# *Supplementary Appendix to*
# (Under)Mining Local Residential Property Values: A Semiparametric Spatial Quantile Autoregression*

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**Abstract**

Rock mining operations, including limestone and gravel production, have considerable adverse effects on residential quality of life due to elevated noise and dust levels resulting from dynamite blasting and increased truck traffic. This paper provides the first estimates of the effects of rock mining—an environmental disamenity—on local residential property values. We focus on the relationship between a house's price and its distance from nearby rock mine. Our analysis studies Delaware County, Ohio which, given its unique features, provides a natural environment for the valuation of property-value-suppressing effects of rock mines on nearby houses. We improve upon the conventional approach to valuating adverse effects of environmental disamenities based on hedonic house price functions. Specifically, in a pursuit of robust estimates, we develop a novel (semiparametric) partially linear spatial quantile autoregressive model which accommodates unspecified nonlinearities, distributional heterogeneity as well as spatial dependence in the data. We derive the consistency and normality limit results for our estimator as well as propose a consistent model specification test. We find statistically and economically significant property-value-suppressing effects of being located near an operational rock mine which gradually decline to insignificant near-zero values at a roughly ten-mile distance. Our estimates suggest that, all else equal, a house located a mile closer to a rock mine is priced, on average, at about 2.3–5.1% discount, with more expensive properties being subject to larger markdowns.

**Keywords**: Environmental Disamenity, Hedonic Model, Partially Linear, Quantile Regression, Rock Mines, SAR, Semiparametric, Spatial Lag

**JEL Classification**: C14, C21, R30, Q51

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# B Monte Carlo Simulations

In this section, we evaluate the finite-sample performance of our proposed estimator and the test statistic in a small set of Monte Carlo simulations.

## B.1 Estimator

We generate the data using a random-coefficient "rendition" of our model in (2.1). Specifically, our PLSQAR model can be motivated by the following random-coefficient partially linear model:

$$y_{i,n} = \rho_0^*(\upsilon_{i,n}) \sum_{j \neq i} w_{ij,n} y_{j,n} + \mathbf{x}_{i,n}' \boldsymbol{\beta}_0^*(\upsilon_{i,n}) + \alpha_0^*(\mathbf{z}_{i,n}, \upsilon_{i,n}), \tag{B.1}$$

where $\upsilon_{i,n} \perp (\mathbf{X}_n, \mathbf{Z}_n, \mathbf{M}_n)$ is the scalar random disturbance. In the structural framework, $\upsilon_{i,n}$ can be interpreted as capturing heterogeneity in the outcome variable $y_{i,n}$ due to some unobserved factors. Further, if following Chernozhukov & Hansen (2005, 2006) one were to assume that $\upsilon_{i,n} \sim$ *i.i.d.* $\mathbb{U}(0,1)$ and that the so-called structural quantile function of interest

$$q\left(\sum_{j \neq i} w_{ij,n} y_{j,n}, \mathbf{x}_{i,n}, \mathbf{z}_{i,n}, \tau\right) = \rho_0^*(\tau) \sum_{j \neq i} w_{ij,n} y_{j,n} + \mathbf{x}_{i,n}' \boldsymbol{\beta}_0^*(\tau) + \alpha_0^*(\mathbf{z}_{i,n}, \tau) \tag{B.2}$$

is such that $\partial q(\cdot, \tau)/\partial \tau > 0$, the event $\{y_{i,n} \leq \rho_0^*(\tau) \sum_{j \neq i} w_{ij,n} y_{j,n} + \mathbf{x}_{i,n}' \boldsymbol{\beta}_0^*(\tau) + \alpha_0^*(\mathbf{z}_{i,n}, \tau)\}$ becomes equivalent to the event $\{\upsilon_{i,n} \leq \tau\}$. Then, it is straightforward to establish the following quantile restriction:

$$\Pr[u_{i,n}^* \leq 0 | \mathbf{X}_n, \mathbf{Z}_n, \mathbf{M}_n] = \tau, \tag{B.3}$$

where, in an analogy to our model in (2.1), the new quantile error term is defined as $u_{i,n}^* \equiv y_{i,n} - \rho_0^*(\tau) \sum_{j \neq i} w_{ij,n} y_{j,n} - \mathbf{x}_{i,n}' \boldsymbol{\beta}_0^*(\tau) - \alpha_0^*(\mathbf{z}_{i,n}, \tau)$. Clearly, (B.1) and (B.3) are respectively analogous to (2.1) and (2.2).

