounded	Model 11.1 New non-ICE EV Suppliers	Model 11.2 Avg. Range of EV Models (t+2), rounded	Model 12.1 Uniqueness of EV Components	Model 12.2 Avg. Range of EV Models (t+2), rounded
Shared ICE-EV Suppliers		0.135				
		(0.025)				
		[0.086,0.184]				
		$p = 0.000$				
New non-ICE EV Suppliers				0.044		
				(0.053)		
				[-0.060,0.147]		
				$p = 0.408$		
Uniqueness of EV Components						-0.538
						(0.627)
						[-1.766,0.690]
						$p = 0.390$
Brokerage in EV Network	0.010	-0.011	-0.155	-0.007	-0.031	-0.010
	(0.014)	(0.002)	(0.077)	(0.004)	(0.005)	(0.006)
	[-0.017,0.036]	[-0.015,-0.006]	[-0.306,-0.005]	[-0.016,0.002]	[-0.041,-0.021]	[-0.022,0.002]
	$p = 0.481$	$p = 0.000$	$p = 0.043$	$p = 0.105$	$p = 0.000$	$p = 0.110$
Proportion of Advanced Battery Chemistry	0.126	0.316	0.677	0.369	0.163	0.393
	(0.625)	(0.340)	(1.933)	(0.445)	(0.130)	(0.444)
	[-1.098,1.350]	[-0.351,0.982]	[-3.112,4.465]	[-0.504,1.241]	[-0.092,0.418]	[-0.477,1.263]
	$p = 0.840$	$p = 0.353$	$p = 0.726$	$p = 0.408$	$p = 0.211$	$p = 0.376$
Return on Assets	-13.201	-1.806	-42.875	-3.510	-3.061	-3.652
	(5.283)	(2.841)	(37.946)	(3.399)	(2.385)	(3.562)
	[-23.556,-2.845]	[-7.374,3.762]	[-117.248,31.498]	[-10.171,3.152]	[-7.736,1.613]	[-10.633,3.328]
	$p = 0.012$	$p = 0.525$	$p = 0.259$	$p = 0.302$	$p = 0.199$	$p = 0.305$
Num. of ICE Models	-0.007	0.008	-0.203	0.004	0.001	0.004
	(0.015)	(0.003)	(0.112)	(0.006)	(0.008)	(0.006)
	[-0.037,0.022]	[0.001,0.015]	[-0.423,0.017]	[-0.008,0.017]	[-0.016,0.017]	[-0.008,0.016]
	$p = 0.616$	$p = 0.019$	$p = 0.071$	$p = 0.485$	$p = 0.945$	$p = 0.532$
ICE Suppliers Network Density	-2.989	4.946	258.142	4.625	5.684	5.271
	(5.030)	(1.532)	(132.528)	(1.778)	(1.467)	(2.148)
	[-12.847,6.869]	[1.943,7.948]	[-1.608,517.892]	[1.141,8.110]	[2.809,8.558]	[1.061,9.481]
	$p = 0.552$	$p = 0.001$	$p = 0.051$	$p = 0.009$	$p = 0.000$	$p = 0.014$
EV Suppliers Network Density	-3.358	2.161	-11.681	1.228	1.424	1.275
