Online Appendix for the paper: A Structural Model on the Impact of Prediscovery Licensing and Research Joint Ventures on Innovation and Product Market Efficiency

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Appendix A

We are interested in evaluating the impact of PDLAs ($PDLA^S_{it-1}$) on firm-level R&D investments (RD^S_{it}), both at the semiconductor level. However, firm-specific R&D investments at the semiconductor level are unobserved to the econometrician, and only available at the overall firm-level (RD_{it}). To overcome this missing data problem, we first estimate a relationship between overall firm-level R&D investments and PDLAs, i.e., $\log(RD_{it}) = \tilde{\alpha_1}\log(RD_{it-1}) + \tilde{\alpha_2}\log(PDLA^S_{it-1})$. This relationship will be replaced with a similar relationship that concentrates on the semiconductor-specific level, i.e., $\log(RD^S_{it}) = \alpha_1 \log(RD^S_{it-1}) + \alpha^S_2 \log(PDLA^S_{it-1})$ and inserted into equation (2) of our paper. This procedure eventually allows us to substitute for (unobserved) firm-specific R&D investments in the semiconductor industry, which finally enables us to explicitly evaluate the impact of PDLAs on innovation in the semiconductor industry, as shown in equations (1) to (8) in the paper.

Turning to the relationship between overall firm-level R&D investments (RD_{it}) and PDLAs ($PDLA^S_{it-1}$), we specify an autoregressive model that allows for state dependency and an inherently dynamic R&D process, as suggested by Hall et al. (1986):

$$\log(RD_{it}) = \tilde{\alpha_1}\log(RD_{it-1}) + \tilde{\alpha_2}\log(PDLA^S_{it-1}) + \tilde{\alpha_3} RJV^S_{it-1} + \sum_{y=4}^{13} \tilde{\alpha_y} * Year_t + e_{it}, \qquad (1)$$

where the lagged dependent variable RD_{it-1} captures path dependency in R&D investments. We also insert a dummy variable ($PDLA^S_{it-1}$) that takes on a value of 1 if a firm participated in a PDLA in the semiconductor industry in period $t-1$; otherwise it is 0. The PDLA dummy variable provides a first insight into the correlation between PDLAs and overall firm-level investments. Similarly, we insert an RJV dummy variable (RJV^S_{it-1}) that takes on a value of 1 if a firm participated in an RJV in the semiconductor industry in period $t-1$; if not, it is 0. The year dummies $Year_t$ control for variations over time. The error term is normally and independently distributed.

The OLS estimation results are shown in Table A, Column 1, which reports robust standard errors. The coefficient of the lagged R&D variable is significant and explains 96 percent of the current R&D investments. Our estimation results provide evidence that the R&D investments are highly persistent over time. We also find a significantly negative correlation between semiconductor PDLAs and overall firm-level R&D investments. Note that the parameter estimate on the RJV dummy variable is insignificant. We also apply a further regression and lag the impact of PDLAs and RJVs by two periods, as shown in Column 2. The main results remain unchanged.

One drawback of this estimation result is that the negative correlation between PDLAs and overall firm-level R&D investments is vulnerable to a potential aggregation bias. A reduction in overall firm-level R&D investments could be misinterpreted if the reduction is caused in other industries, but not the semiconductor industry itself. Hence, the ultimate correlation between PDLAs and semiconductor-specific firm-level R&D investments remains unclear at this point. We will therefore establish an empirical model (see equations (1) to (8) in the paper) to consider the relationship between firm-specific R&D investments at the industry level and firm-specific patents at the industry level, which eliminates this problem. Moreover, as shown in previous studies and supported by our descriptives, firms self-select into PDLAs, and OLS regression results give rise to a potential endogenous selection bias. We will address this issue in the remainder of this study.

Table A: Impact of PDLAs and RJVs on Overall Firm-level R&D Investments

Variables	$log(RD_{it})$ (1)	$log(RD_{it})$ (2)
$log(RD_{it-1})$	0.960***	0.962***
	(0.002)	(0.002)
$PDLA^S_{it-1}$	-0.100**	
	(0.049)	
$PDLA^S_{it-2}$		-0.223***
		(0.049)
RJV^S_{it-1}	-0.034	
	(0.470)	
RJV^S_{it-2}		0.358
		(0.554)
Year dummies	Yes***	Yes***
Adj. R-squared	0.762	0.831
Observations	38,610	34,749

Table A shows the estimation results for equation (1) shown above. The equation is estimated by OLS. ***,**, and * refers to a 1%, 5%, and 10% significance level, respectively. Sources: Thompson Financial, Inc., Moody's and U.S. Patent and Trademark Office.

