THE
CRITERION
JOURNAL ON INNOVATION

VOL. 4 2019

Hedonic Prices and Patent Royalties: Epilogue

J. Gregory Sidak[*] *& Jeremy O. Skog*[†]

Hedonic price analysis is an econometric methodology that enables one to isolate the value attributable to each component of a multicomponent product. By regressing a product's total price on the product's characteristics, hedonic price analysis enables one to determine how much consumers are willing to pay for individual components of a multicomponent product. For example, for a multicomponent product like a smartphone, a hedonic price analysis could quantify how much consumers value features such as screen size, battery life, memory, or even the smartphone's brand.

In our 2017 article, *Hedonic Prices and Patent Royalties*, we developed a hedonic price model for memory modules used in enterprise servers to estimate the incremental value attributable to the DDR4 LRDIMM standard above and beyond the next-best technology standard (which was the RDIMM standard).[1] After estimating the incremental value of the DDR4 LRDIMM standard using our hedonic price model, we apportioned that value across holders of patents essential to the DDR4 LRDIMM standard on the basis of a forward-citation weighting methodology to calculate the value attributable to each standard-essential patent (SEP). We then used that information to determine a royalty range that would be reasonable and nondiscriminatory

* Chairman, Criterion Economics, Washington, D.C. Email: jgsidak@criterioneconomics.com.

† Vice President, Criterion Economics, Washington, D.C. Email: jskog@criterioneconomics.com.
We thank Jihyuon Park for invaluable research assistance and Henry Brooke, Joseph Linfield, Douglas Maggs, Pengyu Qin, Urška Petrovčič, Blount Stewart, Andrew Vassallo, and Xiuying Yu for helpful comments. The views expressed here are solely our own.

1 J. Gregory Sidak & Jeremy O. Skog, *Hedonic Prices and Patent Royalties*, 2 CRITERION J. ON INNOVATION 673 (2017). RDIMM is the previous memory module standard defined by the Joint Electron Device Engineering Council (JEDEC) standard-setting organization, which has also defined the LRDIMM standard. We emphasize the difference between "competing standards," such as the simultaneous competition between VHS and Betamax, and successive standards whereby a later standard builds on and supersedes the technology in a previous standard to solve the same technological question in a more advanced manner.

(RAND) for a given SEP holder to charge to license its SEPs on the basis of the value that it contributed to the standard.[2]

More recently, in our 2019 article, *Hedonic Prices for Multicomponent Products*, we used a hedonic price model to test the hypothesis that a smartphone's brand possesses statistically significant explanatory power for a smartphone's price above and beyond the smartphone's functional features.[3] We selected the independent variables included in our hedonic price model using the least absolute shrinkage and selection operator (LASSO) regression—an objective variable-selection methodology that applies a machine-learning algorithm to the data on smartphone prices and features. We found that, even after accounting for the functional features of a smartphone that are most predictive of a smartphone's price, a smartphone's brand provides statistically significant predictive power for explaining the smartphone's price.

In this epilogue, we supplement the hedonic price analysis contained in our 2017 article by examining whether the specification of our hedonic price model for memory modules is robust to an objective variable-selection methodology based on a machine-learning algorithm. Put differently, we analyze whether using a LASSO regression to select independent variables on an objective basis would produce a specification of the hedonic price model similar to our original model in the 2017 article, and we find that it does.

A LASSO Regression on the LRDIMM Data

The price and feature data for memory modules are limited, as the standardized devices are distinguished by a few key attributes (far fewer than the various attributes of a smartphone, for example). Our dataset contains only information on (1) the quarter and year in which the memory module was sold, (2) a memory module's memory capacity (in gigabytes, or GB), (3) whether the memory module implements the DDR3 or DDR4 standard, and (4) whether the memory module implements the RDIMM or LRDIMM standard. Furthermore, our dataset included only 171 types of memory modules sold between the first quarter of 2013 and the fourth quarter of 2016. When developing a hedonic price model using data of this scale, it would be reasonable to include all observable features in the dataset that affect a consumer's purchase decision (as we did in our 2017 article). Nonetheless, as a robustness check, we examine here whether an objective variable-selection

[2] To be clear, our hedonic price analysis can assess whether a given offer to license an SEP (or a portfolio of SEPs) pursuant to a RAND obligation is reasonable. The methodology does not speak to the question of whether that offer is nondiscriminatory within the meaning of the same RAND obligation. However, when a hedonic price analysis is used in conjunction with other forms of analysis, such as an analysis of comparable licenses, the expert can assess whether a given offer to license an SEP portfolio was reasonable and nondiscriminatory.