Thus, we use the following two processes to generate the data:

$$y_i = \rho_0(\upsilon_i) \sum_{j \neq i} w_{ij} y_j + x_{1,i} \beta_{1,0}(\upsilon_i) + \alpha_0(z_{1,i}, \upsilon_i) \qquad \text{[DGP \#1]} \tag{B.4}$$

$$y_i = \rho_0(\upsilon_i) \sum_{j \neq i} w_{ij} y_j + x_{1,i} \beta_{1,0}(\upsilon_i) + x_{2,i} \beta_{2,0}(\upsilon_i) + \alpha_0(z_{1,i}, z_{2,i}, \upsilon_i), \quad \text{[DGP \#2]} \tag{B.5}$$

where the variables are randomly drawn as follows: $z_{1,i} \sim$ *i.i.d.* $\mathbb{U}(-1,1)$, $z_{2,i} \sim$ *i.i.d.* $\mathbb{N}(0,1)$, $x_{1,i} = 0.5 z_{1,i} + \xi_i$ with $\xi_i \sim$ *i.i.d.* $\mathbb{N}(0,1)$, $x_{2,i} \sim$ *i.i.d.* $\mathbb{N}(1,1)$, and $\upsilon_i \sim$ *i.i.d.* $\mathbb{U}(0,1)$. Fixed parameters are specified as $\rho_{\tau,0} \equiv \rho_0(\upsilon)\big|_{\upsilon=\tau} = 0.5 + 0.15\Phi^{-1}(\upsilon)$, $\beta_{\tau,1,0} \equiv \beta_{1,0}(\upsilon)\big|_{\upsilon=\tau} = 0.2 + 0.15\Phi^{-1}(\upsilon)$, and $\beta_{\tau,2,0} \equiv \beta_{2,0}(\upsilon)\big|_{\upsilon=\tau} = 1 + 0.25\Phi^{-1}(\upsilon)$. For each data-generating process, we consider two specifications of a nonparametric intercept function:

$$\alpha_{\tau,0}(z_1) \equiv \alpha_0(z_1, \upsilon)\big|_{\upsilon=\tau} = \sin(1 + 1.5 z_1) + \begin{cases} 0.15\Phi^{-1}(\upsilon) & \text{[DGP \#1A]} \\ 0.15 \exp\{-z_1^2\}\Phi^{-1}(\upsilon) & \text{[DGP \#1B]} \end{cases}$$

$$\alpha_{\tau,0}(z_1, z_2) \equiv \alpha_0(z_1, z_2, \upsilon)\big|_{\upsilon=\tau} = \sin(1 + 1.5 z_1) \times z_2 + z_2 + \begin{cases} 0.15\Phi^{-1}(\upsilon) & \text{[DGP \#2A]} \\ 0.15 \exp\{-z_1^2\}\Phi^{-1}(\upsilon). & \text{[DGP \#2B]} \end{cases}$$

We allocate spatial units on a lattice of $25 \times (n/25)$ squares and construct $\mathbf{W}_n$ using a contiguity-based first-order "queen" structure; the spatial weights matrix is then normalized by dividing

