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What is the Effect of Rock Quarries on Home Prices? An Empirical Analysis of Three Cities

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Abstract: For many Americans, a home is their most valuable asset. Naturally, the threat of a reduction in home values causes concern, which leads to opposition to several sorts of economic development projects and essential infrastructure. Opposition to rock quarries is one example. Evidence on the effects of quarries on home values is scant; the studies are often limited to a single city, leading to questions about generalizability, and use home sales occurring long after the quarry begins operations, introducing selection bias. In this POLICY PAPER, I apply multiple empirical methods to data on homes sales from three cities in Ohio. I find no evidence to suggest quarries reduce home values. I also offer evidence to suggest that the typical approach to quantify such effects—a home's distance from the quarry—may be unreliable given the idiosyncrasies of real estate markets.

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I. Introduction

Hedonic models of home prices seek to explain sales prices by accounting for housing characteristics (e.g., square footage, acres, and so forth) and other factors that affect home values. Typically included in the set of covariates is the distance from a city's center or its central business district ("CBD"), or several such districts, with the expectation that home prices fall as distance from these employment centers rises.[1]

Along the same lines, researchers sometimes include the distance to an amenity or disamenity—a beach, an airport, a landfill—to quantify the effect of proximity to such establishments on home values.[2] For instance, rock quarries are sometimes subject to "not in my backyard" ("NIMBY") resistance due to their alleged effect on home values. Yet, research on the effect of rock quarries on home values is scarce. Opposition to quarries based on home valuations relies almost universally on Hite (2006), a brief report analyzing data from a few thousand homes sales around a single quarry in Delaware, Ohio.[3] Using an unconventional regression model and data on transactions within five miles of the quarry occurring decades after the quarry opened, the report finds a positive relationship between home prices and distance from the quarry. In contrast to Hite (2006), Rabianski and Carn (1987), Dorrian and Cook (1996), Bureau of Mines (1981), Grant (2017) and various other reports find no consistent relationship between

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1 The "monocentric" assumption originated in the works of W. Alonso, LOCATION AND LAND USE: TOWARD A GENERAL THEORY OF LAND RENT (1964); E.S. Mills, STUDIES IN THE STRUCTURE OF THE URBAN ECONOMY (1972); R.F. Muth, CITIES AND HOUSING: THE SPATIAL PATTERN OF URBAN RESIDENTIAL LAND USE (1969).

2 *See*, *e.g*., J.P. Cohen and C.C. Coughlin, *Spatial Hedonic Models of Airport Noise, Proximity, and Housing Prices*, FEDERAL RESERVE BANK OF ST. LOUIS WORKING PAPER No. 2006-026 (2006) (available at: https://research.stlouisfed.org/wp/more/2006-026); M. Rahmatian and L. Cockerill, *Airport Noise and Residential Housing Valuation in Southern California: A Hedonic Pricing Approach*, 1 INTERNATIONAL JOURNAL OF ENVIRONMENTAL SCIENCE AND TECHNOLOGY 17–25 (2004) (available at: https://doi.org/10.1007/BF03325812); M. Thayer, H. Albers, and M. Rahmatian, *The Benefits of Reducing Exposure to Waste Disposal Sites: A Hedonic Valuation Approach*, 7 JOURNAL OF REAL ESTATE RESEARCH 265-282 (1992); R.B. Palmquist, *Estimating the Demand for the Characteristics of Housing*, 66 REVIEW OF ECONOMICS AND STATISTICS 394-404 (1984); P. Graves, J.C. Murdoch, M.A. Thayer and D. Waldman, *The Robustness of Hedonic Price Estimation: Urban Air Quality*, 64 LAND ECONOMICS 220-233 (1988).

3 For a discussion of the Hite (2006) model, *see* G.S. Ford and R.A. Seals, *Quarry Operations and Property Values: Revisiting Old and Investigating New Empirical Evidence*, PHOENIX CENTER POLICY PAPER NO. 53 (March 2018) (available at: https://www.phoenix-center.org/pcpp/PCPP53Final.pdf).

property values and proximity to a quarry.[4] Two recent studies offer conflicting evidence. Malikov, Sun and Hite (2018) look again at home prices around the quarry in Delaware, Ohio, and report price attenuation for homes nearer the quarry. Ford and Seals (2018) estimate plausibly causal effects for two quarries using Difference-in-Differences ("DiD") and find no effect of the quarry on home prices. Also, Ford and Seals (2018) study the Delaware quarry and find no effect of the quarry on home values, though the available data precluded a DiD analysis for this quarry.[5]

In this POLICY PAPER, I return to the question of the effect of rock quarries on home prices, although many of our findings are also relevant for any other sorts of spatially-centered disamenities. Given the idiosyncrasies of real estate markets across cities, there is little reason to suspect the results on a single quarry can be generalized to other cities. Here, I use data on three cities in Ohio, including, once more, the city of Delaware. Estimates of the effects are based on Ordinary Least Squares regression ("OLS"), Robust Regression ("RREG"), Quantile Regression ("QREG"), Spatial Regression ("SREG"), and Semiparametric Regression ("SPR"). As in most studies of disamentities and rock quarries, all home sales occur after the quarry began operations, so selection bias may be an issue. Like Hite (2006) and Malikov, Sun and Hite (2018), I am unable to make causal claims. Nonetheless, this sort of evidence is routinely used to address the effect of quarries on home values, so it is worth undertaking such analysis.

To establish expectations, I begin with an analysis of the geographic scope of quarry blasting, since blasting is a root cause of the disamenity nature of a quarry. This analysis, based on standard methods, reveals a narrow geographic impact of blasting (less than one-half mile across a wide range of charge strengths). For the three quarries, I find no attenuation of prices based on proximity to the quarry. I likewise evaluate the statistical validity of distance-from-site variables in econometric models. As in Ford and Seals (2018), Randomized Inference reveals that these sorts of models can produce very high rejection rates for the distance-

4 A.M. Dorrian and C.G. Cook, *Do Rock Quarry Operations Affect Appreciation Rates of Residential Real Estate*, Working Paper (1996); J. Rabianski and N. Carn, *Impact of Rock Quarry Operations on Value of Nearby Housing, Prepared for the Davidson Mineral Properties* (August 25, 1987); M. Radnor, D. Hofler, et al., *Social, Economic and Legal Consequences of Blasting in Strip Mines and Quarries*, U.S. Bureau of Mines (May 1981); A. Grant, *Estimating the Marginal Effect of Pits and Quarries on Rural Residential Property Values in Wellington County, Ontario: A Hedonic Approach*, Master's Thesis, University of Guelph (June 2017).