	(2.082)	(0.816)	(11.630)	(0.778)	(0.707)	(0.864)
	[-7.439,0.723]	[0.562,3.759]	[-34.476,11.114]	[-0.296,2.752]	[0.038,2.811]	[-0.419,2.969]
	$p = 0.107$	$p = 0.008$	$p = 0.315$	$p = 0.114$	$p = 0.044$	$p = 0.140$
World Green Car Candidate	0.007	-0.269	0.011	-0.327	0.171	-0.298
	(0.153)	(0.137)	(0.900)	(0.158)	(0.067)	(0.159)
	[-0.293,0.308]	[-0.537,-0.000]	[-1.753,1.776]	[-0.636,-0.018]	[0.040,0.302]	[-0.610,0.015]
	$p = 0.961$	$p = 0.050$	$p = 0.990$	$p = 0.038$	$p = 0.010$	$p = 0.062$
Avg. MPGe of EV Models	-0.003	-0.003	0.029	-0.003	-0.002	-0.004
	(0.003)	(0.002)	(0.020)	(0.002)	(0.001)	(0.002)
	[-0.008,0.002]	[-0.006,0.001]	[-0.010,0.068]	[-0.008,0.001]	[-0.004,0.000]	[-0.008,0.001]
	$p = 0.302$	$p = 0.137$	$p = 0.147$	$p = 0.134$	$p = 0.067$	$p = 0.128$
Num. of New ICE Suppliers	0.150	-0.060	-1.297	-0.016	-0.162	-0.031
	(0.093)	(0.025)	(0.765)	(0.042)	(0.036)	(0.042)
	[-0.032,0.331]	[-0.109,-0.012]	[-2.797,0.203]	[-0.098,0.066]	[-0.231,-0.092]	[-0.112,0.050]
	$p = 0.106$	$p = 0.015$	$p = 0.090$	$p = 0.706$	$p = 0.000$	$p = 0.456$
Num. of ICE Suppliers	0.057	0.039	0.095	0.049	0.005	0.049
	(0.033)	(0.015)	(0.081)	(0.021)	(0.011)	(0.021)
	[-0.008,0.123]	[0.010,0.068]	[-0.064,0.254]	[0.008,0.091]	[-0.017,0.027]	[0.009,0.090]
	$p = 0.086$	$p = 0.008$	$p = 0.241$	$p = 0.021$	$p = 0.631$	$p = 0.017$
Num. of Dual Purpose Factories	0.039	0.063	-0.392	0.074	0.074	0.079
	(0.068)	(0.023)	(0.284)	(0.030)	(0.035)	(0.031)
	[-0.094,0.172]	[0.018,0.108]	[-0.949,0.165]	[0.016,0.132]	[0.005,0.143]	[0.019,0.139]
	$p = 0.564$	$p = 0.006$	$p = 0.167$	$p = 0.012$	$p = 0.037$	$p = 0.010$
Num. of In-house Components	0.139	0.006	0.425	0.031	0.108	0.041
	(0.043)	(0.018)	(0.258)	(0.024)	(0.022)	(0.024)
	[0.055,0.224]	[-0.029,0.041]	[-0.082,0.931]	[-0.015,0.078]	[0.065,0.152]	[-0.005,0.087]
	$p = 0.001$	$p = 0.738$	$p = 0.100$	$p = 0.186$	$p = 0.000$	$p = 0.081$
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63	63	63	63	63	63