Table B.1. Simulation Results for the Estimator: DGP #1

| | $\boldsymbol{\tau = 0.25}$ | | | | $\boldsymbol{\tau = 0.50}$ | | | | $\boldsymbol{\tau = 0.75}$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $n = 125$ | $n = 250$ | $n = 500$ | $n = 1000$ | $n = 125$ | $n = 250$ | $n = 500$ | $n = 1000$ | $n = 125$ | $n = 250$ | $n = 500$ | $n = 1000$ |
| DGP #1A | | | | | | | | | | | | |
| $\rho_{\tau,0}$ | | | | | | | | | | | | |
| RMSE | 0.18423 | 0.11022 | 0.07434 | 0.04942 | 0.14683 | 0.09987 | 0.06263 | 0.03988 | 0.19160 | 0.12091 | 0.07547 | 0.04950 |
| MAE | 0.13588 | 0.08633 | 0.05902 | 0.03920 | 0.10734 | 0.07562 | 0.04834 | 0.03118 | 0.13141 | 0.09172 | 0.05824 | 0.03949 |
| $\beta_{\tau,1,0}$ | | | | | | | | | | | | |
| RMSE | 0.03995 | 0.02919 | 0.02199 | 0.01616 | 0.02895 | 0.02036 | 0.01359 | 0.00926 | 0.04055 | 0.02945 | 0.02196 | 0.01669 |
| MAE | 0.03184 | 0.02373 | 0.01809 | 0.01358 | 0.02322 | 0.01601 | 0.01090 | 0.00726 | 0.03335 | 0.02318 | 0.01803 | 0.01415 |
| $\alpha_{\tau,0}(z_{1,i})$ | | | | | | | | | | | | |
| RMSE | 0.12111 | 0.08855 | 0.06617 | 0.04556 | 0.10063 | 0.07871 | 0.05423 | 0.03777 | 0.12649 | 0.09441 | 0.06580 | 0.04707 |
| MAE | 0.11171 | 0.08166 | 0.06085 | 0.04113 | 0.09239 | 0.07284 | 0.04937 | 0.03376 | 0.11725 | 0.08795 | 0.06099 | 0.04284 |
| DGP #1B | | | | | | | | | | | | |
| $\rho_{\tau,0}$ | | | | | | | | | | | | |
| RMSE | 0.16069 | 0.09800 | 0.06889 | 0.04472 | 0.12321 | 0.08180 | 0.05046 | 0.03291 | 0.18307 | 0.10872 | 0.07107 | 0.04575 |
| MAE | 0.12101 | 0.07731 | 0.05511 | 0.03551 | 0.08780 | 0.05986 | 0.03939 | 0.02579 | 0.12757 | 0.08329 | 0.05736 | 0.03684 |
| $\beta_{\tau,1,0}$ | | | | | | | | | | | | |
| RMSE | 0.04209 | 0.03298 | 0.02518 | 0.02013 | 0.02681 | 0.01875 | 0.01291 | 0.00871 | 0.04355 | 0.03178 | 0.02569 | 0.02075 |
| MAE | 0.03441 | 0.02729 | 0.02159 | 0.01787 | 0.02175 | 0.01474 | 0.01042 | 0.00694 | 0.03624 | 0.02622 | 0.02202 | 0.01854 |
| $\alpha_{\tau,0}(z_{1,i})$ | | | | | | | | | | | | |
| RMSE | 0.10402 | 0.07786 | 0.05969 | 0.04070 | 0.08077 | 0.06240 | 0.04425 | 0.03159 | 0.11827 | 0.08602 | 0.06301 | 0.04454 |
| MAE | 0.09645 | 0.07229 | 0.05557 | 0.03724 | 0.07417 | 0.05743 | 0.04019 | 0.02803 | 0.11032 | 0.08014 | 0.05824 | 0.04023 |