5 Ford and Seals (2018) also demonstrate that the positive results in Hite (2006) may be due to the unconventional estimation method.

from-site variable, suggesting distance-from-site models tend to over-reject the null hypothesis (of no effect). These empirical distributions of distance-from-site coefficients are typically quite wide, encompassing even very large distance-from-site coefficients. Some analysis of the data used in Malikov, Sun and Hite (2018), which is, in part, publicly available, is also provided, revealing sign changes on the distance-from-quarry coefficient under plausible circumstances.

II. Background

There exists a large literature on the effect of disamenities, like airports and landfills, on home values. Rock quarries have received less attention, though "not in my backyard" ("NIMBY") resistance to quarries or quarry expansions is commonplace. Opponents of the quarries, normally residents in the city or county of operation, must rely on scant evidence to support their positions on home valuations. Two analyses are typically offered to support resistance: (1) a six-page description of results from a consulting report by Hite (2006); and (2) a more thorough study of the same quarry (using later data) by Malikov, Sun, and Hite (2018).[6] Only the latter study provides a detailed accounting of the data and analyses, though much of the NIMBY resistance relies on Hite (2006). These reports, like most studies of (dis)amenities, rely on the "distance-from-site" methodology in a hedonic framework. To counter the NIMBY claim, quarry advocates sometimes rely on Ford and Seals (2018), among other studies, which finds no effect (either mere correlation or causal) of quarries on home prices.

Data on sales prices used by Hite (2006) and Malikov, Sun, and Hite (2018) are for sales occurring long after the quarry began operations; the quarry in Delaware, Ohio, opened in 1904. Malikov, Sun and Hite (2018) use data on home sales across the entire county, so much of the sample is for sales many miles from the quarry; the data also span multiple cities. Since quarries are not randomly sited and are often located in rural areas where land prices, home prices, and housing density are low, there is the obvious problem of selection bias.[7] While Malikov, Sun, and Hite (2018) use a sophisticated econometric approach, nothing in the model

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[6] A summary presentation of results for a student project by Sun (2018) on the effects of a surface mine (for gold and silver), for which there is no accompanying paper and no detailed description of the data or methods, is sometimes cited, though mineral mines use very different techniques than do rock quarries. B. Sun, *An Econometric Analysis of the Effect of Mining on Local Real Estate Values*, Unpublished Presentation (Undated).

[7] With the founding literature on home prices suggests prices fall as distance from the city center increases, it is little surprise that home prices may be lower around rock quarries located on the edge of town.

addresses selection bias so there can be no claim of a causal impact, and the authors never formally make a causal claim (though infer it).[8] In large part, the study appears to be more a presentation of a novel econometric methodology (semiparametric quantile spatial regression) than an attempt to quantify the causal effect of a quarry on home values. That is, the study is of academic interest more than of policy interest. Also, Ford and Seals (2018) find no effect of the Delaware quarry on homes prices, and I confirm that result here.

When looking at a single quarry, the generalizability of the result to other quarries is questionable. As demonstrated by Ford and Seals (2018), and again here, the coefficient on a distance-from-site covariate, which tend to statistically significance, may simply reflect the idiosyncrasies of individual real estate markets. Here, I look at three quarries to shed light on the generalizability of the findings.

A. *The Challenge and Advantages of Causal Analysis*

Though common in the literature, distance-from-site models have several serious shortcomings. First, there is selection bias. Available data for home sales often covers periods long after the amenity or disamenity is in place, precluding reliable causal estimation by methods such as Difference-in-Differences ("DiD").[9] Since the location of an amenity or disamenity is presumably not random, the risk of spurious correlation in distance-from-site relationships is high. Does the quarry reduce home prices, or are quarries located in areas where home prices are low? Studies like Hite (2006) and Malikov, Sun, and Hite (2018) cannot say, and my analysis here suffers from the same problem.

Disamenities are often placed away from population centers and where land prices (and thus home prices) are lower. Rock quarries often occupy hundreds of acres, so they are often places where land prices are lower, subject to the desirability of the geography. Public policy also influences site selection and (dis)amenities are sometimes clustered, thus making identification of a single (dis)amenity difficult. For instance, the quarry in Delaware, Ohio, sits on the edge of the city, adjacent to the municipal airport and an outdoor shooting range. Second, the available data on home characteristics varies among county assessors, so omitted variables may be a problem. Third, real estate markets are complex;

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8 The same holds for the Hite (2006) study.

9 *See*, *e.g.*, J.D. Angrist and J. Pischke, MOSTLY HARMLESS ECONOMETRICS: AN EMPIRICIST'S COMPANION (2009); J.D. Angrist and J. Pischke, MASTERING METRICS: THE PATH FROM CAUSE TO EFFECT (2014); S. Cunningham, CAUSAL INFERENCE: THE MIXTAPE (2021); G.S. Ford and R.A. Seals, *supra* n. 3.

home values rise or fall from nearly any location, irrespective of the presence of an amenity or disamenity. Ford and Seals (2018) show that the null hypothesis (no effect) for a distance-from-site coefficient from nearly any location in a city is rejected at rates far exceeding the alpha level of the test. This finding forces the question about how unusual the estimated distance-from-site coefficient really is, irrespective of its statistical significance.

While I do not conduct a DiD analysis of home values here, a concise review of DiD analysis sheds light on why the distance-from-site approach is prone to bias. It also reveals the condition that must be satisfied for the results of such analysis to render a plausibly causal effect. Let us consider a hypothetical scenario. Say a quarry receives approval to begin operations on the outskirts of town. For several reasons, quarries are typically and intentionally located away from housing density where land prices are low. Before even the planning phase of the quarry, assume the average (quality-adjusted) price for a home near the quarry site is $95,000, and the average price is $100,000 for homes far from the future quarry site. This 5% price difference cannot be due to the quarry because the lower average price is present prior to the quarry even being proposed (by assumption).

After the quarry initiates operations, homes are bought and sold, and the prices are observed. Assume, for now, that the quarry has *no effect* on property values (and average prices do not change). If a researcher looked only at post-operations prices, then a 5% price difference is observed, though, by assumption, this price difference is not due to the quarry as the difference preceded the quarry. Nonetheless, this difference may be attributed falsely to the quarry. (The same would be true if home prices near the quarry were initially 5% higher than those far away).

The *true* effect of the quarry on home prices is revealed by the Difference-in-differences estimator,

$$\delta = (P_1^N - P_0^N) - (P_1^F - P_0^F)\,, \tag{1}$$

where δ is the DiD estimator, P is price before (0) and after (1) the quarry begins operations for houses near (N) and far (F) from the quarry. In this "no effect" case, the DiD estimator is zero [(95,000 – 95,000) – (100,000 – 100,000) = 0], correctly identifying the causal effect of the quarry. Using only post-operation prices, the calculated statistic from empirical analysis is,

$$\Delta = P_1^N - P_1^F\,, \tag{2}$$

where Δ equals δ only when $P_0^N - P_0^F = 0$, which seems unlikely given the economics and policies related to siting a quarry. In this hypothetical, the Δ coefficient equals -\$5,000, which is not the effect of the quarry. Thus, when a quarry's effect on home prices draws conclusions from an estimate of Δ and not δ, no plausible claim of a causal effect is possible.