Column k.1 = mediator equation (X -> M); column k.2 = outcome equation (M -> Y, X -> Y).

GSEM estimates; standard errors in parentheses, clustered at the OEM level; 95% confidence intervals in brackets.

Mediator equations: Poisson for the two supplier-count mediators, beta regression (logit link) for Uniqueness of EV Components; outcome equations: Poisson.

Table A1-5. Component-Path Tests of Mediation: Joint Significance of the a- and b-Paths

Model	Hypothesis	Brokerage (X)	Mediator (M)	Outcome (Y)	a-path coef.	a-path SE	a-path p	b-path coef.	b-path SE	b-path p	Joint significance	N
1	H1a	Brokerage in ICE Network	Shared ICE-EV Suppliers	Num. of EV Models (t+2)	0.035	0.013	0.029	0.304	0.063	0.001	Yes (p<0.05)	91
2	H1a	Brokerage in ICE Network	New non-ICE EV Suppliers	Num. of EV Models (t+2)	-0.111	0.076	0.172	-0.006	0.242	0.979	No	91
3	H1a	Brokerage in ICE Network	Uniqueness of EV Components	Num. of EV Models (t+2)	-0.031	0.019	0.017	1.026	2.150	0.688	No	91
4	H1b	Brokerage in ICE Network	Shared ICE-EV Suppliers	Avg. Range of EV Models (t+2) rounded	0.043	0.013	0.006	0.103	0.031	0.008	Yes (p<0.05)	63
5	H1b	Brokerage in ICE Network	New non-ICE EV Suppliers	Avg. Range of EV Models (t+2) rounded	-0.003	0.119	0.983	0.116	0.061	0.169	No	63
6	H1b	Brokerage in ICE Network	Uniqueness of EV Components	Avg. Range of EV Models (t+2) rounded	0.012	0.009	0.331	0.283	0.300	0.418	No	63
7	H2a	Brokerage in EV Network	Shared ICE-EV Suppliers	Num. of EV Models (t+2)	0.017	0.010	0.083	0.343	0.068	0.000	Marginal (p<0.10)	91
8	H2a	Brokerage in EV Network	New non-ICE EV Suppliers	Num. of EV Models (t+2)	-0.004	0.031	0.925	-0.088	0.226	0.708	No	91
9	H2a	Brokerage in EV Network	Uniqueness of EV Components	Num. of EV Models (t+2)	-0.038	0.008	0.000	0.836	2.676	0.834	No	91
10	H2b	Brokerage in EV Network	Shared ICE-EV Suppliers	Avg. Range of EV Models (t+2) rounded	0.010	0.014	0.487	0.135	0.025	0.001	No	63
11	H2b	Brokerage in EV Network	New non-ICE EV Suppliers	Avg. Range of EV Models (t+2) rounded	-0.155	0.077	0.131	0.044	0.053	0.506	No	63
12	H2b	Brokerage in EV Network	Uniqueness of EV Components	Avg. Range of EV Models (t+2) rounded	-0.031	0.005	0.001	-0.538	0.627	0.466	No	63

Note. P-values are obtained using a cluster-robust score bootstrap (Webb weights, 9,999 reps; G = 13 clusters for Models 1-3 and 7-9 and 12 clusters for Models 4-6 and 10-12; Cameron et al. 2008, Roodman et al. 2019).
Joint significance = maximum p-value of a- and b-path < 0.05; marginal significance if maximum p-value of a- and b-path < 0.1.

Table A1-6. Indirect Effects: Point Estimates and Monte Carlo Confidence Intervals

Model	Hypothesis	Brokerage (X)	Mediator (M)	Outcome (Y)	Indirect effect. (a x b)	Monte Carlo SE	95% CI lower	95% CI upper	Monte Carlo p	CI excludes 0	N
1	H1a	Brokerage in ICE Network	Shared ICE-EV Suppliers	Num. of EV Models (t+2)	0.011	0.005	0.002	0.022	0.009	Yes	91
2	H1a	Brokerage in ICE Network	New non-ICE EV Suppliers	Num. of EV Models (t+2)	0.001	0.033	-0.058	0.081	0.935	No	91
3	H1a	Brokerage in ICE Network	Uniqueness of EV Components	Num. of EV Models (t+2)	-0.032	0.081	-0.235	0.099	0.643	No	91
4	H1b	Brokerage in ICE Network	Shared ICE-EV Suppliers	Avg. Range of EV Models (t+2) rounded	0.004	0.002	0.001	0.009	0.002	Yes	63
5	H1b	Brokerage in ICE Network	New non-ICE EV Suppliers	Avg. Range of EV Models (t+2) rounded	0.000	0.016	-0.043	0.024	0.945	No	63
6	H1b	Brokerage in ICE Network	Uniqueness of EV Components	Avg. Range of EV Models (t+2) rounded	0.003	0.006	-0.004	0.018	0.431	No	63
7	H2a	Brokerage in EV Network	Shared ICE-EV Suppliers	Num. of EV Models (t+2)	0.006	0.004	-0.001	0.016	0.089	No, but only marginally includes 0	91
8	H2a	Brokerage in EV Network	New non-ICE EV Suppliers	Num. of EV Models (t+2)	0.000	0.008	-0.017	0.016	0.999	No	91
9	H2a	Brokerage in EV Network	Uniqueness of EV Components	Num. of EV Models (t+2)	-0.031	0.103	-0.244	0.165	0.752	No	91
10	H2b	Brokerage in EV Network	Shared ICE-EV Suppliers	Avg. Range of EV Models (t+2) rounded	0.001	0.002	-0.002	0.006	0.470	No	63
11	H2b	Brokerage in EV Network	New non-ICE EV Suppliers	Avg. Range of EV Models (t+2) rounded	-0.007	0.010	-0.033	0.008	0.423	No	63
12	H2b	Brokerage in EV Network	Uniqueness of EV Components	Avg. Range of EV Models (t+2) rounded	0.017	0.020	-0.022	0.056	0.388	No	63