Appendix B

Remember, Columns 1-3 of Table B below show our main estimation results of the outcome equation (8). We perform several robustness checks regarding the outcome equation estimation. First, we replace the PDLA and RJV dummy variables ($PDLA^S_{it-x}$ and RJV^S_{it-x}) with counters ($NPDLA^S_{it-x}$ and $NRJV^S_{it-x}$) that consider in how many PDLAs and RJVs a firm was ever engaged until period t. The results are shown in Columns 3-6 of Table B ordered by using different time lags for the impact on patents. The results are not significantly different from the previous results with the exception that the estimate on the RJV counter is positively significant already one year after RJV formation. This change in the parameter estimate is reasonable since the counter accumulates RJV activities over several periods and exerts a stronger effect on patenting. We also ran the same three regressions as reported in Column 1-3 and eliminated all non-producing firms. Our results on the effect of PDLAs and RJVs on patents are again confirmed (see Column 7 of Table B). We test whether PDLAs and RJVs also exert a strategic impact on the patenting activity of competing firms. Hence, beyond regressing the semiconductor patents (Pat^S_{it}) on firm i's PDLA and RJV engagements, we control for the number of PDLAs and RJVs formed by other firms in the industry ($PDLA^S_{t-2}$ and RJV^S_{t-2}). Our results are reported in Column 8 and show that own PDLA activity ($PDLA^S_{it-2}$) again returns a significantly negative estimate and own RJV activity (RJV^S_{it-2}) again returns a significantly positive estimate. The strategic effect of PDLAs formed by other firms in the industry ($PDLA^S_{t-2}$) on own patents is negative, confirming the fact that strategic effects are prevalent but of much smaller magnitude than the own effect. This is different for RJVs since the strategic effect of RJVs (RJV^S_{t-2}) is not significant. We perform a further robustness check with regard to our instrument selection. According to the transaction cost argument, the engagement in PDLAs requires profound organizational and legal expertise, organizational, contractual, and administrative efforts which constitute high transaction costs. Previous PDLA experience lowers these transaction costs and will serve as an instrument to engage in PDLAs. Many empirical studies (such as Siebert (2015), Siebert and von Graevenitz (2010) and Banerjee and Siebert (2017)) have found evidence for experience exerting a highly significant impact in the selection equation. For that reason, we performed robustness checks with regard to the other two instruments (multimarket competition and absorptive capacity) and estimated the same set of equations using the same variables but were not declaring the two variables as instruments in the selection equation. Our robustness check returns parameter estimates that are not significantly different from the estimates shown in Table 5, Column 1 and Table 6, Columns 1-3 of our paper. It should also be noted that our results are consistent with the results in Banerjee and Siebert (2017) who show that the instruments are insignificant in the outcome equations, which supports the validity of the chosen instruments. One might also object that the negative impact of PDLAs on patenting does not necessarily reflect a reduction in innovation, but could be associated with the nature of PDLAs, since innovations are shared among members in PDLAs. Wasteful innovative duplications are avoided with PDLAs, and partners are committed ex ante to using the technology under consideration. Moreover, riskier technologies could have been developed in PDLAs, which generated fewer patents but higher efficiencies. Therefore, we ran the same regression as those shown in Table 6, Columns 1-3 of our paper, but we replace the patent counts (Pat_{it}^{S}) with the number of citations a patent received ($Patcite_{it}^{S}$). This robustness check serves to test whether PDLAs and RJVs also affect the quality of innovations rather than the quantity; it might very well be that PDLAs produce more drastic innovations even though they reduce the number of patents. The results are shown in Table B, Columns 9-11. PDLAs decrease semiconductor patent citations, and the effect becomes larger as further lags of the PDLA activity are used. Interestingly, RJVs increase patent citations.