As an alternative scenario assume that the quarry reduces prices for nearby homes to \$90,000 (a reduction of \$5,000), with more distance home prices remaining constant. Looking only at post-quarry transactions materially overstates the effect size [90,000 - 100,000 = -10,000], with selection bias accounting for a \$5,000 overstatement. The DiD estimator, contrariwise, accurately quantifies the effect of the quarry [(90,000 – 95,000) – (100,000 – 100,000) = -5,000]. Absent special circumstances, an analysis restricted to home sales after the quarry becomes operational cannot quantify reliably the effect of the quarry on home prices.

Conducting a DiD study on home values and quarry operations, while desirable if not necessary, is complicated by the fact many quarries near housing density are decades old and new quarries are almost always located in more rural areas where housing density is low. Even in instances where a new quarry site is selected, obtaining adequate price data on home sales near a quarry site is challenging given low housing density. I do not conduct a DiD analysis here; instead, I use the traditional hedonic models. As such, I can make no causal claims. Still, my analysis speaks to the issue using the methods commonly relied upon and addresses the reliability of existing estimates of a quarry's effects and to the use of distance-from-site covariates generally.

B. *Forming Expectations*

Central to the distance-from-site analysis is that the effects of the (dis)amenity are larger the closer is the home to the (dis)amenity, with presumably stronger effects near the quarry that dissipate over distance. It makes sense, therefore, to consider the practical distances over which a rock quarry's operations may be felt. Local resistance to rock quarries often focuses on the use of explosives that create ground vibrations and sound waves ("overpressure"), both of which can cause annoyance if not damage to property if sufficiently intense. (Other concerns include truck traffic and the water table.) Advances in blasting technology and operator care over the last thirty years has greatly diminished these effects, even if such advances have not reduced NIMBY resistance. An analysis on the geographic scope of blasting may shed light on the distances over which a quarry's operations may influence home values.

The geographic scope of the blasting on a quarry's neighbors is measured by ground vibrations and overpressure. Ground vibration is measured in terms of Peak Particle Velocity ("PPV"), which measures the movement of particles at the surface. Such vibrations may be felt at nearby homes and may cause cosmetic damage (e.g., drywall). A typical (empirical) equation for PPV is,

$$PPV = 160\left(\frac{D}{\sqrt{W}}\right)^{-1.6}, \tag{3}$$

where D is the distance from the charge in meters and W is the charge mass (maximum pounds per 8 millisecond delay).[10] While the parameters of the equation may vary by circumstances (e.g., vibration frequency, rock characteristics, the water table), the listed parameters are recommended absent field blast data at a particular site. The Bureau of Mines' standard for drywall damage is 0.75 inches per second.[11] Home damage is a serious concern, but there is also the potential for human annoyance. Studies suggest that the human perception for blast vibration ground motion is about 0.03 inch/s (0.80 mm/s) and that complaints are unusual below 0.08 inches/s (2.03 mm/s).[12] In a study of

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[10] The parameter selection is based on the INTERNATIONAL SOCIETY OF EXPLOSIVES ENGINEERS BLASTER'S HANDBOOK (18th Edition) (2011) at p. 567; *see also,* R. Kumar, D. Choudhury, and K. Bhargava, *Determination of Blast-Induced Ground Vibration Equations for Rocks Using Mechanical and Geological Properties*, 8 JOURNAL OF ROCK MECHANICS AND GEOTECHNICAL ENGINEERING 341-349 (2016) (available at: https://www.sciencedirect.com/science/article/pii/S167477551600024X).

[11] D.E. Suskind, M.S. Stagg, J.W. Kopp, and C.H. Dowding, *Structure Response and Damage Produced by Ground Vibration from Surface Mine Blasting*, United States Bureau of Mines RI-8507 (1980), Appendix B.

[12] *See*, *e.g.*, Suskind *et al.*, *id.*; T. Ongen, G. Konak, and D. Karakus, *Vibration Discomfort Levels Caused by Blasting According to Gender*, 7 ENVIRONMENTAL AND EARTH SCIENCES RESEARCH JOURNAL 109-115 (2020) (available at: https://www.iieta.org/journals/eesrj/paper/10.18280/eesrj.070303); B.T. Lusk, *An Analysis and Policy Implications of Comfort Levels of Diverse Constituents with Reported Units for Blast Vibrations and Limits: Closing the Communication Gap*, Ph.D. Thesis the Faculty of the Graduate School of the University of Missouri-Rolla in Mining Engineering (2006); Q. Yao, X. Yang, and H. Li, *Comparative Analysis on the Comfort Assessment Methods and Standards of Blasting Vibration*, 17 JOURNAL OF VIBROENGINEERING 1017-1036 (2015); A.K. Raina, M. Baheti, A. Haldar, M. Ramulu, A.K. Chakraborty, P.B. Sahu, C. Bandopadhayay, *Impact of Blast Induced Transitory Vibration and Air-Overpressure/Noise on Human Brain – An Experimental Study*, 14 INTERNATIONAL JOURNAL OF ENVIRONMENTAL HEALTH RESEARCH 143-14 (2004); A.K. Raina, A. Haldar, A.K. Chakraborty, P.B. Choudhury, M. Ramulu, and C. Bandyopadhyay, *Human Response to Blast-Induced Vibration and Air-Overpressure and Indian Sceranio*, 63 BULLETIN OF ENGINEERING GEOLOGY AND THE ENVIRONMENT 209-214 (2004); K. Medearis, *The Development of Rational Damage Criteria for Low-Rise Structures Subjected to Blasting Vibrations*, Final Report for the National Crushed Stone Association (1976).

human perception of blasting at a rock quarry, Ongen, Konak, and Karakus (2020) report perception occurring only at a PPV of 0.03 inches/s (0.80 mm/s), no annoyance at a PPV of 0.033 inches/s (0.84 mm/s), and slight annoyance at a PPV of 0.09 inches/s (2.27 mm/s).[13]

In addition to ground vibration, a blast produces a shock wave. This overpressure—the pressure (above normal atmospheric pressure) caused by a shock wave— may be felt and heard. Overpressure is measured in linear decibels ("dBL").[14] To limit structural damage to property, the U.S. Bureau of Mines sets a threshold of 133 dBL.[15] Again, the threshold for human annoyance may be different than that for structural damage. The U.S. Bureau of Mines sets the annoyance threshold at 120 dBL. In Australia and New Zealand, the Environmental Council sets the annoyance threshold at 115 dBL.[16] In studying sonic booms, NASA found that none of participants viewed as annoying a sonic boom producing a dBL of 121 and only 10% of respondents were annoyed by a boom of 128 dBL.[17] To avoid annoyance, NASA recommended a sonic boom should not exceed 125 dBL. Overpressure may be estimated using the formula,[18]

$$P = 164.8\left(\frac{D}{\sqrt[3]{W}}\right)^{-0.0696}. \tag{4}$$

Using these two formulae, it is possible to establish the distance from a quarry at which nearby residences and businesses may experience either structural damage or annoyance.

