



Article Estimating Bargaining Power in Real Estate Pricing Models: Conceptual and Empirical Issues

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Abstract: The relative bargaining power of the buyer and seller is a key feature of real estate pricing models. Classic real estate studies have sought to address bargaining effects in hedonic regression models. Prior research proposes a procedure to estimate bargaining effects in hedonic regression models that depends critically on a substitution to eliminate omitted variables bias. This study shows that the proposed solution that is often cited in the real estate economics literature does not solve the omitted variables problem given that both models are merely different parameterizations of the same model, and thus produces biased estimates of bargaining power when certain property characteristics are omitted. A classic hedonic regression model of real estate prices using Corsican apartment data supports our contention, even when the assumption of bargaining power symmetry is relaxed.

Keywords: bargaining power; omitted variables bias; hedonic regression

1. Background and Introduction

Hedonic regression models, wherein portions of the value of goods or services are attributed to individual characteristics of the goods or service, have become a staple in empirical studies of residential real estate pricing. Moreover, as researchers have moved into the exploration of non-residential real estate (e.g., farms and hunting land), and even further into other unique aspects of real estate pricing, such as the impact on residential real estate prices of tourism, wireless tower locations, natural disasters (e.g., Hurricane Katrina), and the attractiveness of real estate brokers, hedonic regression models have followed.¹ Today, hedonic regression models are applied to other goods, such as diamonds, beer, wine, art, cryptocurrency tokens and horses.²

The relative bargaining power of the buyer and seller is a key feature of many of the types of market transactions listed above. Classic real estate studies have therefore sought to address bargaining effects in hedonic regression models. Prominent among these is the study by Harding et al. (2003), which attempted to conceptualize (contextualize) the nature of the buyer–seller interaction in real estate markets, and to reflect the nature of this interaction in the hedonic pricing structure. Prior to this publication, there was a paucity of mainstream real estate research investigating the relative bargaining power of buyers and sellers or their unobserved characteristics. Thus, the extension to the real estate literature made by Harding et al. (2003) is at least an important conceptual or theoretical one.

¹ For studies on farmland pricing, see Cotteleer et al. (2008) and Hanson et al. (2018). See Carrasco-Gallego et al. (2017) for research on hunting land pricing. For studies on the unique aspects of real estate pricing, see Biagi et al. (2016), Affuso et al. (2018), Salter and King (2009), and Salter et al. (2012).

² Examples of these studies include Lee et al. (2015), Smith et al. (2016), Caudill and Mixon (2016), Galbraith and Hodgson (2018), Fedderke and Li (2020), Shorish (2019) and Hansen and Stowe (2018).

The study by Harding et al. (2003) is, however, often relied upon by others because it proposes a procedure to estimate bargaining effects in hedonic regression models that depends critically on a substitution to eliminate an (provide a solution to) omitted variables bias.³ In referring to the omitted variables bias, Harding et al. (2003) state that "[o]vercoming this problem is the key difficulty that must be addressed if bargaining effects are to be estimated." This study re-examines the Harding et al. (2003) solution to omitted variables bias in hedonic regressions that capture bargaining effects. In doing so we show that their proposed solution does not solve the omitted variables problem, and thus produces biased estimates of bargaining power when certain property characteristics are omitted.

In terms of organization, we first present the Harding et al. (2003) model, the estimation problem, and the Harding et al. (2003) solution. Next, we show that their solution does not address the omitted variables problem, and under their assumption about omitted variables, must also lead to biased parameter estimates. Finally, we show that the Harding et al. (2003) proposal to solve to the omitted variables problem, which is based on the construction and inclusion of the sums and differences of buyer and seller characteristics, is merely a different parametrization of the original hedonic regression model. Thus, if the original model suffers from omitted variables bias, so does the solution proposed in Harding et al. (2003). Finally, we derive algebraic expressions for the relationships between the parameters in the original hedonic regression model and the parameters in the Harding et al. (2003) proposed model. These relationships are then confirmed with empirical examples that rely on various assumptions about the symmetry of the relative bargaining powers of the contracting parties.