Table B.2. Simulation Results for the Estimator: DGP #2

| | **$\tau = 0.25$** | | | | **$\tau = 0.50$** | | | | **$\tau = 0.75$** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $n=125$ | $n=250$ | $n=500$ | $n=1000$ | $n=125$ | $n=250$ | $n=500$ | $n=1000$ | $n=125$ | $n=250$ | $n=500$ | $n=1000$ |
| DGP #2A | | | | | | | | | | | | |
| $\rho_{\tau,0}$ | | | | | | | | | | | | |
| RMSE | 0.12047 | 0.07488 | 0.04086 | 0.03127 | 0.10060 | 0.05742 | 0.03408 | 0.02528 | 0.11522 | 0.06573 | 0.04315 | 0.02829 |
| MAE | 0.09624 | 0.06070 | 0.03188 | 0.02485 | 0.07512 | 0.04514 | 0.02688 | 0.02036 | 0.09166 | 0.05296 | 0.03492 | 0.02247 |
| $\beta_{\tau,1,0}$ | | | | | | | | | | | | |
| RMSE | 0.07851 | 0.05477 | 0.03535 | 0.02445 | 0.06743 | 0.04191 | 0.02962 | 0.01898 | 0.08208 | 0.04992 | 0.03714 | 0.02365 |
| MAE | 0.06166 | 0.04377 | 0.02793 | 0.02003 | 0.05270 | 0.03363 | 0.02364 | 0.01519 | 0.06459 | 0.03999 | 0.02895 | 0.01845 |
| $\beta_{\tau,2,0}$ | | | | | | | | | | | | |
| RMSE | 0.09674 | 0.06012 | 0.04142 | 0.03076 | 0.07076 | 0.04495 | 0.03024 | 0.01863 | 0.08992 | 0.05955 | 0.04045 | 0.03135 |
| MAE | 0.07643 | 0.04728 | 0.03337 | 0.02478 | 0.05537 | 0.03601 | 0.02399 | 0.01481 | 0.07153 | 0.04802 | 0.03274 | 0.02570 |
| $\alpha_{\tau,0}(z_{1,i}, z_{2,i})$ | | | | | | | | | | | | |
| RMSE | 0.33723 | 0.23694 | 0.15820 | 0.11017 | 0.29306 | 0.20501 | 0.13821 | 0.09355 | 0.33899 | 0.23138 | 0.16123 | 0.11114 |
| MAE | 0.25209 | 0.17558 | 0.11470 | 0.08022 | 0.21896 | 0.14960 | 0.09860 | 0.06637 | 0.25232 | 0.16783 | 0.11724 | 0.08097 |
| DGP #2B | | | | | | | | | | | | |
| $\rho_{\tau,0}$ | | | | | | | | | | | | |
| RMSE | 0.11767 | 0.07192 | 0.03947 | 0.02926 | 0.09197 | 0.05241 | 0.03196 | 0.02250 | 0.10870 | 0.06212 | 0.04138 | 0.02785 |
| MAE | 0.09411 | 0.05752 | 0.03054 | 0.02371 | 0.06905 | 0.04119 | 0.02505 | 0.01795 | 0.08697 | 0.04946 | 0.03367 | 0.02177 |
| $\beta_{\tau,1,0}$ | | | | | | | | | | | | |
| RMSE | 0.07519 | 0.05241 | 0.03422 | 0.02398 | 0.06344 | 0.03982 | 0.02768 | 0.01780 | 0.07955 | 0.04804 | 0.03565 | 0.02349 |
| MAE | 0.05868 | 0.04212 | 0.02708 | 0.01962 | 0.04975 | 0.03187 | 0.02234 | 0.01416 | 0.06237 | 0.03847 | 0.02806 | 0.01874 |
| $\beta_{\tau,2,0}$ | | | | | | | | | | | | |
| RMSE | 0.09402 | 0.05940 | 0.04205 | 0.03199 | 0.06679 | 0.04250 | 0.02877 | 0.01782 | 0.08721 | 0.05868 | 0.04119 | 0.03245 |
| MAE | 0.07521 | 0.04710 | 0.03431 | 0.02638 | 0.05271 | 0.03373 | 0.02278 | 0.01421 | 0.06949 | 0.04701 | 0.03384 | 0.02683 |
| $\alpha_{\tau,0}(z_{1,i}, z_{2,i})$ | | | | | | | | | | | | |
| RMSE | 0.31431 | 0.22122 | 0.14864 | 0.10362 | 0.27249 | 0.18753 | 0.12578 | 0.08387 | 0.31707 | 0.21627 | 0.15044 | 0.10482 |
| MAE | 0.23516 | 0.16520 | 0.10909 | 0.07686 | 0.20397 | 0.13636 | 0.08963 | 0.05930 | 0.23700 | 0.15841 | 0.11013 | 0.07771 |

its elements by its largest eigenvalue.[20] We conduct the experiments at three different quantiles $\tau = \{0.25, 0.50, 0.75\}$ for each of which the considered sample sizes are $n = \{125, 250, 500, 1000\}$. For each $\tau$-$n$ pair, we simulate the model 500 times. We use cubic B-splines (the tensor product thereof, in a multivariate case) to approximate unknown function $\alpha_0(\cdot)$. For simplicity, we set $L_n = 3$ in our experiments for all sample sizes since the range of $n$ is not that large. We compute the root mean squared error (RMSE) and the mean absolute error (MAE) for each fixed coefficient across 500 iterations. For a varying nonparametric intercept function, RMSE and MAE are first computed for each simulation iteration; reported are their averages computed over 500 iterations.

The results are reported in Tables B.1–B.2. Consistent with our theory, performance of the estimator improves with an increase in the sample size across all quantiles. As one would normally expect, it performs better for "middle" quantiles (median, in our case): RMSE and MAE somewhat worsen when we estimate the model closer to tails of the response distribution.