13 Ongen, *et al., id*.

14 dBL is a linear scale and thus different from the logarithmic scale typically used for sound.

15 D. E. Suskind, V.J. Stachura, M.S. Stagg, and J.W. Kopp, *Structure Response and Damage Produced by Airblast from Surface Mining*, United States Bureau of Mines RI-8485 (1979).

16 *Technical Basis for Guidelines to Minimise Annoyance Due to Blasting Overpressure and Ground Vibration*, Australian and New Zealand Environment Council (1990).

17 *Environmental Impact State for the Kennedy Space Center*, National Aeronautics and Space Administration (1979) at pp. 5-40.

18 Parameters are based on conversations with J. Straw, Vice President and Area Manager, GeoSonics, Inc. (https://www.geosonicsvibratech.com), which are based on testing at quarry locations. A typical charge weight for quarry operation is 78.75 kg/ft^3.

Table 1. Miles from Blast for Threshold PPVs and Overpressures

	PPV inch/s			Overpressure dBL		
W	**0.75**	**0.08**	**0.03**	**133**	**125**	**115**
50 kg	0.038	0.155	0.286	…	0.036	0.122
75 kg	0.047	0.190	0.350	…	0.042	0.140
100 kg	0.054	0.219	0.404	…	0.046	0.154
125 kg	0.060	0.245	0.452	0.020	0.050	0.166
150 kg	0.066	0.268	0.495	0.021	0.053	0.177
175 kg	0.071	0.290	0.535	0.023	0.056	0.186
200 kg	0.076	0.310	0.572	0.024	0.059	0.194

Table 1 summarizes the two measures for varying blast charges at different levels of PPV and Overpressure. For PPV, the values are 0.75 for drywall damage and 0.08 for annoyance and 0.03 for human detection. For overpressure, the values are 133 dBL for structural damage, 125 dBL based on NASA's threshold for annoyance, and 115 based on the Environmental Council's threshold for annoyance. The potential for damage is quickly exhausted (less than one-tenth of a mile), mild human annoyance is exhausted at less than one-third mile from the quarry, and human perception at about one-half mile. Overpressure does not appear to be problem for damage or annoyance at distances greater than two-tenths of a mile. The claim that a rock quarry affects homes prices up to ten miles, as reported by Malikov, Sun and Hite (2018) seems incredible, at least with respect to the influence of blasting.

C. *Randomized Inference*

Hedonic regression analysis with distance-from-site variables quantifies the relationship between home prices and distance from some location of interest. Usually, only a few distance-from-site variables are included in hedonic models. Yet, real estate markets are complex and may include a wide array of (dis)amenities. It is possible, if not likely, that in many cities a statistically-significant coefficient on a distance-from-site covariate will be observed from many locations, not simply the location(s) of a researcher's interest. Thus, rejecting the null hypothesis at a particular location using the traditional asymptotic approach (e.g., a t-test) may overstate how unusual is the price-to-distance relationship. Moreover, failing to account for all amenities, disamenities, or market idiosyncrasies (the latter being very difficult), the distance-from-site coefficient at one location may simply reflect the influence of another location.

Randomized Inference can shed some light on this problem. Randomized inference is a statistical technique that randomly assigns a treatment, in this case distance from a randomly-selected location, for the purpose of creating a reference distribution under the null hypothesis of "no effect."[19] How unusual a particular measured distance-from-site effect may be quantified by comparing the estimated coefficient (or its t-statistic) for a particular distance-from-site coefficient to this reference distribution. For instance, say the regression analysis indicates that a 10% increase in distance from a quarry reduces home prices by 5%, and this relationship has a one-tailed p-value of 0.05, allowing for the rejection of the null hypothesis of no effect. If, however, the effect of distance is also 5% for 30% of randomly-selected locations in a city, then the "true" one-tailed p-value would be 0.30 (or 60% in a two-tailed test), which does not permit a rejection of the null hypothesis (*i.e.*, the 5% effect is not very rare).

Property values rise and fall across the area of a city for a host of reasons, so testing for a price difference from a given location is prone to find prices rising or falling. Ford and Seals (2018), using data from Delaware, Ohio, find that a statistically significant coefficient on a distance-from-site variable is almost certain to appear. Selecting one thousand locations at random within a city, Ford and Seals (2018) find the null hypothesis of "no effect of distance" was rejected in 93% of cases at the 10% level. A statistically-significant positive or negative distance-from-site coefficient is almost guaranteed. Of course, the observed rejection rate may vary by city, model specification, variables included, and the estimation method.

I apply Randomized Inference for the cities in our sample. One thousand locations are randomly chosen, and a hedonic regression is used to estimate the distance-from-site coefficient. The distance-to-quarry coefficient can then be compared to this null-reference distribution to determine whether the coefficient indicates an "unusual" relationship by computing the one-tail p-values. Or, the estimated distance-to-quarry coefficient can be evaluated against the 90% or 95% confidence interval of the reference distribution, thus mimicking the traditional approach of using 10% or 5% significance levels.

19 R.A. Fisher, THE DESIGN OF EXPERIMENTS (1951).

III. Data

Data on home sales are obtained for three cities in Ohio of similar size: the cities of Delaware, Findlay, and Lima.[20] These data are obtained from the relevant county assessor's webpage. Prices from arms-length transactions of single-family homes within five miles of the quarry (as in Hite 2006) and on ten acres or less are included in the samples.[21] Data are obtained for years 2010 through 2021. Some summary statistics are provided in Table 2.[22] Prices and home sizes in Delaware are much higher than in the other cities, and home prices are correlated with median income.

