Online Appendix to *Exclusive Secrets*

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1 Dataset construction

Marklines' contract dataset. In the contract dataset already restricted to "large OEMs" as defined in Section 4.1.1, we identified around 2.8% (3,696) of contracts as supplied in-house, either by the term "in-house" in the supplier name or because the supplier name is identical to the OEM name. A further 136 contracts show some overlap between supplier and OEM name. Additionally, another 1.8% of observations (precisely, 2,336) are contracts between different OEMs, both within the same corporate group and between competing OEMs, again identified because the supplier name contains the (brand) name of an automotive OEM. We exclude all such cases of in-house production and supply by other OEMs because we are unable to accurately assign a supplier country.[1] Finally, we remove 137 observations coming from OEMs solely manufacturing trucks and other commercial vehicles. After these exclusions, our final sample for calculating the number of supply relationships per supplier firm consists of 123,071 supply contracts.

Matching supplier country information from the supplier dataset to the contract dataset. In the contract dataset, suppliers are identified only by their full legal name. To assign supplier countries, we primarily use direct string matching with another Marklines dataset

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[1] Besides, our conceptual framework best describes the relationship between an OEM and an independent supplier firm, where knowledge leakage and hold-up threats are more relevant.

containing information about worldwide automotive parts suppliers, the *supplier dataset*, successfully identifying the home country of 2,903 suppliers this way (91.7% of all suppliers, representing 96.6% of contracts). Where a direct match was not possible, we first employed a fuzzy-string matching algorithm (matching 69 suppliers, 2.2%, 0.9% of contracts), followed by a manual search in the database for an additional match of 31 suppliers (1%, 0.8% of contracts). Next, we inferred the country from obvious geographical indicators in their name (e.g., "Borg-Warner Poland Sp. z o.o." is clearly a firm incorporated in Poland) for 75 suppliers (2.4%, 0.8% of contracts) and from legal suffixes for another 8 suppliers (0.2% of suppliers and contracts). Manual web searches led to the identification of a country for another 86 suppliers (2.7%, 0.7% of contracts). Only 9 supplier names remained finally without country information, accounting for 64 contracts. Only 10 supplier names correspond to more than one country, 9 of which end up in our main regression dataset. This is possible because in all other cases, the exact name of a supplier's foreign subsidiary differs from that of its parent company. A small fraction of observations (3,310, i.e., 2% of observations representing 24 suppliers) could not be assigned a country because the supplier name was that of another OEM. Given that all large OEMs have production operations in several different countries, it was impossible to accurately fill in missing production country data for specific production inputs.

Matching state information for US-based suppliers. For the majority of US-based suppliers, Marklines' supplier dataset also provides a postal address including the state in which the supplier produces. For 84 suppliers (accounting for 237 industry observations), however, addresses were unavailable in Marklines' data, prompting us to perform web searches instead. When we found that a supplier operates in multiple states, we assign the state location of the supplier's headquarters. In the handful of cases where the headquarters location was ambiguous or clearly uninvolved in production, we randomly selected one of the available states. Similarly, we randomly selected one state for firms where Marklines' supplier database featured locations in more than a single state for the same input part, although such cases were so rare that removing those supplies from regressions does not significantly influence our results.

Mapping the relation-specificity index to Marklines' industry classification. We construct a mapping between the "Part" description in (Head et al., 2004, Table IV) and one or several values of Marklines' "product" or "category" variable. Some of these mappings are straightforward. For instance, the part named "Axles" in HRS confidently corresponds to the value "Axle" of Marklines' *product* variable. Similarly, the HRS part "Steering" corresponds to the value "Steering" of Marklines' *category* variable. For less clear associations, we extrapolated from the non-missing values of the *category* it belongs to or a *product* under the same *category*. For example, the product "Fuel Filter" belongs to the same category "Fuel System" as does

product "Fuel Pump" (matched to HRS' "Fuel pumps"); and product "Tire" belongs to the same category "Wheel & Tire" as does product "Wheel" (matched to HRS' "Wheels").

We define four alternative mappings between the two auto part classifications that are mostly nested with each other. A "broad" definition covering all observations is used to produce all results in this paper except those presented in Table A.5. The alternatives comprise a "narrow" definition that is restricted to more obvious correspondences and a "more conservative" version of each the broad and the narrow definition that omit some further correspondences that required additional research on our part. Moreover, we include two categories in the analysis that are not present in HRS. Firstly, we assign an ECR rating of zero to the category "General/Small Parts", which contains non-specific auto parts such as bearings, ducts, and fasteners. Secondly, we assign a maximum value of 10 to the category "HV/PHV/EV Parts", electric vehicle components that did not exist in the market at the time of the writing of Monteverde and Teece (1982). Neither of these two decisions significantly alter our results.

Matching Marklines to Connor's (2020) cartel dataset. We use the Connor (2020) dataset version from 2019-08-30. This dataset identifies cartels in 1528 markets. Cartels in automotive supplier industries are labeled "Auto parts, " followed by a brief market description. The dataset contains 55 such cartels, after excluding five cartels of aftermarket part suppliers, one in tooling and one in parts pricing software. Similar to the approach used for matching with the relation-specificity classification, we construct a correspondence between the cartel market description and Marklines' product and category industry variables. For instance, the cartel market "Auto parts, occupant safety equipment, new" is matched to Marklines category "Airbag & Safety Related Products". The cartel market "Auto parts, Bearings, EU, US, and JP", instead, is matched to three different product industries "Bearing" (part of category "General/Small Parts"), "Engine Bearing" (category "Main Engine Parts"), and "Wheel Bearing" (category "Wheel & Tire").