## B.2 Specification Tests

We next examine the small-sample performance of our proposed bootstrap specification test. To conserve space, we only consider $\tau = 0.50$. The sample sizes are $n = \{100, 200, 400\}$, and the number of simulation replications is 500. Residuals under $H_1$ are obtained via our proposed PLSQAR model using cubic B-splines (the tensor product thereof, in a multivariate case) to approximate the unknown function $\alpha_0(\cdot)$. Residuals under $H_0$ are obtained via Su & Yang's (2011) estimator. Given the sample size, for each simulation, we calculate our modified test statistic $J_n$ from the simulated data plus 199 bootstrap test statistics $J_n^b$. Then, from the 200 test statistic values, we obtain the 1%, 5%, 10% and 20% upper percentile (critical) values.

To assess power and size of the test, we consider the following experimental designs for the DGP #1 in (B.4):

(1A) The null in (3.2) is true: $\rho_{\tau,0} \equiv \rho_0(\upsilon)\big|_{\upsilon=\tau} = 0.5 + 0.15\Phi^{-1}(\upsilon)$, $\beta_{\tau,1,0} \equiv \beta_{1,0}(\upsilon)\big|_{\upsilon=\tau} = 0.2 + 0.15\Phi^{-1}(\upsilon)$ and $\alpha_{\tau,0}(z_1) \equiv \alpha_0(z_1, \upsilon)\big|_{\upsilon=\tau} = 0.5 + 0.5z_1 + 0.15\Phi^{-1}(\upsilon)$;

(1B) The null in (3.3) is true: $\rho_{\tau,0} \equiv \rho_0(\upsilon)\big|_{\upsilon=\tau} = 0.5 + 0.15\Phi^{-1}(\upsilon)$, $\beta_{\tau,1,0} \equiv \beta_{1,0}(\upsilon)\big|_{\upsilon=\tau} = 0.2 + 0.15\Phi^{-1}(\upsilon)$ and $\alpha_{\tau,0}(z_1) \equiv \alpha_0(z_1, \upsilon)\big|_{\upsilon=\tau} = 0.5 + 0.15\Phi^{-1}(\upsilon)$ for all $z_1$;

(1C) The alternative in (3.4) is true: $\rho_{\tau,0} \equiv \rho_0(\upsilon)\big|_{\upsilon=\tau} = 0.5 + 0.15\Phi^{-1}(\upsilon)$, $\beta_{\tau,1,0} \equiv \beta_{1,0}(\upsilon)\big|_{\upsilon=\tau} = 0.2 + 0.15\Phi^{-1}(\upsilon)$ and $\alpha_{\tau,0}(z_1) \equiv \alpha_0(z_1, \upsilon)\big|_{\upsilon=\tau} = \sin(1 + 1.5z_1) + 0.15\Phi^{-1}(\upsilon)$;

and the following designs for the DGP #2 in (B.4):

(2A) The null in (3.2) is true: $\rho_{\tau,0} \equiv \rho_0(\upsilon)\big|_{\upsilon=\tau} = 0.5 + 0.15\Phi^{-1}(\upsilon)$, $\beta_{\tau,1,0} \equiv \beta_{1,0}(\upsilon)\big|_{\upsilon=\tau} = 0.2 + 0.15\Phi^{-1}(\upsilon)$, $\beta_{\tau,2,0} \equiv \beta_{2,0}(\upsilon)\big|_{\upsilon=\tau} = 1 + 0.25\Phi^{-1}(\upsilon)$ and $\alpha_{\tau,0}(z_1, z_2) \equiv \alpha_0(z_1, z_2, \upsilon)\big|_{\upsilon=\tau} = 0.5 + 0.5z_1 + z_2 + 0.15\Phi^{-1}(\upsilon)$;