Table 2. Cities in Sample

City	Sample Size	Average Price	Average Sqft	Average Price/Sqft	Population (2019)	Median Income (2019)
Findlay	2,843	154,227	1,600	95.4	41,335	51,002
Delaware	2,439	234,378	1,901	124.9	40,568	69,087
Lima	1,169	86,049	1,351	64.6	37,117	35,779

Delaware and Findlay are an interesting pair. The Delaware quarry is the only one analyzed in Hite (2006) and Malikov, Sun, and Hite (2018), and is also studied in Ford and Seals (2018). Like Delaware, the quarry in Findlay is in the Southwest corner of the city and sits adjacent to the municipal airport (a disamenity frequently studied in the literature). We might expect, therefore, similar results for the distance-from-site covariate in both cities. Note, however, that given these quarries' proximity to these other disamentities (an airport in both and an outdoor

[20] The locations of the quarries are: Findlay (41.013530, -83.690632); Delaware (40.281032, -83.136392); and Lima (40.751028, -84.083442). Delaware is in Delaware County; Findlay is in Hancock County; and Lima is in Allen County.

[21] A valid sale is an "arm's length, open market transaction as of a specific date whereby there is a willing buyer and seller, each acting in what he/she considers his/her best interest; a reasonable time is allowed for exposure in an open market; payment is made in terms of cash or comparable financial arrangements; and the price represents the normal consideration for the property sold unaffected by special or creative financing or sales concessions granted by anyone associated with the sale (https://wedge1.hcauditor.org/page/Glossary)." Valid sales are typically by Warranty Deed and these samples are restricted to Warranty Deeds or comparable deeds. Deeds such as Quit Claim and Survivorship Deeds are excluded since these deeds, while valid transfers, are not arms-length transactions. A minimum price of $10,000 is imposed and mobile homes are excluded.

[22] Population and income data available at: https://datausa.io. Also see home value statistics from Zillow: Findlay (https://www.zillow.com/findlay-oh/home-values); Delaware (https://www.zillow.com/delaware-oh/home-values); Lima (https://www.zillow.com/lima-oh/home-values).

shooting range in Delaware), it is impossible to say which "disamenity" might be correlated with lower home prices. Normally, we expect airports and shooting ranges to be sited away from higher-value housing, so low prices may simply reflect the choice of site rather than any causal effect on home prices. By most standards, the proximity to another disamenity (or two) would disqualify the city for analysis, but these prior studies on the Delaware quarry have ignored this possibility.

As is standard in hedonic models of home prices, data is collected on a variety of home characteristics. Some county assessors provide more detail than others and the lack of some characteristics may lead to omitted variables bias and fail to address selection bias. Home and area characteristics included, when possible, are square footage, acreage, indicators for the number of bedrooms and (full and half) bathrooms, basement square footage, an indicator for single-story homes, indicators for the number of fireplaces (one, two, or three or more), the age of the home at the sale date, an indicator for homes remodeled in the ten years prior to the sale, the distance (in miles) to the city center and the rock quarry, indicators for the assessor's grade of the quality of construction materials and the condition of the home, indicators for the type of garage (attached, detached, finished, unfinished), and sale-year fixed effects. Demographic data on median income, the share of the White population, and the share of vacant homes is also used.[23]

IV. Regression Model

Home prices are affected by many factors, so I proceed with multivariate regression analysis. As is standard, the regression model takes the general form,

$$P_{it} = \Delta M_i + \beta X_{it} + \alpha Z_{it} + \tau_t + \varepsilon_{it} \ , \tag{5}$$

where P_i is the sale price of home i at time t, M_i is the home's distance in miles from the rock quarry, X_{it} is a vector of home- and transaction-specific characteristics such as square footage, acres, and distance from the city center, Z_{it} is a vector of area characteristics such as median income, τ_t is a year fixed effect, and ε_{it} is the econometric disturbance term. As home prices vary considerably, the dependent variable is the natural log of price. Standard errors are clustered at the census tract level when feasible. The same model is used for OLS, RREG, and QREG.

Housing markets are an archetype case of spatial correlation—the price of a home depends, in part, on the prices of nearby homes (which also affect the

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[23] Data available at: https://docs.safegraph.com/docs/open-census-data.

valuation for mortgage approval). In OLS, the assumption is that the disturbances (ε) are independent, so the presence of spatial relationships requires an alternative estimation approach. Failing to account for these spatial relationships represents a form of omitted variables bias (though there are other justifications for spatial regression), which may or may not bias the coefficients.[24] For all cities in this analysis, Moran's test indicates the presence of spatial correlation. So, in addition to the traditional regression analysis, I perform spatial regression including a spatially-lagged dependent variable and spatial errors (a Spatial Durbin Model, or "SDM"). Spatial analysis is based on a row -normalized spatial weight matrix (W) where distance is truncated at three miles. The spatial regression model is,

$$\begin{aligned} P_{it} &= \Delta M_i + \beta X_{it} + \alpha Z_{it} + \tau_t + \theta WP + \mu_{it} \\ \mu_{it} &= \lambda_t W \mu_{it} + \varepsilon_{it} \end{aligned} , \tag{6}$$

where WP is the spatial lag of price and μ_{it} is the spatial error term. With a spatial regression model, the effect of a variable has a direct, indirect, and total effect, though here the sign on the Δ coefficients are of primary interest. For comparison purposes, I also estimate the Spatial Lag Model ("SAR"),

$$P_{it} = \Delta M_i + \beta X_{it} + \alpha Z_{it} + \tau_t + \theta WP + \mu_{it} \ , \tag{7}$$

and the Spatial Error Model ("SEM"),

$$P_{it} = \Delta M_i + \beta X_{it} + \alpha Z_{it} + \tau_t + \lambda W \varepsilon_i + \mu_{it} \ . \tag{8}$$

I also estimate a semiparametric relationship between home prices and quarry-distance,

$$P_{it} = g(M_i) + \beta X_{it} + \alpha Z_{it} + \tau_t + \theta WP + \nu_{it} \ , \tag{9}$$

where $g(M_i)$ permits a non-parametric and flexible relationship between prices and quarry distance. Since g(Mi) is not a parameter, the semi-parametric results are graphed (though confidence intervals may be computed). The other covariates enter parametrically and include the WP regressor (the spatial lag).

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[24] *See, e.g.*, J. LeSage and R.K. Pace, INTRODUCTION TO SPATIAL ECONOMETRICS (2008); M.D. Ward and K.S. Gleditsch, SPATIAL REGRESSION MODELS (2018).

Outliers are a potential problem in home sales data due to the idiosyncrasies of transactions and perhaps coding problems. I have tried to limit such problems by looking only at arms-lengths transactions, but it may be worth evaluating the effect of potential outliers. I mark outliers as those transactions with a Cook's D exceeding $4/N$.[25] RREG and QREG are also employed to limit the effect of outliers.

A. *Findlay, Ohio*

I begin my analysis with Findlay, Ohio, in Hancock County. The county assessor provides extensive data on home characteristics. Like Delaware, the quarry in Findlay is in the Southwest corner of the city and adjacent to the municipal airport. Presumably, if the distance-to-quarry coefficient truly measures the effect of the quarry, then the Δ coefficients should be similar across the two cities. For Findlay, there are 2,843 homes sales meeting the sample restrictions over the 2010-2021 period. There are two distance-from-site covariates (measured in miles) including distance from the city center and distance from the rock quarry. About 5.6% of sales are identified as outliers based on Cook's D; these outliers are marked with a dichotomous indicator.