Table B: Impact of PDLAs on Semiconductor Patents and Patent Citations

Variables	Pat_{it}^{S} (1)	Pat_{it}^{S} (2)	Pat_{it}^{S} (3)	Pat_{it}^{S} (4)	Pat_{it}^{S} (6)	Pat_{it}^{S} (6)	Pat_{it}^{S} (7)	Pat_{it}^{S} (8)	$Patcite_{it}^{S}$ (9)	$Patcite_{it}^{S}$ (10)	$Patcite_{it}^{S}$ (11)
$PDLA_{it-1}^{S}$	-7.790***								-51.739***		
	(1.273)								(2.269)		
$PDLA_{it-2}^{S}$		-10.729***					-3.649***	-14.009***		-67.502***	
		(0.985)					(1.041)	(1.058)		(2.480)	
$PDLA_{it-3}^{S}$			-22.217***								-103.59***
			(1.462)								(3.498)
$NPDLA_{it-1}^{S}$				-1.088***							
				(0.113)							
$NPDLA_{it-2}^{S}$					-1.572***						
					(0.119)						
$NPDLA_{it-3}^{S}$						-2.835***					
						(0.168)					
RJV_{it-1}^{S}	-2.106								238.907***		
	(1.418)								(26.855)		
RJV_{it-2}^{S}		28.865***					22.327**	32.068***		521.765***	
		(1.860)					(11.335)	(1.941)		(33.862)	
RJV_{it-3}^{S}			37.575***								1,403.897***
			(1.749)								(52.597)
$NRJV_{it-1}^{S}$				1.355***							
				(1.578)							
$NRJV_{it-2}^{S}$					22.364***						
					(1.889)						
$NRJV_{it-3}^{S}$						60.079***					
						(2.619)					
$PDLA_{t-2}^{S}$								-0.483**			
								(0.214)			
RJV_{t-2}^{S}								0.091			
								(0.749)			
Pat_{it-1}^{S}	0.946***	0.954***	0.992***	0.962***	0.974***	0.995***	0.967***	0.965***			
	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)	(0.005)	(0.003)	(0.005)			
$Patcite_{it-1}^{S}$									0.965***	0.927***	0.954***
									(0.005)	(0.006)	(0.001)
$PMNOF_{it-1}^{S}$	0.052***	0.053***	0.035***	0.025***	0.018***	0.035***	-0.131	-0.011	0.071	-0.294	-0.279
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.096)	(0.092)	(0.081)	(0.084)	(0.099)
$GDPEL_{t-1}^{S}$	0.255***	0.299***	0.260***	0.156***	0.138***	0.210***	0.664*	1.250	0.957	-0.226	0.154
	(0.022)	(0.022)	(0.019)	(0.019)	(0.019)	(0.019)	(0.392)	(0.665)	(0.333)	(0.344)	(0.399)
PSM_{it-1}^{S}	0.016***	0.016***	0.017***	0.014***	0.014***	0.019***	0.039***	0.018***	0.323***	0.311***	0.393***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.001)	(0.012)	(0.012)	(0.015)
$CT1_{it-1}$	-19.137***	-24.247***	-18.047***	-10.815***	-7.028***	-12.929***	27.228*	-34.473***	75.229***	237.628***	252.064***
	(1.406)	(1.525)	(1.516)	(1.449)	(1.466)	(1.559)	(16.029)	(1.820)	(25.990)	(27.950)	(32.905)
$CT0_{it-1}$	24.671***	27.255***	21.106***	13.516***	11.063***	18.377***	-1.936	37.359***	62.618***	-81.415***	-63.925***
	(1.551)	(1.386)	(1.223)	(1.134)	(1.149)	(1.226)	(9.267)	(1.692)	(20.358)	(22.130)	(26.092)
Year dummies	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***	Yes*	Yes***	Yes**	Yes***	Yes***
Observations	38,610	34,749	30,888	38,610	34,749	30,888	1,413	34,749	38,610	34,749	30,888

Table B shows the estimation results for the outcome equation (8) in the paper. Robust standard errors are shown in parentheses. ** (*) refers to a 1% (5%) significance level. Sources: Thomson Financial, Gartner, Inc., and the U.S. Patent and Trademark Office.