This mapping associates 42 cartel markets with 102 product industries. 10 cartel markets remain unmatched due to either lack of coverage of Marklines' contract dataset (possibly because the cartels are in a lower-tier industry, supplying higher-tier suppliers instead of OEMs) or its insufficiently disaggregated industry classification. Examples comprise "fuel senders" and "anti-vibration devices". We further disregard three cartels "thermal systems (heating & AC)", "braking systems, hydraulic, EC" and "braking systems, electronic, EC" due to only broad category-level association (with "Climate Control" and "Brake", respectively). Considering the variety of product industries covered by each, we decided a reliable match would have to be made at the firm rather than the industry level, which was beyond the scope for this supplementary analysis.

We augment the list of matched product industries with the geographical scope (worldwide

in all but three cases) and start and end year of the corresponding cartel. The cartel matched to product "Dash Panel" is geographically restricted to Spain, while all observed suppliers in this industry are from other countries, leading to 101 cartelized industries referenced in Section 5.3.

Matching Marklines to ORBIS. We primarily used ORBIS' *batch search* function provided by BvD as part of the web interface. This automated search compares the supplier name and country (from our regression dataset) and the supplier's street address (from Marklines' *supplier dataset*, where available) against ORBIS' internal database, also considering previous names a company may have used. Where a good-enough match is found, the batch search assigns a match score of "A", which we accepted without further checks.

For matches with score "B" or lower, we proceeded as follows:

1. We prioritized name matches over address matches when deciding between candidates.
2. Among similarly named candidates, we preferred those listed on stock markets, prioritizing the operator's accounting data over the production plant's precise address.
3. We excluded all matching candidates with insufficient similarity in both company name and address, as well as any candidate associated with a different country than the one recorded by Marklines.
4. For unmatched records, we first performed another batch search after removing legal form abbreviations from the company name, followed by web searches for (i) alternative addresses, (ii) recent name changes, or (iii) the identity of the parent company. We used any such information in this order for further manual matching attempts.

The availability of financial data for private firms varies by country. Restricting the sample to observations from suppliers with at least one annual non-missing value of turnover data therefore changes the country composition of the data. Most notably, the share of US suppliers decreases from nearly 16% to 5.5%, while that of Thai suppliers increases from 7.5% to 12.5%. Despite these shifts, means and variances of the variables used in regression remain essentially unchanged.

2 Instrumental variable regressions

In our IV analysis, we use three groups of instruments to account for variation in TS protection. Table 1 presents summary statistics for all instrumental variables used. The first group comprises dummy variables indicating the origins of a country's legal system, obtained from La Porta et al. (1999). This approach follows Nunn (2007) and Biancini and Bombarda (2021), who use these variables to instrument for contract enforcement and patent protection, respectively.

The second group of IVs consists of two indexes of IP protection strength in areas other than trade secrets.[2] Different IP protection levels are commonly correlated across countries. However, since our focus is on confidential business information, specifically protected under trade secrets law, these other forms of IP protection should not directly impact our outcome variable. To further increase the likelihood of instrument exogeneity, we use past values of the indexes as instruments. Specifically, we use the 2000 index of plant varieties protection from Campi and Nuvolari (2015) and the index of the extent of copyright piracy from the 2009 International Property Rights Index, summarized in Dedigama (2009).[3] Despite the availability of several indexes of patent protection, we consciously chose to not include those as IVs. Our rationale is the much greater potential we see for a direct causal relationship between patent protection and automotive OEM's decisions to engage in business in a country, which in turn would influence our outcome variable.

The final group of IVs captures various aspects of a country's approach to protection of and access to information. Our argument is based on the premise is that this approach in areas unrelated to our outcome variable is correlated with its inclination to protect trade secrets.[4] Specifically, we use a measure of the extent of information disclosure to a company's shareholders

[2]We know of only two instances in which authors used aspects of IP protection to instrument a variable measuring legal IP protection, Maskus and Penubarti (1995) and Lerner (2002). Lerner (2002) uses dummy variables capturing temporal proximity of a change in patent protection to a country's signing of major IP agreements, leveraging time variation that is absent our data. Maskus and Penubarti (1995) use dummy variables for membership in patent conventions and legal provisions for pharmaceutical and chemical product patents at the beginning of their sample period as instruments for an index of patent protection. In contrast, we use lagged values of measures of protection of unrelated types of IP.

[3]While the first IPRI report published in 2007 already included the level of copyright piracy, the number of covered countries was greatly increased for the 2009 edition.

[4]Beyond the economic arguments underlying the establishment of IP law in general (most importantly, incentivizing the costly spending of resources to generate value), the existence of TS law has been explained using a variety of philosophical arguments. These include the existence of a fundamental right to privacy (Paine, 1991), implying a right to control disclosure; the concept of "personhood" of the TS owner (Hill, 1999), implying "moral rights" over one's resources and the product of one's labor; and the concept of contractarianism (Risch, 2007), promoting the idea that society members would hypothetically agree on the rules of TS law behind a "veil of ignorance". We argue that a country's stance on these principles in the area of TS law likely mirrors its approach in other legal and behavioral domains. As long as decisions in these other areas do not directly impact the number of OEMs that a domestic supplier firm engages with, they serve as suitable instruments for a country's attitude toward TS law.

(from the World Bank's 2006 Doing Business report, termed the "Extent of disclosure index"), a measure of government efforts to censor the media (from Coppedge et al. (2023) as part of the Varieties of Democracy Project, with the methodology described in Pemstein et al. (2023), for the year 2000, variable name `v2mecenefm`, referenced 3.11.0.1 in the codebook), a measure of the "freedom and independence of media & expression" (from Freedom House's Freedom in the World index, with disaggregated data reaching back to the year 2000 available via the Fraser Institute's Human Freedom Index (Vásquez et al., 2022)), and a measure for the existence of privacy protection law (obtained from Mechkova et al. (2022) as part of the Digital Society Project (Mechkova et al., 2019), for 2000, variable name `v2smprivex`, referenced 2.3.2 in the codebook).