2. Omitted Variables Bias in Capturing Bargaining Effects in Hedonic Regressions

Harding et al. (2003) modify the usual hedonic regression model to incorporate the bargaining effects for buyers and sellers. They begin with a general hedonic regression model, including buyer and seller characteristics, which is given below as:

$$P_{i} = s_{1}C_{1i} + s_{2}C_{2i} + \sum_{k=1}^{K} \left[b_{k}^{sell} D_{k}^{sell} + b_{k}^{buy} D_{k}^{buy} \right] + e_{B},$$
(1)

where *P* represents the sales price of a property, C_{ji} represents the characteristics of the property, and s_j represents the hedonic prices which are influenced by the buyers and sellers. Bargaining power enters the model through a set of *K* buyer and seller characteristics, D_k^{buy} and D_k^{sell} . The main parameters of interest are the bargaining effects, which are the coefficients of the buyer and seller characteristics, b_k^{buy} and b_k^{sell} . The direct ordinary least squares (OLS) estimation of the model is not possible because, as Harding et al. (2003) suggest, some of the characteristics of the property, namely C_2 , are known to the market participants but not observed by the researcher. That is, these characteristics are unobserved and cannot be included in the model.

The model estimated without C_2 is:

$$P_{i} = s_{1}C_{1i} + \sum_{k=1}^{K} \left[b_{k}^{sell} D_{k}^{sell} + b_{k}^{buy} D_{k}^{buy} \right] + e_{B}.$$
(2)

As Harding et al. (2003) suggest, the characteristics the property included in C_2 are correlated with buyer and seller characteristics.⁴ Thus, OLS estimates of b_k^{sell} and b_k^{buy} in (2) above are subject to an omitted variables bias. As the basis of their proposed solution to the omitted variables problem,

³ A recent Google Scholar search by the authors reveals that the Harding et al. (2003) study has garnered 248 citations to date. Recent applications of the Harding et al. (2003) model include Steegmans and Hassink (2017), Ling et al. (2018), and Hayunga and Munneke (2019).

 $^{^4}$ Cotteleer et al. (2008) use the same setup as Harding et al. (2003), but assume the missing variables in C₂ are not correlated with buyer and seller characteristics. This allows for the direct OLS estimation of (2) with no omitted variables bias.

Harding et al. (2003) represent the correlation between C_2 and the buyer and seller characteristics, D_k^{buy} and D_k^{sell} , with the following regression relationship:

$$s_2 C_2 = \sum_{k=1}^{K} \left[d_k^{sell} D_k^{sell} + d_k^{buy} D_k^{buy} \right] + e_D.$$
(3)

As their solution to the omitted variables bias problem, Harding et al. (2003) substitute (3) into (1) to yield:

$$P = s_1 C_1 + \sum_{k=1}^{K} \left[(b_k^{sell} + d_k^{sell}) D_k^{sell} + (b_k^{buy} + d_k^{buy}) D_k^{buy} \right] + \varepsilon,$$
(4)

where all terms are previously defined save for the random error term, ε , which is $e_B + e_D$.

This substitution leads to an identification problem as all of the coefficients of buyer and seller characteristics are composites. For example, the expressions in parentheses in (4) can be written as:

$$\Omega_k^{sell} = b_k^{sell} + d_k^{sell} \tag{5}$$

and

$$\Omega_k^{buy} = b_k^{buy} + d_k^{buy}, \tag{6}$$

for k = 1 to K. Only Ω_k^{sell} and Ω_k^{buy} are identified, so parameter restrictions are needed in order to identify b_k^{sell} , b_k^{buy} , d_k^{sell} , and d_k^{buy} . To address this issue, Harding et al. (2003) make two assumptions, resulting in parameter restrictions on the model. They refer to the first assumption as *symmetric bargaining power*, which implies that $b_k^{sell} = -b_k^{buy}$. As the name suggests, this constraint assumes that buyers and sellers have equal bargaining power. The second constraint that Harding et al. (2003) impose on the estimation is referred to as *symmetric demand*, which implies that $d_k^{sell} = d_k^{buy}$, meaning that seller and buyer characteristics have the same impact on the value of the unknown property characteristics.