Note. The indirect effect is the product of the a- and b-path coefficients.
Standard errors and 95% confidence intervals are from the Monte Carlo method with 20,000 draws (Preacher and Selig, 2012).
Mediation is established by the joint-significance criterion in Table A1-5.

APPENDIX 2: BROKERAGE AND EV ENTRY

After formulating and testing our hypotheses, we sought post hoc evidence on which aspects of brokerage influence an OEM's decision to have at least one EV model in a given year, rather than the number of EV models. These analyses would demonstrate whether brokerage effect is static or dynamic. That is, whether brokerage matters only for a company's decision to engage in technological adaptation or for continuous adaptation by adding (or dropping) new technology models.

To this end, we recoded our dependent variable — the number of EV models — into a binary indicator set to 1 if the OEM had at least one EV model in a given year and 0 otherwise. The model was estimated with Stata's logit command with OEM fixed effects and standard errors clustered by OEM. The logit command drops the five OEMs (GM, Nissan, BMW, Volkswagen, Kia) that offered at least one EV model in every observation year because their fixed effects perfectly predict the outcome. As a result, the estimation sample includes 8 OEMs' 56 OEM-year observations. Model 1 in Table A2 shows no significant effect of either ICE or EV brokerage on the OEM's decision to have at least one EV model.

These results demonstrate a dynamic effect of brokerage on the number of EV models: changes in old technology brokerage are associated with changes in the number of EV models, but not with the transition from zero models to at least one model. This is because resolving technology, supply, and demand uncertainty through supply chain activities is a continuous, not binary, process.

Table A2. Brokerage and EV Entry

	Model 1 DV: Any EV Model (t+2)
Brokerage in ICE Network	0.320
	(0.230)
	[-0.132,0.771]
	$p = 0.165$
Brokerage in EV Network	-0.122
	(0.099)
	[-0.315,0.072]
	$p = 0.217$
Num. of New ICE Suppliers	0.146
	(0.210)
	[-0.265,0.557]
	$p = 0.487$
Return on Assets	4.605
	(15.479)
	[-25.734,34.943]
	$p = 0.766$
Num. of ICE Models	-0.439
	(0.291)
	[-1.009,0.131]
	$p = 0.131$
ICE Suppliers Network Density	-39.104
	(23.472)
	[-85.109,6.900]
	$p = 0.096$
EV Suppliers Network Density	17.116
	(17.396)
	[-16.979,51.212]
	$p = 0.325$
World Green Car Candidate	-2.856
	(2.311)
	[-7.386,1.674]
	$p = 0.217$
Avg. MPGe of EV Models	-0.026
	(0.026)
	[-0.076,0.025]
	$p = 0.314$
Num. of Dual Purpose Factories	0.639
	(0.471)
	[-0.283,1.562]
	$p = 0.174$
Num. of In-house Components	-0.631
	(0.773)
	[-2.145,0.884]
	$p = 0.414$
Num. of ICE Suppliers	0.263
	(0.158)
	[-0.047,0.573]
	$p = 0.097$
Proportion of Advanced Battery Chemistry	5.373
	(4.897)
	[-4.225,14.972]
	$p = 0.273$
Firm fixed effects	Yes
Observations	56
Log-likelihood	-20.751

Logit with OEM fixed effects; standard errors clustered by OEM in parentheses.
95% confidence intervals in brackets; p-values reported as p = value.