[3] J. Gregory Sidak & Jeremy O. Skog, *Hedonic Prices for Multicomponent Products*, 4 Criterion J. on Innovation 301 (2019).

methodology based on a LASSO regression would also select all those features when applied to our dataset.

In our 2019 article concerning smartphones, we excluded the *NAND Flash (GB)* categorical variable from the LASSO regression because the LASSO regression is designed to select (or drop) an explanatory variable in its entirety, and not a particular level of that variable.[4] Unfortunately, every independent variable included in our 2017 hedonic price model for memory modules is a categorical variable. Thus, strictly for purposes of this epilogue, we include each level of the categorical variables as an independent binary variable in the LASSO regression. Table 1 reports (1) the results of the ordinary least squares (OLS) hedonic price regression for memory modules reported in our 2017 article in column 1 and (2) the results of a LASSO regression including each level of the categorical variables as an independent binary variable in column 2.

Table 1. Regression Results for a Hedonic Price Model for LRDIMM Modules

Variable		Estimated Coefficient (OLS Regression)	Estimated Coefficient (LASSO Regression)
LRDIMM		100.4716*** (35.0722)	–
	0	–	0
	1	–	102.3616
DDR4		48.74588*** (15.87077)	–
	0	–	0
	1	–	47.90889
GB			
	4	–	0
	8	61.42727* (31.9943)	49.72406
	16	108.5513*** (34.46838)	96.49474
	32	223.0828*** (45.34008)	209.5637
	64	577.4247*** (63.90946)	562.358
	128	1457.388*** (69.20657)	1442.006

[4] *Id.* at 316.

Variable		Estimated Coefficient (OLS Regression)	Estimated Coefficient (LASSO Regression)
Year			
	2013	–	0
	2014	−9.392964 (23.6438)	0
	2015	−61.01791** (23.37634)	−53.11457
	2016	−128.272*** (23.00999)	−120.1784
Constant		46.66667* (25.57373)	51.56419
Observations		171	171
R^2		0.8981	0.8980
Prob > F		0.0000	–
Root Mean Squared Error		88.59	–
alpha		–	1.0000
lambda		–	0.2071
Cross-Validation Mean Squared Error		–	9023.0330

Source: De Dios & Associates (2016). The transactional prices for memory modules are a proprietary database available for purchase from De Dios & Associates. *See* De Dios & Associates, https://dedios.com.
Notes: * indicates statistical significance at the 90-percent confidence level, ** indicates statistical significance at the 95-percent confidence level, and *** indicates statistical significance at the 99-percent confidence level.

As column 2 shows, the LASSO regression estimates a non-zero coefficient for each of the indicator variables for levels of the *LRDIMM*, *DDR4*, *GB*, and *Year* variables, except the indicator variable for 2014. The coefficient of zero on the indicator variable for 2014 in column 2 means that the indicator variable for 2014 did not add sufficient explanatory power for memory module prices to justify its selection by the LASSO regression. In other words, prices in 2014 were predicted sufficiently well by other indicator variables and the constant term. The results of the LASSO regression indicate that one should include all indicator variables for levels of the *LRDIMM*, *DDR4*, *GB*, and *Year* variables, except the indicator variable for 2014, in the OLS hedonic price regression.

In the OLS hedonic price regression in our 2017 article, a year indicator variable measured that year's price relative to the base year of 2013. In the LASSO regression above, the exclusion of the indicator variable for year 2014 is comparable to the finding in our 2017 article that the coefficient on the indicator variable for products sold in 2014 was not statistically significantly different from zero.

Conclusion

In sum, when the LASSO regression treats each level of the categorical variables as an independent binary variable, the LASSO regression estimates a non-zero coefficient for every independent variable that we included in the hedonic price model in our 2017 article, except the indicator variable for 2014. Put differently, an objective variable-selection algorithm that relies on machine learning produces a model that is nearly identical to the hedonic price model that appears in our 2017 article, which supports the conclusion that we correctly specified our model.