Imposing these constraints and collecting terms results in the construction of the sum and difference variables based on buyer and seller characteristics, which is a distinctive feature of the Harding et al. (2003) solution. The result is an equation that Harding et al. (2003) describe as readily estimable by OLS:

$$P = s_1 C_1 + \sum_{k=1}^{K} \left[b_k (D_k^{sell} - D_k^{buy}) + d_k (D_k^{sell} + D_k^{buy}) \right] + \varepsilon,$$
(7)

where the b_k provide direct measures of the effect of seller and buyer characteristics on bargaining power and the d_k measure their effect on demand. Harding et al. (2003) note that (7) and (4) are observationally equivalent. In the next section, we show that the same can be said for the model in (2) above, thus giving rise to another statistical problem. This problem emanates from the fact that the solution of Harding et al. (2003) is based on the assumption that there is an omitted variables bias in the estimation of (2) but not in the estimation of (7). Below, we show the two models are the same, and, thus, under their assumptions, both suffer from omitted variables bias. Intuitively, the substitution suggested by Harding et al. (2003)—(3) into (1)—cannot provide any relief from the omitted variables problem because the regression relationship describing the omitted variables in (3) is solely a function of independent variables that are already in the model. That is, there is no new explanatory power introduced to take the place of the omitted variables. Let us more closely examine the buyer and seller characteristics. Returning to (7), multiplying and rearranging terms to return to the original variable definitions in (2), we have:

$$P_{i} = s_{1}C_{1} + \sum_{k=1}^{K} \left[(b_{k} + d_{k})D_{k}^{sell} + (d_{k} - b_{k})D_{k}^{buy} \right] + \varepsilon,$$
(8)

and by analogy with (2) and a little algebra, we see that:

$$b_k^{sell} = b_k + d_k \text{ for } k = 1, K,$$
(9a)

$$b_k^{buy} = d_k - b_k \text{ for } k = 1, K,$$
 (9b)

$$b_k = \frac{b_k^{sell} - b_k^{buy}}{2}$$
 for $k = 1, K$, (9c)

and

$$d_k = \frac{b_k^{buy} + b_k^{sell}}{2}$$
 for $k = 1, K.$ (9d)

Thus, models (2) and (7) are the same. The implications of these algebraic relationships are twofold. First, as (2) and (7) are the same model, both must be subject to the assumed omitted variables bias. Thus, the proposed Harding et al. (2003) solution fails to address this issue. Second, the coefficients of buyer and seller characteristics in (2), b_k^{sell} and b_k^{buy} , can be estimated directly and then transformed via (9c) and (9d) to obtain estimates of b_k and d_k . As such, there is no need to estimate (7) and no need to justify the estimation of (7) as the solution to an omitted variables problem.

3. Econometric Demonstration

In order to validate the relationships above, we employ a classic hedonic regression model of real estate prices using Corsican apartment data (n = 8243).⁵ The dependent variable in this model is the logarithm of the sales price and the model includes several apartment characteristics. In addition, the data set provides information on buyer and seller characteristics. In this empirical example, we have information on the county in which the property is located and also on the counties of residence of both buyer and seller. We use this information to create two dummy variables. These are D^{buy} , which is equal to 1 if the buyer resides in the same county as the apartment, and zero otherwise, and D^{sell} , which is equal to 1 if the seller resides in the same county as the apartment, and zero otherwise. From these two dummy variables, we also create the Harding et al. (2003) sum and difference variables that are discussed in the previous section.

3.1. Empirical Results

We estimate two versions of a hedonic regression model and the results are given in Table 1. Column 2 of the table contains the hedonic regression model, including the dummy variables D^{buy} and D^{sell} . This model is based on the relationship given in (2). The second version of the model is given in column 3 of the table and includes the constructed sum and difference variables of buyer and seller characteristics suggested by Harding et al. (2003). This version of the model is based on the relationship in (7).

⁵ For information on the data, see https://www.perval.fr.