Table 1: Summary statistics for the instrumental variables in the regression dataset.

Summary statistics	Minimum	Median	Maximum	Mean	S.D.	Obs.
IV group 1:						
Legal origins: British	0	0	1	0.29	0.45	7,267
Legal origins: German	0	0	1	0.42	0.49	7,267
Legal origins: French	0	0	1	0.12	0.33	7,006
Legal origins: Soviet	0	0	1	0.14	0.35	7,006
Legal origins: Scandinavian	0	0	1	0.00	0.07	7,006
IV group 2:						
Plant Protection Index (2000)	0.40	3.31	4.66	3.20	0.89	6,123
Level of Copyright Piracy (2009)	1.00	7.70	8.65	6.05	2.81	7,006
IV group 3:						
Corporate Disclosure Requirement (2006)	2.00	7.00	10.00	7.43	1.65	7,006
Government Censorship Effort (2000)	0.62	9.09	9.84	7.76	2.59	7,006
Freedom of media & expression (2000)	1.62	9.78	10.00	9.11	1.51	7,006
Existence of privacy protection law (2000)	−1.92	0.63	1.79	0.55	1.29	7,006

Table 2: Instrumental-variables regression: first stage for legal origins IVs

Dependent variable:	(1) TSPI	(2) TSPI × medium RS	(3) TSPI × high RS
Dummy: British legal origins	0.640***	0.031***	0.026***
	(0.009)	(0.010)	(0.009)
Dummy: German legal origins	0.153***	−0.137***	−0.107***
	(0.020)	(0.017)	(0.015)
Dummy: French legal origins	0.282***	0.111***	0.095***
	(0.019)	(0.013)	(0.011)
Dummy: Soviet legal origins	−0.164***	0.207***	0.193***
	(0.012)	(0.016)	(0.015)
Medium RS × British legal origins	0.000	0.504***	0.006
	(0.005)	(0.018)	(0.010)
Medium RS × German legal origins	−0.001	0.485***	0.013***
	(0.004)	(0.006)	(0.004)
Medium RS × French legal origins	−0.021	−0.077***	−0.010
	(0.022)	(0.024)	(0.008)
Medium RS × Soviet legal origins	0.002	−0.873***	0.006
	(0.010)	(0.006)	(0.004)
High RS × British legal origins	0.011**	0.011	0.484***
	(0.005)	(0.011)	(0.018)
High RS × German legal origins	0.004	−0.005	0.515***
	(0.004)	(0.005)	(0.006)
High RS × French legal origins	−0.091***	0.006	−0.212***
	(0.024)	(0.011)	(0.032)
High RS × Soviet legal origins	−0.001	−0.002	−0.872***
	(0.009)	(0.004)	(0.005)
Dummy: medium RS	0.000	3.547***	−0.001
	(0.002)	(0.003)	(0.003)
Dummy: high RS	−0.005*	0.002	3.542***
	(0.003)	(0.004)	(0.003)
No. suppliers in industry	−0.000	−0.000**	0.000***
	(0.000)	(0.000)	(0.000)
No. OEMs in industry	0.000	−0.000	−0.000*
	(0.000)	(0.000)	(0.000)
No. industries active	−0.001***	0.000	−0.000***
	(0.000)	(0.000)	(0.000)
Avg. distance to OEM ctries (th. km, log.)	0.333***	0.091***	0.115***
	(0.023)	(0.021)	(0.019)
Absence of trade barriers (GCI)	−0.302***	−0.120***	−0.081***
	(0.027)	(0.022)	(0.019)
Infrastructure quality (GCI)	0.162***	0.071***	0.040***
	(0.010)	(0.008)	(0.007)
GDP per capita (current USD, log.)	0.410***	0.109***	0.122***
	(0.007)	(0.008)	(0.007)
Constant	1.975***	−0.381***	−0.491***
	(0.169)	(0.141)	(0.125)
Observations	7,006	7,006	7,006
F test:	7,085.98	4,280.98	6,310.93
Sanderson-Windmeijer multivariate F test:	2,648.62	9,959.44	12,196.49
Sanderson-Windmeijer chi-squared test:	26,569.67	99,908.10	1.2e+05

Standard errors in parentheses. The dummy for "Scandinavian legal origins" (in our dataset this only applies to Sweden) is the excluded base group.

Table 3: Instrumental-variables regression: first stage for "irrelevant IPRs" IVs