(2B) The null in (3.3) is true: $\rho_{\tau,0} \equiv \rho_0(\upsilon)\big|_{\upsilon=\tau} = 0.5 + 0.15\Phi^{-1}(\upsilon)$, $\beta_{\tau,1,0} \equiv \beta_{1,0}(\upsilon)\big|_{\upsilon=\tau} = 0.2 + 0.15\Phi^{-1}(\upsilon)$, $\beta_{\tau,2,0} \equiv \beta_{2,0}(\upsilon)\big|_{\upsilon=\tau} = 1 + 0.25\Phi^{-1}(\upsilon)$ and $\alpha_{\tau,0}(z_1, z_2) \equiv \alpha_0(z_1, z_2, \upsilon)\big|_{\upsilon=\tau} = 0.5 + 0.15\Phi^{-1}(\upsilon)$ for all $z_1$ and $z_2$;

(2C) The alternative in (3.4) is true: $\rho_{\tau,0} \equiv \rho_0(\upsilon)\big|_{\upsilon=\tau} = 0.5 + 0.15\Phi^{-1}(\upsilon)$, $\beta_{\tau,1,0} \equiv \beta_{1,0}(\upsilon)\big|_{\upsilon=\tau} = 0.2 + 0.15\Phi^{-1}(\upsilon)$, $\beta_{\tau,2,0} \equiv \beta_{2,0}(\upsilon)\big|_{\upsilon=\tau} = 1 + 0.25\Phi^{-1}(\upsilon)$ and $\alpha_{\tau,0}(z_1, z_2) \equiv \alpha_0(z_1, \upsilon)\big|_{\upsilon=\tau} = \sin(1 + 1.5z_1) \times z_2 + z_2 + 0.15\Phi^{-1}(\upsilon)$.

Table B.3. Simulation Results for the $J_n$ Statistic with $\tau = 0.50$

| | Estimated Size | | | Estimated Power | | |
|---|---|---|---|---|---|---|
| Signif. Level | $n = 100$ | $n = 200$ | $n = 400$ | $n = 100$ | $n = 200$ | $n = 400$ |
| **Case of $\mathbf{H}_0(i)$** | | | | | | |
| | | DGP #1A | | | DGP #1C | |
| 1% | 0.012 | 0.004 | 0.008 | 0.888 | 0.988 | 1.000 |
| 5% | 0.034 | 0.040 | 0.062 | 0.980 | 1.000 | 1.000 |
| 10% | 0.086 | 0.084 | 0.106 | 0.990 | 1.000 | 1.000 |
| 20% | 0.214 | 0.170 | 0.208 | 0.994 | 1.000 | 1.000 |
| **Case of $\mathbf{H}_0(ii)$** | | | | | | |
| | | DGP #1B | | | DGP #1C | |
| 1% | 0.036 | 0.018 | 0.030 | 0.966 | 0.966 | 0.996 |
| 5% | 0.070 | 0.048 | 0.060 | 1.000 | 0.998 | 0.998 |
| 10% | 0.102 | 0.068 | 0.088 | 1.000 | 1.000 | 1.000 |
| 20% | 0.192 | 0.184 | 0.182 | 1.000 | 1.000 | 1.000 |
| **Case of $\mathbf{H}_0(i)$** | | | | | | |
| | | DGP #2A | | | DGP #2C | |
| 1% | 0.010 | 0.008 | 0.008 | 0.336 | 0.858 | 0.996 |
| 5% | 0.048 | 0.032 | 0.046 | 0.658 | 0.972 | 1.000 |
| 10% | 0.100 | 0.110 | 0.102 | 0.752 | 0.984 | 1.000 |
| 20% | 0.186 | 0.224 | 0.218 | 0.852 | 0.992 | 1.000 |
| **Case of $\mathbf{H}_0(ii)$** | | | | | | |
| | | DGP #2B | | | DGP #2C | |
| 1% | 0.008 | 0.010 | 0.002 | 0.992 | 1.000 | 1.000 |
| 5% | 0.050 | 0.044 | 0.044 | 1.000 | 1.000 | 1.000 |
| 10% | 0.106 | 0.094 | 0.110 | 1.000 | 1.000 | 1.000 |
| 20% | 0.186 | 0.178 | 0.224 | 1.000 | 1.000 | 1.000 |

Note: The reported are the rejection frequencies over 500 simulations.

The results presented in Table B.3 show that the bootstrap test has quite an accurate size across all null hypotheses regardless of $n$. Furthermore, the test exhibits superb power which increases with the sample size, as expected.