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Variables	Model from (2)	Model from (7)
	11.01 ***	11.01 ***
constant	(616.6)	(616.6)
Furnished	0.214 ***	0.214 ***
	(18.52)	(18.52)
Number of Rooms	0.180 ***	0.180 ***
	(36.01)	(36.01)
Number of Baths	0.160 ***	0.160 ***
Number of Buins	(13.44)	(13.44)
Floor of Americant Complex	0.011 ***	0.011 ***
Floor of Apartment Complex	(4.55)	(4.55)
New Construction	0.244 ***	0.244 ***
New Construction	(26.35)	(26.35)
Garden	0.203 ***	0.203 ***
Guruen	(10.24)	(10.24)
Square Meters	0.003 ***	0.003 ***
Squure Wielers	(22.08)	(22.08)
Time to Nearest Beach	-0.014 ***	-0.014 ***
Time to Wearest Deach	(-23.77)	(-23.77)
Time to Nearest Doctor	-0.005 **	-0.005 **
	(-1.98)	(-1.98)
Time to Nearest Pharmacy	-0.010 ***	-0.010 ***
	(-4.27)	(-4.27)
Time to Nearest Primary School	0.023 ***	0.023 ***
time to ivearest i rimary sensor	(13.46)	(13.46)
Time to Downtown	-0.008 ***	-0.008 ***
Time to Downtown	(-22.42)	(-22.42)
Time to Nearest Main Town	-0.004 ***	-0.004 ***
	(-7.86)	(-7.86)
Sea View	0.001 *	0.001 *
	(1.74)	(1.74)
$d(D^{sell} + D^{buy})$	_	-0.006
		(-0.92)
$b(D^{sell} - D^{buy})$	_	0.055 ***
		(8.35)
b^{buy} (variable is D^{buy})	-0.060 ***	_
	(-6.48)	
$b^{sell}(variable is D^{sell})$	0.049 ***	_
(/	(5.72)	
R^2	0.607	0.607

Table 1. Bargaining power regressions.

Notes: The numbers in parentheses above are t-ratios. *** (**) [*] denotes the 0.01 (0.05) [0.10] level of significance.

A comparison of the estimation results for the two models instantly reveals that the coefficient estimates for the intercept and all hedonic prices, their *t*-ratios, and the model R^2 are identical.⁶ These findings support our assertion that the substitution of Equation (3) into (1) adds no new information to the regression model. Additionally, we are able to empirically confirm the coefficient relationships in (9a) and (9b) above. The estimation results in Table 1 show that $b^{buy} = -0.06038$, $b^{sell} = 0.04918$, b = 0.05478, and d = -0.00560. As we state in (9a), $b^{sell} = (b + d)$, which implies 0.04918 = 0.05478 - 0.00560, which is correct and confirms the relationship. In (9b), we state that $b^{buy} = (d - b)$, which implies -0.06038 = -0.00560 - 0.05478, which is correct and confirms the relationship. The standard errors for the parameter estimates in (2) can be obtained from (7), and vice-versa, using the relevant variance and covariance terms. These results confirm our assertion that the model in (2) and the model in (7) are merely different parametrizations of the same model. Under the Harding et al. (2003) assumption, both suffer from omitted variables bias.

⁶ Harding et al. (2003) indicate an awareness of this similarity in a footnote in their paper.

3.2. Sensitivity Analysis

Currently, we use $(D^{sell} - D^{buy})$ as the variable of interest. In order to evaluate the impact of relaxing the assumption of bargaining symmetry underlying this variable construction, we re-estimated the model using several transformations.⁷ In particular, in turn, we replaced the original variable above with $(D^{sell} - 0.5D^{buy})$, $(D^{sell} - 2D^{buy})$, $(0.5D^{sell} - D^{buy})$, and $(2D^{sell} - D^{buy})$. The results of these regressions are presented in Table 2.

Table 2. Bargaining power regressions with asymmetry.