Dependent variable:	(1) TSPI	(2) TSPI × medium RS	(3) TSPI × high RS
IP protection of plant varieties	−0.156***	0.065***	0.064***
	(0.014)	(0.009)	(0.007)
Level of piracy	0.132***	−0.053***	−0.055***
	(0.012)	(0.010)	(0.007)
Medium RS × IP protection of plant varieties	0.002	−0.337***	−0.006
	(0.011)	(0.010)	(0.004)
Medium RS × Level of piracy	−0.001	0.293***	0.002*
	(0.003)	(0.003)	(0.001)
High RS × IP protection of plant varieties	−0.009	0.003	−0.366***
	(0.011)	(0.005)	(0.010)
High RS × Level of piracy	0.002	−0.001	0.303***
	(0.003)	(0.001)	(0.003)
Dummy: medium RS	−0.003	3.024***	0.012
	(0.021)	(0.018)	(0.008)
Dummy: high RS	0.013	0.002	3.059***
	(0.020)	(0.010)	(0.018)
No. suppliers in industry	0.000	−0.000*	0.000*
	(0.000)	(0.000)	(0.000)
No. OEMs in industry	−0.000	0.000**	−0.000
	(0.000)	(0.000)	(0.000)
No. industries active	−0.000***	−0.000***	−0.000
	(0.000)	(0.000)	(0.000)
Avg. distance to OEM ctries (th. km, log.)	0.729***	0.246***	0.226***
	(0.033)	(0.020)	(0.017)
Absence of trade barriers (GCI)	0.140***	0.035***	0.053***
	(0.020)	(0.010)	(0.007)
Infrastructure quality (GCI)	−0.094***	−0.035***	−0.010**
	(0.008)	(0.005)	(0.005)
GDP per capita (current USD, log.)	0.551***	0.180***	0.163***
	(0.031)	(0.025)	(0.019)
Constant	0.082	−0.933***	−1.025***
	(0.232)	(0.132)	(0.103)
Observations	6,121	6,121	,6121
F test:	25.58	11,675.61	15,469.29
Sanderson-Windmeijer multivariate F test:	56.57	21,170.29	25,310.29
Sanderson-Windmeijer chi-squared test:	226.89	84,903.02	1.0e+05

Table 4: Instrumental-variables regression: first stage for attitude towards information IVs

	(1)	(2)	(3)
Corporate disclosure requirement	0.038***	−0.024***	−0.021***
	(0.006)	(0.002)	(0.002)
Government censorship effort	0.035***	−0.021***	−0.020***
	(0.005)	(0.002)	(0.002)
Freedom of media & expression	0.127***	−0.014***	−0.009***
	(0.006)	(0.002)	(0.002)
Existence of privacy protection law	0.085***	−0.022***	−0.030***
	(0.012)	(0.006)	(0.005)
Medium RS × Corporate disclosure requirement	0.000	0.119***	0.001
	(0.009)	(0.008)	(0.002)
Medium RS × Government censorship effort	−0.006	0.105***	−0.001
	(0.007)	(0.008)	(0.002)
Medium RS × Freedom of media & expression	−0.011	0.164***	0.001
	(0.009)	(0.010)	(0.003)
Medium RS × Existence of privacy protection law	0.020	0.182***	0.004
	(0.013)	(0.012)	(0.004)
High RS × Corporate disclosure requirement	−0.018**	0.000	0.104***
	(0.009)	(0.003)	(0.008)
High RS × Government censorship effort	−0.009	−0.001	0.102***
	(0.006)	(0.002)	(0.007)
High RS × Freedom of media & expression	0.004	0.002	0.176***
	(0.009)	(0.002)	(0.009)
High RS × Existence of privacy protection law	−0.001	0.001	0.164***
	(0.014)	(0.004)	(0.012)
Dummy: medium RS	0.117	0.475***	−0.006
	(0.132)	(0.134)	(0.032)
Dummy: high RS	0.154	−0.012	0.511***
	(0.128)	(0.034)	(0.130)
No. suppliers in industry	0.000	−0.000	0.000*
	(0.000)	(0.000)	(0.000)
No. OEMs in industry	−0.001**	−0.000	−0.000***
	(0.000)	(0.000)	(0.000)
No. industries active	0.000**	−0.000	0.000***
	(0.000)	(0.000)	(0.000)
Avg. distance to OEM ctries (th. km, log.)	0.651***	0.200***	0.134***
	(0.027)	(0.020)	(0.014)
Absence of trade barriers (GCI)	0.217***	0.059***	0.003
	(0.025)	(0.018)	(0.012)
Infrastructure quality (GCI)	−0.015	−0.011	−0.018**
	(0.012)	(0.008)	(0.008)
GDP per capita (current USD, log.)	0.333***	0.100***	0.106***
	(0.010)	(0.007)	(0.007)
Constant	−1.186***	−0.428***	−0.104
	(0.160)	(0.096)	(0.074)
Observations	7,006	7,006	7,006
F test:	223.75	3,324.97	4,117.30
Sanderson-Windmeijer multivariate F test:	309.93	6,514.87	8,401.17
Sanderson-Windmeijer chi-squared test:	3,109.04	65,353.94	84,276.30

Table 5: Supplementary analysis 1: bargaining power and cartelization ("table 6")