Four models are estimated including two by OLS (with one including the outlier indicator), one by RREG and another by QREG. Given the large number of covariates, a detailed summary of the estimates is placed in Appendix A (for all models and cities). The estimated coefficients are mostly as expected. Home prices rise in square footage and acreage, fall in age, and rise over time. Prices are higher as the condition of the home is better.

Table 3. Summary of Regression Results, Findlay

Variable	Model A OLS	Model B OLS	Model C RREG	Model D QREG
ln(Quarry Dist.)	-0.030	-0.033	-0.031***	-0.042***
ln(City Center Dist.)	0.011	0.001	0.032***	0.034***
ln(sqft)	0.386***	0.409***	0.484***	0.482***
ln(acres)	0.041	0.086**	0.067***	0.059***
Outlier Indicator	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Standard Errors	Clustered	Clustered	…	Robust
Observations	2,843	2,843	2,843	2,843
R^2	0.645	0.723	0.838	…

Stat. Sig. * 10% ** 5% *** 1%

[25] R.D. Cook, *Detection of Influential Observations in Linear Regression*, 19 TECHNOMETRICS 15-18 (1977).

Table 3 provides a summary of the results for a few key parameters. As expected, the coefficient on square footage is positive, large, and statistically significant at better than the 1% level; prices rise with larger lots. A positive coefficient is estimated for the distance-from-city center covariate, but the coefficient is statistically different from zero only in RREG and QREG. Turning to the quarry, the quarry-distance variable has negative coefficients across the board suggesting home prices fall as distance-from-the-quarry increases. The quarry-distance coefficients are statistically different from zero only in Models C and D. Home prices, conditioned on many variables, tend to be lower as distance from the quarry increases.

Table 4. Summary of Spatial Regression Results, Findlay

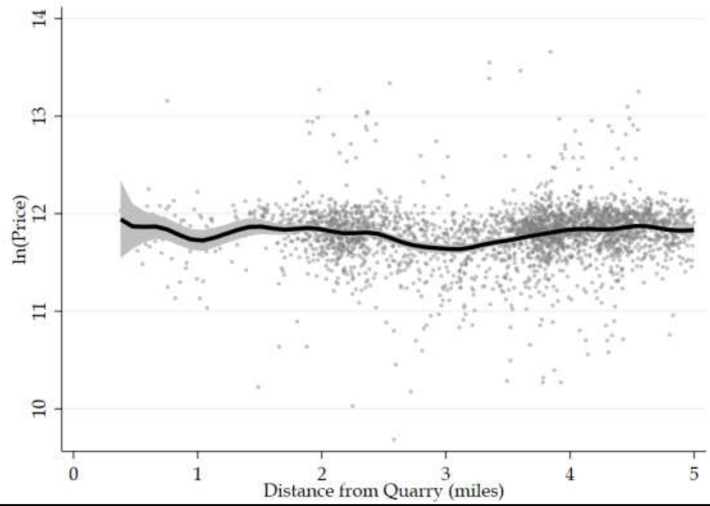
Variable	Model E SDR	Model F SDR	Model G SAR	Model H SEM
ln(Quarry Dist.)	-0.030	-0.036	-0.009	-0.056**
ln(City Center Dist.)	-0.027	-0.042**	-0.001	0.011
ln(sqft)	0.345***	0.366***	0.341***	0.361***
ln(acres)	0.038**	0.085***	0.015	0.107***
Spatial Lag	0.912***	0.907***	0.880***	…
Spatial Error	0.941***	0.953***	…	3.012***
Outlier Indicator	No	Yes	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes
Standard Errors	Robust	Robust	Robust	Robust
Observations	2,843	2,843	2,843	2,843

Stat. Sig. * 10% ** 5% *** 1%

Turning the spatial regression model, Moran's test statistic is 144.3, which is statistically significant at the 1% level. As expected, the data are spatially related. A summary of Spatial Regression results is provided in Table 4; standard errors are robust to heteroskedasticity. Again, the coefficients on the quarry-distance covariate are negative and of similar size to the non-spatial models, but now most of the coefficients are statistically insignificant. Only in the SEM variant is the quarry-distance coefficient statistically different from zero (at the 5% level). In the spatial models, home prices are mostly uncorrelated with distance from the quarry.

I turn now to semiparametric regression where the relationship between prices and quarry distance is non-parametric. For ease of interpretation, the distance from the quarry covariate is measured in miles (not its natural log). Results are illustrated in Figure 1, which includes the confidence interval. Consistent with the regression analysis, prices tend to fall as distance from the quarry increases, though the effect is small. The low housing density near the quarry is apparent in the scatter plot and the large confidence interval around the estimated relationship when near the quarry. While some statistically significant coefficients are found, across all the models there is very little evidence to suggest the quarry is affecting home prices.

Figure 1. Semiparametric Regression, Findlay



Following Ford and Seals (2018), an empirical distribution of a distance-from-site coefficient is crafted using Randomized Inference. One thousand locations are chosen randomly, and then the distance-from-site coefficient is estimated.[26] The quarry-distance covariate is excluded (but replaced by the distance from the random site) but all other variables are included in the regression, so the model most closely resembles Model A from Table 3 with a coefficient on the quarry-distance variable of -0.030 with a p-value of 0.285. The 95% confidence interval on the simulated coefficient distribution is -0.095 to 0.074, a wide range that easily encompasses the coefficient value of -0.030. The -0.03 coefficient cuts off 26.1% of the empirical distribution (a one-tail cutoff, a two-tail p-value of 52.2%). Across all simulations, the null hypothesis for the coefficient on simulated locations is rejected 11.8% of the time at the 10% level for tract-clustered errors, which is close to the alpha level. For robust standard errors, the rejection rate is 33.6%, more than three-times the alpha level. The choice of standard errors is important. These rejection rates are well below that reported in Ford and Seals (2018), suggesting randomized inference may produce different rejections rates in different cities (confirmed *infra*) and for models with different covariates (our model has many more covariates than in Ford and Seals 2018). For instance, removing the census-

[26] The maximum distance from the city center in the sample is six miles, so the random locations are chosen within five miles of the city center.

level variables from the model increases the rejection rates to 16.9% for clustered and 58.2% for robust standard errors.