# C Additional Results

In this section, we briefly comment on the results corresponding to hedonic attributes other than the distance to rock mine included in the estimated house price function. Their fixed parameter estimates (with bootstrap confidence bounds) across quantiles of the house price distribution are reported in Table C.1. For the estimates of median marginal effects of statistically significant covariates, see Table C.2. Among these non-distance variables, log square footage of house, log acreage and story height are the only ones consistently found to be significant across all estimated quantiles of the house price distribution. Interestingly, no other house attribute has a significant impact on property values in the 0.95th quantile. Houses in this top quantile include older (historic) houses in Delaware City as well as recently built McMansion-style houses. More generally, we find that the number of bedrooms and bathrooms in the house, the presence of an attic and the garage being attached to the main house are largely statistically insignificant across all quantiles which

[20] We have also experimented with lattices of larger sizes where spatial units are allocated on squares randomly as well as with simpler one-dimensional "circular" spatial structures. The results change little.

Table C.1. Semiparametric Estimates of Constant Parameters on House Attributes in the Conditional Quantile Regression of Property Value across Quantiles

| | *Quantiles of Property Value* | | | |
|---|---|---|---|---|
| | 0.25th | 0.50th | 0.75th | 0.95th |
| Log Sq. Footage | **0.59100** | **0.58160** | **0.59024** | **0.58871** |
| | (0.53217; 0.64599) | (0.53713; 0.62548) | (0.54446; 0.63067) | (0.49993; 0.74361) |
| Log Acreage | **0.04253** | **0.06913** | **0.08138** | **0.09038** |
| | (0.01883; 0.06745) | (0.04775; 0.08817) | (0.06252; 0.09893) | (0.02675; 0.11778) |
| Story Height | **–0.05092** | **–0.09042** | **–0.09235** | **–0.13096** |
| | (–0.09016; –0.00927) | (–0.11479; –0.06307) | (–0.11880; –0.06453) | (–0.18673; –0.05093) |
| # Bedrooms | –0.00629 | –0.01029 | –0.02846 | –0.14829 |
| | (–0.14271; 0.10882) | (–0.11146; 0.08000) | (–0.11103; 0.06366) | (–0.35613; 0.20943) |
| # Bedrooms$^2$ | –0.00420 | –0.00227 | 0.00006 | 0.01576 |
| | (–0.02006; 0.01373) | (–0.01471; 0.01206) | (–0.01374; 0.01176) | (–0.03296; 0.04323) |
| # Bathrooms | 0.06181 | **0.06611** | 0.00290 | –0.03061 |
| | (–0.00550; 0.12941) | (0.01357; 0.11258) | (–0.05774; 0.05336) | (–0.14870; 0.09881) |
| # Bathrooms$^2$ | –0.00041 | 0.00180 | **0.01322** | **0.02173** |
| | (–0.00877; 0.00853) | (–0.00366; 0.00784) | (0.00655; 0.02102) | (0.00243; 0.03575) |
| Full Basement | **0.17764** | **0.11541** | **0.10999** | 0.07606 |
| | (0.12002; 0.23109) | (0.07540; 0.15296) | (0.08254; 0.14185) | (–0.01222; 0.22164) |
| Partial Basement | **0.14850** | **0.07297** | **0.06104** | 0.01918 |
| | (0.09096; 0.20614) | (0.03693; 0.11070) | (0.03572; 0.09072) | (–0.06952; 0.15137) |
| Attic | 0.02001 | 0.00833 | **0.02287** | 0.01788 |
| | (–0.00580; 0.04998) | (–0.01016; 0.02775) | (0.00395; 0.04785) | (–0.03912; 0.08237) |
| Attached Garage | 0.02530 | 0.01621 | –0.03072 | –0.11543 |
| | (–0.03024; 0.07103) | (–0.01856; 0.04644) | (–0.07117; 0.00431) | (–0.23245; 0.04623) |
| Garage Capacity | **0.02446** | **0.02412** | **0.02613** | 0.03682 |
| | (0.00620; 0.04629) | (0.01226; 0.03812) | (0.01350; 0.04132) | (–0.02873; 0.07669) |
| # Fireplaces | **0.05920** | **0.05461** | **0.03577** | 0.02552 |
| | (0.03759; 0.08208) | (0.03640; 0.07530) | (0.01886; 0.05363) | (–0.02504; 0.08159) |
| Central A/C | **0.13311** | **0.11955** | **0.08045** | 0.01313 |
| | (0.06906; 0.19630) | (0.05463; 0.17715) | (0.03524; 0.13024) | (–0.09633; 0.11826) |
| Age | **–0.00603** | **–0.00464** | **–0.00258** | –0.00108 |
| | (–0.00793; –0.00372) | (–0.00611; –0.00313) | (–0.00400; –0.00120) | (–0.00490; 0.00250) |
| Age$^2$ | **0.00001** | **0.00001** | **0.00001** | 0.00001 |
| | (0.00000; 0.00003) | (0.00000; 0.00003) | (0.00000; 0.00002) | (–0.00002; 0.00003) |