	(1)	(2)	(3)	(4)	(5)	(6)
	Bargaining power			Cartelization		
TS index	−0.126	0.226		−0.159	−0.213	−0.213
	(0.276)	(0.344)		(0.296)	(0.250)	(0.250)
Dummy: medium RS	−0.597	0.513	0.519	−0.541	−0.891**	−0.891**
	(0.403)	(0.983)	(0.971)	(0.430)	(0.437)	(0.437)
Dummy: high RS	−0.033	0.475	1.098	−0.043	−0.223	−0.223
	(0.583)	(1.345)	(1.090)	(0.586)	(0.292)	(0.292)
Ia. medium RS × TS index	0.194*	−0.233	−0.240	0.205*	0.376***	0.376***
	(0.108)	(0.211)	(0.208)	(0.112)	(0.138)	(0.138)
Ia. high RS × TS index	−0.004	−0.195	−0.344	0.016	0.082	0.082
	(0.141)	(0.302)	(0.244)	(0.142)	(0.080)	(0.080)
Dummy: fewer OEMs than suppliers	−0.414***	0.887	0.771			
	(0.131)	(0.967)	(0.972)			
Fewer OEMs than suppliers × TS index		−0.438**	−0.390*			
		(0.209)	(0.234)			
Medium RS × Fewer OEMs than suppliers		−1.505	−1.351			
		(1.110)	(1.115)			
High RS × Fewer OEMs than suppliers		−0.622	−1.000			
		(1.026)	(0.939)			
Medium RS × Fewer OEMs than suppliers × TS index		0.592**	0.560**			
		(0.257)	(0.255)			
High RS × Fewer OEMs than suppliers × TS index		0.234	0.319			
		(0.228)	(0.215)			
Dummy: cartelized industry				0.300**	−0.001	−0.001
				(0.131)	(0.935)	(0.935)
Cartelized industry=1 × TS index					0.162	0.162
					(0.234)	(0.234)
Medium RS × Cartelized industry					1.142**	1.142**
					(0.555)	(0.555)
High RS × Cartelized industry					0.709	0.709
					(0.732)	(0.732)
Medium RS × Cartelized industry × TS index					−0.536***	−0.536***
					(0.144)	(0.144)
High RS × Cartelized industry × TS index					−0.229	−0.229
					(0.184)	(0.184)
Constant	1.658	0.572	1.394***	1.297	1.335	1.335
	(3.899)	(3.780)	(0.355)	(4.012)	(4.028)	(4.028)
Country fixed effects			yes			yes
Observations	7248	7248	7248	7019	7019	7019
R^2	0.079	0.082	0.107	0.076	0.080	0.080

Standard errors are clustered by supplier country and industry in all regressions. Compared to previous tables, regressions do not include industry-specific covariates nor industry fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3 Between- vs within-firm variation: firm fixed effects in the pooled dataset

Table 6: Firm fixed effects in the pooled sample: comparing multi- and single-industry firms

	(1)	(2)	(3)	(4)
Sample restriction:	Single-RS-group firms		Multi-RS-group firms	
TS index	0.057			
	(0.194)			
Dummy: medium RS	−1.919***		−1.456	
	((0.542)		(0.869)	
Dummy: high RS	0.067		−0.703	
	(0.552)		(0.755)	
Dummy: medium RS × TS index	0.634***	0.711***	0.388*	0.568**
	(0.166)	(0.225)	(0.220)	(0.208)
Dummy: high RS × TS index	−0.025	−0.166	0.191	0.233
	(0.145)	(0.166)	(0.184)	(0.192)
No. suppliers in industry	−0.012***		−0.025***	
	(0.004)		(0.008)	
No. OEMs in industry	0.056***		0.117***	
	(0.009)		(0.023)	
No. industries active	0.126**	0.146***		
	(0.052)	(0.045)		
Avg. distance to OEM ctries (th. km, log.)	−0.804**			
	(0.365)			
Absence of trade barriers (GCI)	−0.858***			
	(0.205)			
Infrastructure quality (GCI)	−0.095			
	(0.122)			
GDP per capita (current USD, log.)	0.202*			
	(0.118)			
Constant	5.653***	1.321***	0.544	1.765***
	(1.689)	(0.328)	(0.339)	(0.391)
Country fixed effects		yes		
Industry fixed effects		yes		yes
Firm fixed effects			yes	yes
Observations	2,622	2,589	3,621	3,614
R^2	0.079	0.193	0.331	0.423

Standard errors in parentheses clustered by country and industry. In column (4), country fixed effects are absorbed into the firm fixed effects. Note that the restriction in columns (3) and (4) allows firms to be active in multiple industries as long as those all belong to the same RS group. Restricting the sample to firms active in a single industry further increases regression coefficients to 0.8-0.9 while reducing the sample by about one-half.

4 Alternative explanations of our main results

Our main specification uses two interaction terms with the RS_i dummies in addition to the level values of the TSPI index. When examining an alternative explanation, any added proxy variable would itself need to be interacted with the RS_i dummies, resulting in at least two pairs of extremely strongly correlated variables that prevent reliable interpretation of coefficient estimates (Greene, 2020, p. 134). For this reason, in this section we restrict attention to observations from industries in the medium-specificity range as defined by the medium-RS dummy, the only sample for which our preferred specification finds a positive association between TSPI and the outcome.

As for alternative explanations, we investigate the following six areas in turn. (1) Stronger TS protection may encourage technological innovation, thereby making domestic suppliers more attractive to OEMs. We therefore control for suppliers' technological competence by their stock of recent patent applications as well as relevant indexes from the Global Competitiveness Index (GCI) (Table 7). (2) The TSPI may be correlated with the overall strength and effectiveness of a country's legal system, including the ability to enforce contracts. This may make domestic suppliers generally more attractive business partners. This explanation is very close in spirit to the role of TS protection in our model and could therefore be considered a valid alternative way of measuring the protection of an OEM's private information. Nonetheless, we add a range of indexes measuring the quality of a country's legal system (Table 8). (3) Relatedly, suppliers in countries with strong TS protection may be generally seen as more trustworthy business partners, which we attempt to control for in Table 9.

(4) Stronger TS protection may help not only the OEMs we look at but all firms active in the country to protect their source of competitive advantage more effectively, thereby influencing the general level of "competitiveness" in a market. We account for this by adding indexes of the intensity of competition and the efficiency or markets as well as the number of firms on both sides of the market (Table 10). (5) Related in spirit but differing in mechanism, TS protection may be correlated with a country's broader efforts of creating a "pro-business" environment (Table 11). (6) TS protection may be correlated with a country's level of development or its integration into global markets, which both are associated with denser supply networks (Table 12).