B. *Delaware, Ohio*

Like Hite (2006), Malikov, Sun, and Hite (2018), and Ford and Seals (2018), data on home prices from the city of Delaware, Ohio, are analyzed. The sample include 2,439 home sales subject to the established criteria. Like Findlay, the quarry is in the Southwest corner of the city and adjacent to the municipal airport, which perhaps should disqualify this city from analysis (there are two treatments). The outdoor shooting range just North of the quarry may represent a third treatment. Nonetheless, the city of Delaware has been studied before, so it worth looking at again.

Table 5. Summary of Regression Results, Delaware

Variable	Model I OLS	Model J OLS	Model K RREG	Model L QREG
ln(Quarry Dist.)	-0.019	-0.022	0.011	0.009
ln(City Center Dist.)	0.066**	0.049	0.063***	0.070***
ln(sqft)	0.557***	0.596***	0.530***	0.535***
ln(acres)	0076***	0.081***	0.090***	0.075***
Outlier Indicator	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Standard Errors	Clustered	Clustered	…	Robust
Observations	2,439	2,439	2,439	2,439
R^2	0.705	0.736	0.881	…

Stat. Sig. * 10% ** 5% *** 1%

Table 5 summarizes both the OLS, RREG and QREG results. About 6.4% of observations are marked as outliers. Prices rise in distance from the city center, square footage, and acreage. The Δ coefficients on the quarry-distance covariate are of mixed sign across model types but none are statistically different from zero and all are quite small. Homes prices are uncorrelated with distance from the quarry.

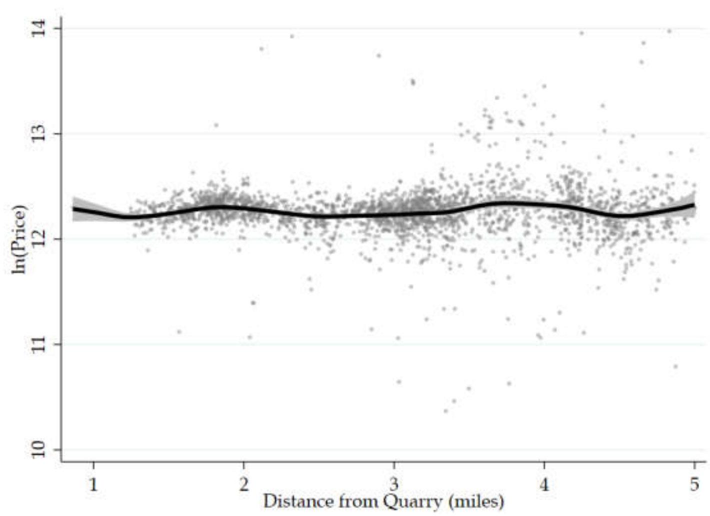
Table 6. Summary of Spatial Regression Results, Delaware

Variable	Model M SDR	Model N SDR	Model O SAR	Model P SEM
ln(Quarry Dist.)	-0.078*	-0.081**	-0.025	-0.034
ln(City Center Dist.)	0.088***	0.038*	0.014	0.072***
ln(sqft)	0.555***	0.582***	0.522***	0.551***
ln(acres)	0.067***	0.073***	0.070***	0.068***
Spatial Lag	-0.271***	-0.133	0.293***	…
Spatial Error	0.903***	0.915***	…	0.582***
Outlier Indicator	No	Yes	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes
Standard Errors	Robust	Robust	Robust	Robust
Observations	2,439	2,439	2,439	2,439

Stat. Sig. * 10% ** 5% *** 1%

Turning to the Spatial Regressions summarized in Table 6, Moran's test statistic is 120.7, which is statistically significant at the 1% level. For the spatial models, the coefficients on the quarry-distance covariate are always negative and statistically different from zero in the two OLS models. If anything, there is a decay in home prices as distance from the quarry increases.

Figure 2. Semiparametric Regression, Delaware



Semiparametric regression, illustrated in Figure 2, offers little more insight than does the regression analysis. Consistent with much of the regression analysis, there is no apparent relationship on prices as distance from the quarry increases, and the thin market near the quarry produces a wide confidence interval.

Randomized Inference is conducted using Model I to determine whether the coefficient is truly unusual. One thousand random locations are selected within seven miles of the city center including locations more than five miles from the quarry. The 95% confidence interval on the empirical coefficient distribution is -0.064 to 0.184, a very wide range that easily encompasses the coefficient value of -0.019 from Model I. The coefficient is not unusual at all, but the t-test indicates the same. Across all simulations, the null hypothesis for the coefficient on simulated locations is rejected 16.1% of the time at the 10% level for tract-clustered errors. For robust standard errors, the rejection rate is 38.5%. As in Ford and Seals (2018), rejection rates for distance coefficients are above the alpha level, though not as high as the earlier study reports.

C. *Lima, Ohio*

If the three quarries analyzed here, the quarry in Lima is closest to the city's center. Of the three cities, Lima has the smallest population and lowest median income, the lowest home prices, and the smallest homes. A sample of 1,169 home sales meeting the sample criteria are included in the analysis. Results are summarized in Table 7 for OLS, RREG, and QREG models. About 4.4% of sales are identified as outliers.

Table 7. Summary of Regression Results, Lima

Variable	**Model Q OLS**	**Model R OLS**	**Model S RREG**	**Model T QREG**
ln(Quarry Dist.)	0.019	-0.025	-0.110**	-0.018
ln(City Center Dist.)	0.085	0.081	0.074**	0.082*
ln(sqft)	0.490***	0.439***	0.537***	0.469***
ln(acres)	0.136**	0.124**	0.054	0.093**
Outlier Indicator	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Standard Errors	Clustered	Clustered	…	Robust
Observations	1,169	1,169	1,169	1,169
R^2	0.342	0.421	0.606	…

Stat. Sig. * 10% ** 5% *** 1%

For Lima, three of the four quarry-distance coefficients are negative but only one is statistically significant (RREG). The one positive coefficient is not statistically different from zero. In Lima, there is little-to-no evidence of the quarry being correlated with lower home prices. Prices rise as distance from the city center increases (with two of four coefficients statistically significant) and as home and lot sizes increase.