Variables	Model from (7)	Model from (7)	Model from (7)	Model from (7)
constant	11.01 ***	11.01 ***	11.01 ***	11.01 ***
	(616.6)	(616.6)	(616.6)	(616.6)
Furnished	0.214 ***	0.214 ***	0.214 ***	0.214 ***
	(18.52)	(18.52)	(18.52)	(18.52)
Number of Rooms	0.180 ***	0.180 ***	0.180 ***	0.180 ***
	(36.01)	(36.01)	(36.01)	(36.01)
Number of Baths	0.160 ***	0.160 ***	0.160 ***	0.160 ***
	(13.44)	(13.44)	(13.44)	(13.44)
Floor of Angentus ant Community	0.011 ***	0.011 ***	0.011 ***	0.011 ***
Floor of Apartment Complex	(4.55)	(4.55)	(4.55)	(4.55)
New Construction	0.244 ***	0.244 ***	0.244 ***	0.244 ***
New Construction	(26.35)	(26.35)	(26.35)	(26.35)
Garden	0.203 ***	0.203 ***	0.203 ***	0.203 ***
	(10.24)	(10.24)	(10.24)	(10.24)
	0.003 ***	0.003 ***	0.003 ***	0.003 ***
Square Meters	(22.08)	(22.08)	(22.08)	(22.08)
	-0.014 ***	-0.014 ***	-0.014 ***	-0.014 ***
Time to Nearest Beach	(-23.77)	(-23.77)	(-23.77)	(-23.77)
Time to Nearest Doctor	-0.005 **	-0.005 **	-0.005 **	-0.005 **
	(-1.98)	(-1.98)	(-1.98)	(-1.98)
Time to Nearest Pharmacy	-0.010 ***	-0.010 ***	-0.010 ***	-0.010 ***
	(-4.27)	(-4.27)	(-4.27)	(-4.27)
Time to Nearest Primary School	0.023 ***	0.023 ***	0.023 ***	0.023 ***
	(13.46)	(13.46)	(13.46)	(13.46)
Time to Downtown	-0.008 ***	-0.008 ***	-0.008 ***	-0.008 ***
	(-22.42)	(-22.42)	(-22.42)	(-22.42)
Time to Nearest Main Town	-0.004 ***	-0.004 ***	-0.004 ***	-0.004 ***
	(-7.86)	(-7.86)	(-7.86)	(-7.86)
Sea View	0.001 *	0.001 *	0.001 *	0.001 *
	(1.74)	(1.74)	(1.74)	(1.74)
$d(D^{sell} + D^{buy})$	0.013 **	-0.024 ***	-0.024 ***	0.013 **
	(2.00)	(-3.58)	(-3.58)	(2.00)
$b(D^{sell} - 0.5D^{buy})$	-0.073 ***			
	(-8.35)	—	—	_
$b(D^{sell} - 2D^{buy})$	_	-0.037 *** (8.35)	_	_
$b(0.5D^{sell} - D^{buy})$	_		-0.073 *** (-8.35)	_
$b(2D^{sell} - D^{buy})$	_	_	(-0.00)	-0.037 ***
()				(8.35)
R^2	0.607	0.607	0.607	0.607

Notes: The numbers in parentheses above are t-ratios. *** (**) [*] denotes the 0.01 (0.05) [0.10] level of significance.

In no case is the explanatory power of the model changed, nor is there any change in the magnitudes, signs, and statistical significance of any other coefficient in the model, with the exception of the coefficient attached to the constructed sum (i.e., $(D^{sell} + D^{buy})$) and those attached to the difference variables. These results indicate that an algebraic relationship between the transformed coefficients (in column 3 of Table 1) and the untransformed coefficients (in column 2 of Table 1) exists regardless

⁷ We are grateful to an anonymous reviewer for suggesting these additional tests.

of the assumption made about the symmetry of the bargaining power, and that none of the above transformations provide a solution to the omitted variables problem in this case.

4. Conclusions

The relative bargaining power of the buyer and seller is a key feature of residential and other types of real estate transactions. Classic real estate studies have therefore sought to address bargaining effects in hedonic regression models, but, in doing so, have grappled with omitted variables bias. Recent studies have relied on a statistical procedure to estimate bargaining effects in hedonic regression models that depends critically on a substitution to eliminate the omitted variables bias. This study contends that the proposed solution cited in many real estate economics studies does not solve the omitted variables problem, and thus produces biased estimates of bargaining power when certain property characteristics are omitted. More specifically, our mathematic approach indicates that the substitution to eliminate omitted variables bias cannot provide any relief from the omitted variables problem because the regression relationship in the proposed solution describing the omitted variables is solely a function of independent variables that are already in the model.

Our contention is also supported by a classic hedonic regression model of real estate prices using Corsican apartment data. The dependent variable in this model is the logarithm of the sales price, and the model includes several apartment characteristics. A comparison of the estimation results for the two models (i.e., the original model suffering omitted variables bias and the model purporting to address this bias) instantly reveals that the coefficient estimates for the intercept and all hedonic prices, their *t*-ratios, and the model R^2 are identical. These results confirm our assertion that the two models are merely different parametrizations of the same model, and that both suffer from omitted variables bias, regardless of the assumption made about bargaining power symmetry.