Table 7: Alternative explanation 1: innovation

	(1)	(2)	(3)	(4)	(5)
TS index	0.702***	0.660**	0.697**	0.324	0.749*
	(0.242)	(0.299)	(0.328)	(0.357)	(0.364)
Alternative explanation	0.222***	0.152	0.261	0.564*	0.257
	(0.051)	(0.230)	(0.238)	(0.311)	(0.213)
Correlation coefficient:	0.303	0.778	0.726	0.905	0.675
Observations	1,958	2,162	2,162	2,162	2,162
R^2	0.194	0.162	0.162	0.163	0.163

Standard errors in parentheses clustered by country and industry. All regressions additionally contain the usual set of covariates. The regression sample is restricted to the group of medium-RS industries to mitigate the issue of multicollinearity between the TSPI and the variable capturing the *alternative explanation*, and especially their respective interactions with the RS dummies. The same applies to the five following tables presenting checks of alternative explanations. The correlation coefficient is calculated using the same sample as the corresponding regression. The alternative explanation measure in each column is: (1) the logarithm of the number of patent application families filed worldwide in 2001-2010 (from PATSTAT, counting DOCDB families), (2) the innovation index that is part of the Global Competitiveness Index (GCI), averaged over the years 2011-2015 (published as part of the Global Competitiveness Report by the World Economic Forum), (3) the GCI subindex for "capacity for innovation", (4) the GCI subindex measuring the "availability of the latest technologies" in the country, and (5) the GCI subindex for domestic companies' R&D spending. All GCI indexes are measured on a scale from 1 to 7, with 7 corresponding to the best situation.

Table 8: Alternative explanation 2: strength of overall legal system

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TS index	0.529**	0.326	0.559*	0.569*	0.930**	0.660**	0.651**	0.353
	(0.244)	(0.340)	(0.290)	(0.293)	(0.402)	(0.270)	(0.275)	(0.244)
Alternative explanation	−0.263*	0.196*	0.247	0.124	0.314*	0.052	0.322*	5.216***
	(0.135)	(0.099)	(0.244)	(0.156)	(0.177)	(0.243)	(0.175)	(1.850)
Correlation coefficient:	0.622	0.843	0.829	0.810	0.651	0.528	0.661	0.843
Observations	2,162	2,162	2,162	2,162	2,162	2,162	2,162	2,156
R^2	0.163	0.163	0.162	0.162	0.165	0.162	0.164	0.166

For additional details see the notes below Table 7. The alternative explanation measure in each column is: (1) The subindex of legal enforcement of contracts, averaged over the years 2011-2015, published as part of the Index of Economic Freedom (EFI) by the Heritage Foundation, (2) the EFI subindex of judicial independence, (3) the EFI index measuring the theme "Legal System & Property Rights", (4) the EFI subindex measuring the impartiality of courts of law, (5) the EDI subindex of the protection of property rights, (6) the GCI index measuring the efficiency of a country's legal framework in settling disputes, (7) the GCI index of judicial independence, and (8) the Rule of Law index compiled by the World Justice Project for 2012/13. The EFI indexes are measured on a scale from 0 to 10, the GCI indexes from 1 to 7, and the Rule of Law index from 0 to 1.

Table 9: Alternative explanations 3: firms in countries with strong TSP may be generally seen as more trustworthy business partners

	(1)	(2)	(3)	(4)	(5)	(6)
TS index	0.822***	0.651**	0.499**	5.114	1.293**	1.232**
	(0.247)	(0.256)	(0.225)	(2.118)	(0.456)	(0.452)
Alternative explanation	−0.339**	0.314**	1.405***	−0.012	−0.015	−0.044
	(0.122)	(0.134)	(0.339)	(0.004	(0.019)	(0.259)
Correlation coefficient:	-0.118	0.461	0.790	0.041	-0.010	-0.060
Observations	2,162	2,162	2,162	245	559	565
R^2	0.166	0.163	0.169	0.107	0.259	0.260

For additional details see the notes below Table 7. The alternative explanation measure in each column is: (1) the GCI subindex of "hiring and firing practices" (item 7.03), (2) the GCI subindex of "cooperation in labor-employer relations" (item 7.01), (3) the GCI subindex of "local supplier quality" (item 11.02), (4) the supplier's age in 2011 (number of years since incorporation, from ORBIS), (5) the average annual liquidity ratio 2006-2010 (from ORBIS), and (6) the average annual current ratio (2006-2010).

Table 10: Alternative explanations 4: market competitiveness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TS index	0.671**	0.681**	0.679*	0.572**	0.626***	0.762**	0.485**	0.491**
	(0.279)	(0.257)	(0.335)	(0.245)	(0.192)	(0.230)	(0.193)	(0.183)
Alternative explanation	−0.251	−0.442	1.538**	0.731	−0.584***	−0.451*	−0.480***	−0.527***
	(0.629)	(0.551)	(0.694)	(0.535)	(0.177)	(0.248)	(0.099)	(0.098)
No. of suppliers by country-industry pair					0.238***	0.164**	0.118**	0.132***
					(0.079)	(0.075)	(0.046)	(0.045)
Correlation coefficient:	0.701	0.727	0.721	0.782	-0.270	-0.236	-0.165	-0.237
Observations	2,162	2,162	2,162	2,162	1,774	1,774	1,232	1,232
R^2	0.162	0.162	0.167	0.163	0.172	0.170	0.189	0.187

For additional details see the notes below Table 7. The alternative explanation measure in each column is: (1) the GCI aggregate index of competition (index "A"), (2) the GCI subindex of domestic competition, (3) the GCI index of the "intensity of local competition" (index 6.01), (4) the GCI index of "goods market efficiency" ("6th pillar"), (5) the number of OEMs (brands) with supply relations to the supplier country, (6) the number of OEM parent companies with such relations, (7) the number of OEMs (brands) with supply relations to the supplier country *or* its immediate neighbors, and (8) the number of OEM parent companies with such relations.