Reported are the estimates from a semiparametric PLSQAR model. The 95% bootstrap (percentile) confidence bounds in parentheses. Statistically significant estimates are in bold.

likely is due to property heterogeneity inherent with rapid urbanization. Among the statistically significant house attributes, the square footage has by far the largest marginal effect on the property value with its magnitude declining as the house price rises. We document a similar declining marginal effects (across quantiles) for the basement variables, the number of fireplaces and the presence of central air-conditioning system in the house. From Table C.2, it appears that garage capacity is equally valued by all home buyers regardless of the property value, whereas the lot size exhibits increasing importance for buyers of higher priced houses. The estimates of the total marginal effects of story height are negative across all quantiles with larger (absolute) magnitudes estimated at the higher house price quantiles. This likely is an artifact of changing consumer preferences as well as building trends in the area given that single-story houses have become more common in recent years.

Table C.2. Semiparametric Estimates of Median ME of Selected House Attributes on Conditional Quantiles of Property Value across Quantiles

| | *Quantiles of Property Value* | | | |
|---|---|---|---|---|
| | 0.25th | 0.50th | 0.75th | 0.95th |
| Log Sq. Footage | | | | |
| *TME* | 0.8961 | 0.8467 | 0.7950 | 0.7882 |
| *Median DME* | 0.6048 | 0.5928 | 0.5976 | 0.5958 |
| *Median IME* | 0.2914 | 0.2540 | 0.1974 | 0.1925 |
| Log Acreage | | | | |
| *TME* | 0.0645 | 0.1007 | 0.1096 | 0.1210 |
| *Median DME* | 0.0435 | 0.0705 | 0.0824 | 0.0915 |
| *Median IME* | 0.0210 | 0.0302 | 0.0272 | 0.0295 |
| Story Height | | | | |
| *TME* | –0.0772 | –0.1316 | –0.1244 | –0.1753 |
| *Median DME* | –0.0521 | –0.0922 | –0.0935 | –0.1325 |
| *Median IME* | –0.0251 | –0.0395 | –0.0309 | –0.0428 |
| Full Basement | | | | |
| *TME* | 0.2694 | 0.1680 | 0.1481 | 0.1018 |
| *Median DME* | 0.1818 | 0.1176 | 0.1114 | 0.0770 |
| *Median IME* | 0.0876 | 0.0504 | 0.0368 | 0.0249 |
| Partial Basement | | | | |
| *TME* | 0.2252 | 0.1062 | 0.0822 | 0.0257 |
| *Median DME* | 0.1520 | 0.0744 | 0.0618 | 0.0194 |
| *Median IME* | 0.0732 | 0.0319 | 0.0204 | 0.0063 |
| Garage Capacity | | | | |
| *TME* | 0.0371 | 0.0351 | 0.0352 | 0.0493 |
| *Median DME* | 0.0250 | 0.0246 | 0.0265 | 0.0373 |
| *Median IME* | 0.0121 | 0.0105 | 0.0087 | 0.0120 |
| # Fireplaces | | | | |
| *TME* | 0.0898 | 0.0795 | 0.0482 | 0.0342 |
| *Median DME* | 0.0606 | 0.0557 | 0.0362 | 0.0258 |
| *Median IME* | 0.0292 | 0.0238 | 0.0120 | 0.0083 |
| Central A/C | | | | |
| *TME* | 0.2018 | 0.1741 | 0.1084 | 0.0176 |
| *Median DME* | 0.1362 | 0.1219 | 0.0814 | 0.0133 |
| *Median IME* | 0.0656 | 0.0522 | 0.0269 | 0.0043 |

Reported are the medians of point estimates of MEs from the PLSQAR model estimated for a given conditional quantile of property value.

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