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References

- Affuso, Ermanno, J. Reid Cummings, and Huubinh Le. 2018. Wireless Towers and Home Values: An Alternative Valuation Approach using a Spatial Econometric Analysis. *Journal of Real Estate Finance and Economics* 56: 653–76. [CrossRef]
- Biagi, Bianca, Maria Giovanna Brandano, and Steven B. Caudill. 2016. Tourism and House Prices in Italy: A Latent Class Approach. *Tourism Economics* 22: 964–78. [CrossRef]
- Carrasco-Gallego, José A., Steven B. Caudill, Franklin G. Mixon, Jr., and Richard J. Cebula. 2017. Decomposition of Latent Class Regression Model Estimates: An Application to Hunting Land Lease Prices. *Studies in Economics and Econometrics* 41: 1–18.
- Caudill, Steven B., and Franklin G. Mixon, Jr. 2016. Estimating Class-Specific Parametric Models using Finite Mixtures: An Application to a Hedonic Model of Wine Prices. *Journal of Applied Statistics* 43: 1253–61. [CrossRef]
- Cotteleer, Geerte, Cornelis Gardebroek, and Jan Luijt. 2008. Market Power in a GIS-Based Hedonic Price Model of Local Farmland Markets. *Land Economics* 84: 573–92. [CrossRef]
- Fedderke, Johannes W., and Kaini Li. 2020. Art in Africa: Hedonic Price Analysis of the South African Fine Art Auction Market, 2009–2014. *Economic Modelling* 84: 88–101. [CrossRef]
- Galbraith, John W., and Douglas J. Hodgson. 2018. Econometric Fine Art Valuation by Combining Hedonic and Repeat-Sales Information. *Econometrics* 6: 32. [CrossRef]

- Hansen, Charlotte R., and C. Jill Stowe. 2018. Determinants of Weanling Thoroughbred Auction Prices. *Journal of Agricultural and Applied Economics* 50: 48–63. [CrossRef]
- Hanson, Erik D., Bruce J. Sherrick, and Todd H. Kuethe. 2018. The Changing Roles of Urban Influence and Agricultural Productivity in Farmland Price Determination. *Land Economics* 94: 199–2005. [CrossRef]
- Harding, John P., Stuart S. Rosenthal, and Clemon F. Sirmans. 2003. Estimating Bargaining Power in the Market for Existing Homes. *Review of Economics and Statistics* 85: 178–88. [CrossRef]
- Hayunga, Darren K., and Henry J. Munneke. 2019. Examining Both Sides of the Transaction: Bargaining in the Housing Market. *Real Estate Economics*. in press. [CrossRef]
- Lee, Justin A., Steven B. Caudill, and Franklin G. Mixon, Jr. 2015. Shine Bright Like a Diamond: A Hedonic Model of Grading and Pricing an Experience Good. *Applied Economics* 46: 1829–38. [CrossRef]
- Ling, David C., Andy Naranjo, and Milena T. Petrova. 2018. Search Costs, Behavioral Biases, and Information Intermediary Effects. *Journal of Real Estate Finance and Economics* 57: 114–51. [CrossRef]
- Salter, Sean, and Ernest King. 2009. Price Adjustment and Liquidity in a Residential Real Estate Market with an Accelerated Information Cascade. *Journal of Real Estate Research* 31: 421–54.
- Salter, Sean P., Franklin G. Mixon, Jr., and Ernest W. King. 2012. Broker Beauty and Boon: A Study of Physical Attractiveness and its Effect on Real Estate Brokers' Income and Productivity. *Applied Financial Economics* 22: 811–25. [CrossRef]
- Shorish, Jamsheed. 2019. Hedonic Pricing of Cryptocurrency Tokens. Digital Finance 1: 163-89. [CrossRef]
- Smith, Rachel A., C. Nicholas McKinney, Steven B. Caudill, and Franklin G. Mixon, Jr. 2016. Consumer Ratings and the Pricing of Experience Goods: Hedonic Regression Analysis of Beer Prices. *Agricultural and Food Economics* 4: 1–10. [CrossRef]
- Steegmans, Joep, and Wolter Hassink. 2017. Financial Position and House Price Determination: An Empirical Study of Income and Wealth Effects. *Journal of Housing Economics* 36: 8–24. [CrossRef]



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