Table 11: Alternative explanations 5: strong TSP correlates with a country's efforts of creating a "pro-business" environment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TS index	1.154**	0.542*	0.775***	0.788**	0.771**	0.677***	0.494	0.794***	0.805*	0.680*
	(0.459)	(0.263)	(0.268)	(0.361)	(0.287)	(0.211)	(0.293)	(0.266)	(0.405)	(0.370)
Alternative explanation	−0.480	0.056*	−0.613*	−0.238	−0.082	−0.522*	1.154***	0.014*	0.042	−0.604
	(0.314)	(0.031)	(0.310)	(0.276)	(0.094)	(0.299)	(0.368)	(0.008)	(0.052)	(2.807)
Correlation coefficient:	0.903	0.723	0.653	0.757	0.809	0.650	0.800	−0.534	−0.633	0.880
Observations	2162	2162	2162	2162	2162	2162	2162	2162	2162	2162
R^2	0.164	0.162	0.165	0.162	0.162	0.164	0.168	0.164	0.162	0.162

For additional details see the notes below Table 7. The alternative explanation measure in each column is: (1) the EFI aggregate regulation index (index "5", averaged annual values 2011-2015), (2) the EFI subindex measuring the "regulatory burden" (5Cii), (3) the EFI subindex for "Starting a business" (5Ciii), (4) the EFI index of "Business regulations" (5C), (5) the EFI index of "Labor market regulations" (5B), (6) the GCI index of "Labor market efficiency" ("7th pillar"), (7) the GCI index of "business sophistication" ("11th pillar"), (8) the number of days it takes to start a business (from GCI, index 6.07), (9) the number of procedures required to start a business (from GCI, index 6.06), and (10) the World Bank's Ease of Doing Business score (averaged annual values 2011-2014 because of methodology change in 2015).

Table 12: Alternative explanations 6: strong TSP correlates with a country's level of development or integration into global markets

	(1)	(2)	(3)	(4)	(5)	(6)
TS index	0.640**	0.628**	0.737**	0.732**	0.790**	0.901**
	(0.261)	(0.273)	(0.292)	(0.290)	(0.283)	(0.354)
Alternative explanation	0.119	1.519	−0.001	−0.001	0.388	0.567
	(0.233)	(2.773)	(0.004)	(0.003)	(0.321)	(0.567)
Correlation coefficient:	0.859	0.860	-0.283	-0.324	0.362	0.633
Observations	2,162	2,156	2,162	2,162	2,162	2,162
R^2	0.162	0.162	0.162	0.162	0.162	0.162

For additional details see the notes below Table 7. The alternative explanation measure in each column is: (1) GDP per capita (log.), (2) the Human Development Index score (2010), (3) imports as a percentage of GDP (GCI), (4) exports as a percentage of GDP (GCI), (5) the aggregate GCI "foreign competition variable", and (6) a measure of the "burden of customs procedures" (GCI).

5 Entropy balancing and rescaling of the dependent variable

Official statistics on automotive input industries usually do not provide anywhere near the level of disaggregation that we need for our analysis. We therefore rely on Marklines' *supplier database*, a separate dataset provided by Marklines that contains all supplier firms and their industry associations that Marklines was aware of, irrespective of whether their supply relationships are included in the contract dataset. We use this supplier dataset to calculate the share that countries and input industries contribute to the global automotive industry. We then use entropy balancing to attach greater weight to observations representing groups that appear more frequently in the global population than in our regression sample. These weights are then used in our otherwise unchanged regression analysis, with results presented in Table 13. We obtain equivalent results in regressions including fixed effects (unreported). Necessarily, this exercise can only consider country-industry pairs for which we observe at least one supplier's OEM relationships. Entropy balancing is performed using the `ebalance` Stata plugin provided by Hainmueller and Xu (2013).

Reweighing helps address undercoverage in the number of suppliers, which is sufficient as long as the contract data covers all included suppliers perfectly. To allow for the possibility of undercoverage of a given suppliers' relationships, we calculate our regression sample's *coverage* by dividing the number of supplier firms from a country-industry pair by the corresponding number in the supplier database. We then regress the outcome variable on this *coverage* variable to estimate how the outcome varies with sample coverage. Using these estimates, we calculate a "re-scaled" version of the outcome variable that would obtain in case of full coverage of the regression sample, assuming a linear relationship between outcome and *coverage*. The results of this adjustment, using a single rescaling factor for all observations, are presented in columns 8-9 of Tables 13. Similar results obtain when using industry-specific rescaling factors.

Table 13: Using entropy balancing and re-scaling of the dependent variable to improve representativeness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TS index	−0.002	0.320*	0.021	0.351	0.182	0.309*	0.247	−0.013	0.007
	(0.345)	(0.171)	(0.365)	(0.207)	(0.255)	(0.169)	(0.204)	(0.046)	(0.040)
Dummy: medium RS	−1.220**	−0.639	−1.386**	−0.828*	−1.747***	−1.045**	−1.692***	−0.135	−0.273***
	(0.540)	(0.447)	(0.533)	(0.476)	(0.601)	(0.451)	(0.476)	(0.090)	(0.067)
Dummy: high RS	−0.366	0.708	−0.279	0.883	−0.448	0.721	0.207	0.127	0.154*
	(0.754)	(0.580)	(0.850)	(0.696)	(0.676)	(0.474)	(0.403)	(0.156)	(0.089)
Medium RS × TS index	0.328**	0.182	0.372**	0.238	0.505***	0.332**	0.415**	0.051**	0.059**
	(0.138)	(0.142)	(0.135)	(0.148)	(0.161)	(0.150)	(0.152)	(0.024)	(0.023)
High RS × TS index	0.061	−0.228	0.031	−0.285	0.074	−0.209	−0.105	−0.035	−0.053**
	(0.180)	(0.164)	(0.202)	(0.189)	(0.156)	(0.138)	(0.108)	(0.040)	(0.024)
Sample restricted to industry match between WSW and supplier database			yes	yes	yes	yes	yes		yes
Entropy balancing based on:									
Country shares		yes		yes		yes			
Industry shares					yes	yes			
Country × industry shares							yes		yes
Dependent variable rescaled:								yes	yes
Observations	7,006	7,006	6,309	6,309	6,309	6,276	6,309	6,201	6,201
R^2	0.122	0.124	0.129	0.133	0.115	0.116	0.138	0.058	0.096