Note. Five OEMs (GM, Nissan, BMW, Volkswagen, Kia) had EV models every year, so their firm fixed effects perfectly predict the outcome. The logit model therefore drops their observations (N=35) from the original observations (N=91), leaving N = 56.

APPENDIX 3. VALIDATION OF IMPUTED TIES FOR DUAL-POWERTRAIN SUPPLIERS

Our network measures combine two data sources that differ in what they reveal about an OEM-supplier relationship. Marklines records supply at the component level, so we know whether a buyer–supplier tie involves ICE or EV components, and we assigned each Marklines tie to the corresponding (ICE or EV) network. FactSet also records buyer–supplier relationships. It has a larger number of dyads than Marklines, but it does not systematically report whether EV or ICE component is supplied. We therefore imputed the content of each FactSet tie from the Marklines supplier's activity in the same three-year window. That is, when an OEM-supplier relationship appears in FactSet but not in Marklines, we assign it to an ICE or EV network according to the supplier's Marklines deliveries to any OEM in the Americas during the same three-year window. A FactSet tie entered the EV network if the supplier delivered EV components to any OEM in the Americas, and to the ICE network if it delivered ICE components to any OEM in the Americas in the corresponding period. A FactSet tie with a supplier active in both ICE and EV technologies therefore entered both networks.

Because these imputations could affect our results, we assessed their influence in the following steps. We re-estimated the main analysis (Table 3) and mediation models (Table A1) under four different definitions of ICE and EV ties:

(a) Confirmed ICE and EV ties: We rebuild the ICE and EV networks using only Marklines-confirmed ties. Then, we replicated the analysis in Table 3, excluding all imputed FactSet ties.

(b) Supplier EV share: We assigned ICE ties to dyads either when there was a Marklines ICE tie between firms or a combination of Marklines ICE ties and FactSet ties in the same time period. For the EV network, we kept all confirmed Marklines EV ties. Furthermore, we imputed each FactSet tie as EV tie when the focal firm also had at least one Marklines confirmed EV tie elsewhere and the share of its components from Marklines confirmed ties account for at least 10%, 25% or 50% of the supplier's total Americas component records. Below we report only the model with 10% cutoff score, but the results are the same across other cutoff scores.

(c) OEM EV/hybrid production, global: We assigned ICE ties to dyads either when there was a Marklines ICE tie between firms or a combination of Marklines ICE ties and FactSet ties in the same time period. For EV ties, we used the following rule. A FactSet tie is considered as EV tie if the OEM itself produced at least one hybrid or EV vehicle model, in any plant worldwide, during the corresponding time window (t to t-2). We assume that OEMs with some electrified production globally will source EV components via each FactSet tie.

(d) Pair-level validation: a FactSet tie entered a network only with evidence specific to that supplier-OEM pair. A FactSet tie entered the ICE network if Marklines records ICE supply between the same pair in the Americas in any model year from t-7 to t, or if the

pair's FactSet relationship keywords contain an engine or driveline term and no EV term. A FactSet tie entered the EV network if Marklines records EV supply between the same pair in any model year from t-7 to t, if the keywords contain an EV term and no engine term, or if the supplier specializes in EV components (EV share of at least 50% in the window t-2 to t). Marklines-confirmed ties entered the networks as in the main analysis.