Standard errors in parentheses are clustered by supplier country and industry. All regressions contain the usual set of covariates.

6 Within-country trade secret protection

The regressions using the IDD dummy to proxy for TS protection are necessarily restricted to US-based suppliers. Hence, we recalculate the covariates "Number of suppliers in the product industry" and "Number of OEMs in the product industry" using only US firms. The standard versions considering all suppliers and OEMs worldwide yield similar results but with slightly increased standard errors.

Annual real GDP data by state is obtained from the US Bureau of Economic Analysis (2024). We separately control for Michigan's significant role in the US auto industry with a dummy variable. Alternatively, using a variable measuring a state's geographical distance from Michigan instead yields equivalent results.

Due to the small number of clusters, in particular those experiencing a change in the IDD dummy over time, and the sizable variation in cluster size, we used the restricted wild cluster bootstrap (WCR) (Cameron et al., 2008; MacKinnon et al., 2023) to test if the different coefficient estimates involving the IDD dummy are equal to zero. For the specification in column 4 in Table A.8, we can reject the null hypothesis only for the interaction with the medium-RS dummy, using both Rademacher and Webb (Webb, 2023) error weights. As in the present case the number of "treated" clusters is particularly small, MacKinnon and Webb (2018) suggest the ordinary (non-clustered) restricted wild bootstrap (WR) as an additional robustness check after a regression with clustered standard errors. Table A.9 collects p-values for all four combinations and for the IDD dummy alone as well as its interactions with each RS dummy. Only the p-values for the medium-RS interaction are below 0.1.

In further unreported checks, we verified the robustness of the IDD approach using the pooled dataset 2011-2015 which we use in our primary analyses, obtaining qualitatively equivalent results. We also employed propensity-score matching on a series of variables indicative of states industry composition, their reliance on IP protection, and capturing lobbying potential pro and contra adoption of the IDD. This exercise yields substantially increased and significant coefficient estimates of the impact of the IDD in the range between 1.5 and 3.0, though at the cost of substantially reducing the sample size to between 200-250 observations.

Table 14: List of US states and the number of contributed observations, 2006-2016 panel

Adopted before 2006		Rejected before 2006		Rejected during sample period			
					Observations		Year of
State	Obs.	State	Obs.	State	before	after	change
Connecticut	43	California	51	Georgia	7	10	2013
Delaware	1	Florida	3	New Jersey	17	21	2012
Illinois	176	Maryland	16	New York	13	34	2009
Indiana	97	Massachusetts	31	North Carolina	28	7	2014
Iowa	1	Michigan	1,946	Ohio	54	208	2008
Kansas	2	Minnesota	2				
Missouri	29	Texas	9				
Pennsylvania	33	Virginia	2				
Washington	2	Wisconsin	100				
Total	384		2160		119	280	

Note: This table summarizes the number of observations contributed by US states to the sample, categorized by their status regarding the IDD adoption.

Table 15: Summary statistics for the sample comprising only US-based suppliers, 2006-2016 panel

Variable	Min	Median	Max	Mean	SD	Obs.
Dependent variable	1	1	27	2.04	2.18	2,943
Dummy: IDD	0	0	1	0.17	0.38	2,943
Dummy: medium RS	0	0	1	0.33	0.47	2,943
Dummy: high RS	0	0	1	0.26	0.44	2,943
Number of industries active in	1	4	45	9.02	11.01	2,943
Number of US suppliers in industry	1	2	20	2.98	2.45	2,943
Numbr of US OEMs in industry	0	3	14	3.69	2.82	2,943
Real GDP per capita	36.7	41.6	70.1	43.64	5.87	2,943
Dummy: supplier from Michigan	0	1	1	0.66	0.47	2,943
Road quality (0-100)	43.5	87.8	99.9	85.42	8.49	2,724
Auto industry labor force	19.9	1,176.9	1,176.9	932.12	376.17	2,943

7 Patent data and absorptive capacity

In Section 5.5 of the main text, we use patent families as defined by the EPO's DOCDB database (European Patent Office, 2017) instead of individual patent applications to proxy a supplier's absorptive capacity. This approach accounts for national variations in patent law and examination practices (de Rassenfosse et al., 2013). For instance, patent breadth differs by country, affecting the number of patent filings needed to cover the same invention (Sakakibara and Branstetter, 2001). Furthermore, the same patent application must be submitted to multiple patent offices to obtain protection in export markets, resulting in multiple filings for the same application. Another complication is that international patenting may focus on the largest countries representing the most important markets (Nikzad, 2013). Thus, firms from different countries following the same patenting strategy may need to apply for varying numbers of patents. Patent families provide a convenient way to adjust patent counts to such national heterogeneity. Nonetheless, we validated our results by using different alternative counts of patent applications, including counting the number of priority applications submitted globally by a firm, as well as by excluding fixed effects, which we do not report for brevity.

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