Robustness of Hypotheses Tests

The results of the main analysis are presented in Panel A in Table A3-1. Under the strictest definition of ICE and EV ties (specification (a)), ICE brokerage still predicted both the number of EV models (Model 2; $\beta = 0.029$, 95% CI = [0.006, 0.051], $p = 0.012$) and their range (Model 4; $\beta = 0.032$, 95% CI = [0.016, 0.049], $p < 0.001$). EV brokerage was negatively associated with the number of EV models (Model 5; $\beta = -0.024$, 95% CI = [−0.033, −0.014], $p < 0.001$) and was imprecisely estimated for the EV range (Model 6; $\beta = -0.006$, 95% CI = [−0.014, 0.002], $p = 0.145$). Across the four alternative specifications, the coefficient of ICE brokerage remains positive and its 95% confidence intervals all contain the main-specification estimate. The only loss of significance at $p<0.05$ level is in the range model under pair-level validation (d), where the estimate precision is $p<0.1$ (Model 4; $\beta = 0.024$, 95% CI = [-0.004, 0.052], $p = 0.088$). The coefficient of EV brokerage changes sign across specifications and is significant only under specification (a), where it is negative. This pattern mirrors the main analysis: ICE brokerage is positively associated with new technology models and performance across all imputation rules, whereas EV brokerage shows no consistent or precisely estimated effect.

Robustness of Mediation Tests

Panel B of Table A3-1 presents the mediation analysis results using different definitions of imputed ties. Under our main definition, which counts both confirmed and imputed EV ties, *Brokerage in ICE Network* increases *Shared ICE-EV Suppliers*: suppliers that move from the OEM's ICE network into its EV network. *Shared ICE-EV Suppliers* in turn predict both the number and the range of EV models.

When we allow EV imputed ties from FactSet to enter the sample only if the focal OEM produced at least one hybrid or EV model during the same window anywhere in the world, the mediation held for the number of EV models and was marginal for range (specification (c) in Panel B).

The mediation effects disappeared under different definitions of imputed ties (specifications (a), (b), and (d)).

Ultimately, we conclude that our mediation results depend on how we impute EV ties from FactSet data.

Our imputation method would be supported if we can show that imputed FactSet EV ties are the precursors of confirmed Marklines ties for the same pair. In other words, we need to test whether

imputed EV ties in FactSet observed in a given period (t to t-2) appear in Marklines as confirmed EV supply between the same supplier and OEM in the following year (t+1).

To answer this question, we built a panel of supplier–OEM dyads by window year (11,468 dyad-years, 2014–2020). For each observation year t, the panel includes all suppliers and OEMs participating in either the ICE or EV network during the three-year window from year t-2 to t. Across the seven observation windows (2014-2020), this yields 144 unique suppliers and 18 OEMs. The panel includes three sets of dyads: (1) dyads with confirmed ties (labeled as *Confirmed ICE/EV Ties*), (2) imputed ties (labeled as *Imputed ICE/EV Ties*), and (3) unrealized dyads. A confirmed tie is a Marklines record showing that a supplier delivered an EV (ICE) component to an OEM in the Americas. An imputed tie is a dyad only observed in FactSet supplier–OEM relationship without a corresponding Marklines record, included in the EV (ICE) network because the supplier is EV (ICE) capable[5]. The unrealized dyads serve as the reference group and account for 7,266 of the 11,468 total dyad-year observations.

We also included the supplier's annually varying ICE and EV capability indicators (labeled as *Supplier ICE/EV-Capable*) in the models as control variables, comparing imputed ties with unconnected dyads involving equally capable suppliers. We define supplier capability as whether this supplier has supplied ICE or EV components to any OEM during the time period.

We estimated logit models predicting whether an imputed EV tie (in t-2 to t) was confirmed one year later (t+1). Table A3-2 reports models that include supplier fixed effects, controls for suppliers' EV and ICE capabilities, and standard errors clustered at the supplier level. Compared with unrealized dyads, an imputed EV tie observed in FactSet (t to t-2) had 4.1 times the odds of showing up as a confirmed Marklines EV tie in the following year (t+1) ($\beta = 1.412$, 95% CI = [0.630, 2.194], $p < 0.001$ in Model 1). An imputed ICE tie, estimated in the same model, showed no such impact on Marklines confirmed EV ties and its effects were imprecisely estimated.

Similarly, as presented in Model 2 in Table A3-2, an imputed ICE tie in FactSet had 1.9 times the odds of showing up as a confirmed Marklines ICE tie in the following year ($\beta = 0.630$, 95% CI = [0.191, 1.068], $p = 0.005$), while the same model shows that an imputed FactSet EV tie is not associated with the confirmed Marklines ICE tie. Thus, each imputation from one database anticipates confirmed supply mainly in its own technology in a different database.

These results support treating imputed EV ties in FactSet as EV supply relationships that Marklines should record in the future. Suppliers are usually chosen before a vehicle model enters production and captured in FactSet, whereas Marklines records supply through the actual vehicle models that carry the component.

We conclude that the positive association between ICE brokerage and technological adaptation is robust to several alternative imputation assumptions in regression models 2, 4, 5 and 6

[5] A supplier is considered ICE(EV)-capable if, in a given year, it offers any ICE(EV) component to any OEM.

reproduced in Table A3-1, panel A. By contrast, the mediation evidence is sensitive to how EV ties are imputed. Importantly, however, the FactSet-based imputation assumption underlying the mediation results receives external validation from subsequently confirmed supply relationships in Marklines.

Table A3-1. Alternative specifications of EV ties: main results and indirect effects

Panel A. Main analysis results under each specification

Specification	Hyp.	Model	Outcome	FactSet EV ties kept	Coef.	(SE)	[95% CI]	p	N
Paper's specification	H1a	2	Num. of EV Models (t+2)	100.0%	0.041	(0.016)	[0.010, 0.072]	0.009	91
	H1b	4	Avg. Range of EV Models (t+2)	100.0%	0.033	(0.005)	[0.023, 0.043]	0.000	63
	H2a	5	Num. of EV Models (t+2)	100.0%	0.000	(0.012)	[-0.024, 0.024]	0.982	91
	H2b	6	Avg. Range of EV Models (t+2)	100.0%	-0.008	(0.005)	[-0.017, 0.001]	0.091	63
(a) Confirmed ICE and EV ties	H1a	2	Num. of EV Models (t+2)	0.0%	0.029	(0.011)	[0.006, 0.051]	0.012	74
	H1b	4	Avg. Range of EV Models (t+2)	0.0%	0.032	(0.008)	[0.016, 0.049]	0.000	60
	H2a	5	Num. of EV Models (t+2)	0.0%	-0.024	(0.005)	[-0.033, -0.014]	0.000	53
	H2b	6	Avg. Range of EV Models (t+2)	0.0%	-0.006	(0.004)	[-0.014, 0.002]	0.145	42
(b) Supplier EV share $\geq$ 10%	H1a	2	Num. of EV Models (t+2)	61.1%	0.043	(0.017)	[0.010, 0.075]	0.011	91
	H1b	4	Avg. Range of EV Models (t+2)	61.1%	0.030	(0.005)	[0.020, 0.040]	0.000	63
	H2a	5	Num. of EV Models (t+2)	61.1%	-0.011	(0.015)	[-0.040, 0.018]	0.455	91
	H2b	6	Avg. Range of EV Models (t+2)	61.1%	-0.003	(0.005)	[-0.013, 0.006]	0.493	63
(c) OEM EV/hybrid production, global	H1a	2	Num. of EV Models (t+2)	89.8%	0.040	(0.016)	[0.009, 0.072]	0.012	91
	H1b	4	Avg. Range of EV Models (t+2)	89.8%	0.033	(0.005)	[0.023, 0.043]	0.000	63
	H2a	5	Num. of EV Models (t+2)	89.8%	0.009	(0.015)	[-0.021, 0.039]	0.561	78
	H2b	6	Avg. Range of EV Models (t+2)	89.8%	-0.002	(0.005)	[-0.012, 0.007]	0.640	60
(d) Pair-level validation	H1a	2	Num. of EV Models (t+2)	49.5%	0.057	(0.025)	[0.008, 0.105]	0.021	91
	H1b	4	Avg. Range of EV Models (t+2)	49.5%	0.024	(0.014)	[-0.004, 0.052]	0.088	63
	H2a	5	Num. of EV Models (t+2)	49.5%	0.003	(0.009)	[-0.016, 0.021]	0.780	90
	H2b	6	Avg. Range of EV Models (t+2)	49.5%	0.008	(0.004)	[-0.000, 0.016]	0.060	61

Note. N varies across specifications because OEM-years without an EV tie under the stricter rule drop out of the EV brokerage models (and, under specification (a), OEM-years without a confirmed ICE tie drop out of the ICE brokerage models).

Panel B. Indirect effects of Brokerage in ICE Network through Shared ICE-EV Suppliers

Specification	Hyp.	Model (Mediation)	Indirect effect	Monte Carlo SE	95% Monte Carlo CI	p	Joint sig.	N
Paper's specification	H1a	1	0.011	(0.005)	[0.002, 0.022]	0.009	Yes	91
	H1b	4	0.004	(0.002)	[0.001, 0.009]	0.002	Yes	63
(a) Confirmed ICE and EV ties	H1a	1	-0.002	(0.023)	[-0.045, 0.054]	0.984	No	74
	H1b	4	-0.016	(0.015)	[-0.053, 0.004]	0.155	No	60
(b) Supplier EV share $\geq$ 10%	H1a	1	-0.009	(0.013)	[-0.044, 0.007]	0.353	No	91
	H1b	4	0.002	(0.004)	[-0.002, 0.013]	0.348	No	63
(c) OEM EV/hybrid production, global	H1a	1	0.014	(0.006)	[0.003, 0.026]	0.012	Yes	91
	H1b	4	0.004	(0.002)	[0.001, 0.007]	0.007	Marginal	63
(d) Pair-level validation	H1a	1	0.008	(0.027)	[-0.067, 0.046]	0.922	No	91
	H1b	4	-0.000	(0.007)	[-0.012, 0.016]	0.906	No	63

Note. 95 % Monte Carlo interval (20,000 draws) in brackets and Monte Carlo p-value.
Joint significance: Yes if both a and b have Webb-weighted score bootstrap $p < 0.05$ (9,999 replications).
Supplier EV share $\geq$ 25% and $\geq$ 50% give the same results as $\geq$ 10%

Table A3-2. Validation of imputed ties: subsequent confirmed supply between the same supplier and OEM

	Model 1 Confirmed EV tie (t+1)	Model 2 Confirmed ICE tie (t+1)
Imputed EV Tie	1.412	0.421
	(0.399)	(0.373)
	[0.630,2.194]	[-0.310,1.153]
	$p = 0.000$	$p = 0.259$
Imputed ICE Tie	0.247	0.630
	(0.555)	(0.224)
	[-0.841,1.334]	[0.191,1.068]
	$p = 0.657$	$p = 0.005$
Confirmed ICE Tie	1.848	3.291
	(0.547)	(0.190)
	[0.777,2.920]	[2.919,3.663]
	$p = 0.001$	$p = 0.000$
Confirmed EV Tie	3.939	1.306
	(0.264)	(0.426)
	[3.422,4.457]	[0.470,2.141]
	$p = 0.000$	$p = 0.002$
Supplier EV-capable	-1.928	-0.824
	(0.562)	(0.397)
	[-3.029,-0.827]	[-1.603,-0.045]
	$p = 0.001$	$p = 0.038$
Supplier ICE-capable	-1.035	-1.443
	(0.806)	(0.452)
	[-2.615,0.545]	[-2.329,-0.557]
	$p = 0.199$	$p = 0.001$
Supplier fixed effects	Yes	Yes
Observations (dyad-years)	3242	8554
Events	104	974
Suppliers (clusters)	31	83
Log-likelihood	-306.429	-1871.057

Note. Standard errors clustered by supplier in parentheses.
Confidence intervals in brackets.
p-values reported as p = value.
Suppliers whose outcomes exhibit no variation are excluded from the estimation sample.

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