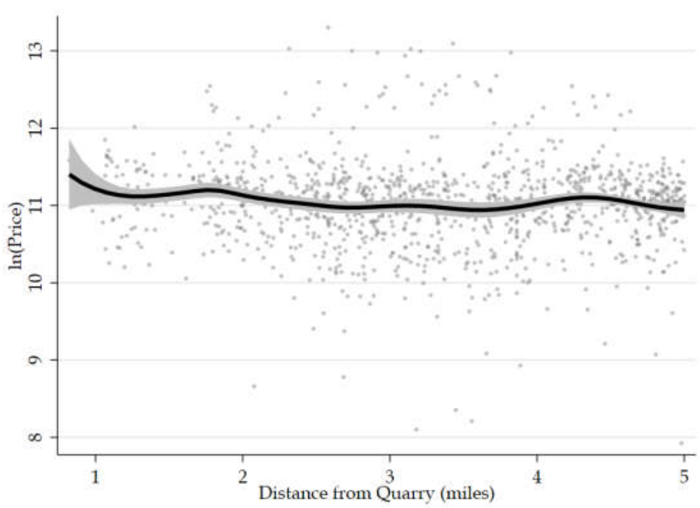
Table 8. Summary of Spatial Regression Results, Lima

Variable	Model U SDR	Model V SDR	Model W SAR	Model X SEM
ln(Quarry Dist.)	-0.065	-0.116	-0.073	-0.011
ln(City Center Dist.)	0.147*	0.158**	0.101**	0.182**
ln(sqft)	0.477***	0.424***	0.475***	0.484***
ln(acres)	0.141***	0.128**	0.138***	0.142***
Spatial Lag	0.520***	0.607***	0.589***	…
Spatial Error	0.234	0.132	…	0.621***
Outlier Indicator	No	Yes	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes
Standard Errors	Robust	Robust	Robust	Robust
Observations	1,169	1,169	1,169	1,169

Stat. Sig. * 10% ** 5% *** 1%

Results from the spatial regression (summarized in Table 8) are comparable. Moran test is 35.5 with probability less than 0.01. For the Spatial Regressions, the quarry-distance covariates are negative but never statistically different from zero at standard levels. Spatial models have very similar coefficients to the non-spatial models with the exception of the two distance variables (as might be expected).

Figure 3. Semiparametric Regression, Lima



Semiparametric regression, illustrated in Figure 3, shows declining prices as distance from the quarry increases, a result consistent with the regression analysis. Confidence intervals are again wide nearer the quarry. There is nothing in the figure, or in the regression results, to suggest that the quarry reduces home prices.

Nor do we expect that the quarry increases home prices but view the negative coefficients as largely an artifact of distance-from-site covariates. Indeed, Randomized Inference on Model Q produces an empirical distribution with a wide range. The 95% confidence interval of the distance coefficients is -1.45 to 1.38, whereas the coefficient on quarry-distance from Model Q is 0.02. The overall rejection for clustered errors is only 74.6% and 81.5% for robust standard errors. Plainly, the generalizability of distance-from-site models is suspect.

V. Analysis of Prior Evidence

A sketch of the data from the Malikov, Sun and Hite (2018) are available online.[27] The data do not permit a reproduction of the paper's results, so only a limited analysis of the data is permitted. For instance, parcels and their locations are not identified, precluding spatial analysis (though OLS and spatial regression produce similar results above). The data covers the entire county (not just Delaware city) and spans years 2009 through the third-quarter of 2011. The data does not include a distance-from-city-center variable or the year of sale indicators, which are omitted variables. There are 5,500 observations in the sample.

Using county level data includes homes quite distant from the quarry (as high 15 miles). In Hite (2006) and here, distance from the quarry was limited to five miles. Presumably, the effects, if any, of the quarry would be limited to a few miles, as suggested by the analysis above. So, I estimate the model when limiting the distance to the quarry to five miles (Model Z). Standard errors are clustered at the block-group level, since a variable in the dataset is block-group level. Results are summarized in Table 9.

Table 9. Summary of Regression Results

Variable	Model Y	Model Z
ln(Quarry Dist.)	0.068***	-0.124***
ln(sqft)	0.693***	0.662***
ln(acres)	0.089***	0.122***
Outlier Indicator	No	No
Year Fixed Effects	No	No
Standard Errors	Clustered	Clustered
Observations	5,500	1,173
R^2	0.658	0.514

Stat. Sig. * 10% ** 5% *** 1%

27 Data available at: http://qed.econ.queensu.ca/jae/2019-v34.1/malikov-sun-hite.

For the full sample (Model Y) of the Malikov, Sun, and Hite (2018) study, the coefficient on the quarry-distance variable is positive and statistically different from zero. When limiting the date to home sales within five-miles of the quarry (Model Z), the coefficient is negative and statistically different from zero. A review of the data indicates that the average home size rises sharply at about six miles, so it appears there is an anomaly in the real estate market far from the quarry that may be driving the positive coefficient.[28] The results from a distance-from-site hedonic model appear very sensitive to model specification and the data used.

VI. Conclusion

For many Americans, a home is their most valuable asset. Naturally, the threat of a reduction in home values causes concern. Opposition to rock quarries, which are typically located in rural areas with low housing density, is motivated, in large part, by a fear of a loss in home values. Yet, the geographic scope of a quarry's activities is narrow and usually less than one-half mile. Modern quarrying methods have greatly reduced the influence of quarry operations on surrounding areas. Evidence supporting the effect of a quarry on home values is scant, which is something I attempt to rectify here with the most extensive study to date. Evidence from three cities for thousands of home sales reveals no robust effect of quarries on home values.

Like most prior studies, I do not estimate plausibly causal effects. Ideally, Difference-in-Differences methods, or some other causal model, would be used, as in Ford and Seals (2018). An impediment to causal analysis is the difficulty in obtaining sufficient samples of home sales around new quarry sites given their mostly rural locations. Correlation studies are most frequently cited before regulators, so these results are useful in that respect. However, I stress that this study, as well as the commonly cited Hite (2006) study, as well as Malikov, Sun and Hite (2018), need not offer plausibly causal estimates of the effect of quarries on home sales.

I note that efforts to establish the effect of a (dis)amenity on home prices is not merely an academic exercise. Such studies may be relied upon for public policy decisions restricting property rights of landowners and potentially affecting millions of dollars in economic activity. Distance-from-site regressions, as I demonstrate here, are unreliable and often plagued by selection bias. Results are often sensitive to the richness of the model, the estimation method, and the

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[28] The average square footage within five miles of the quarry is 1,901. Between five and ten miles from the quarry, the average home size is 2,887.

geographic scope of the data. A serious effort to assess the robustness of any estimate, using different methods, models, data, and inference procedures (including Randomized Inference), seems prudent if not essential.

APPENDIX:

Variable Definitions

Variable	**Description**
ld_quarry	Natural log of distance from quarry in miles.
ld_center	Natural log of distance from the city center in miles
lsqft	Natural log of home's square footage.
lacres	Natural log of home's lot size in acres.
basementshare	Percentage of square footage in basement.
onestory	House has one story.
lage	Natural log of age of home.
remodel10	Home remodeled in the 10 years prior to sale.
airc	Home has central air conditioning.
bedroomsN	Home as N bedrooms. "m" indicates "or more."
fullbathN	Home has N full bathrooms. "m" indicates "or more."
halfbathN	Home has N half bathroom. "m" indicates "or more."
fireplaceN	Home has N fireplaces. "m" indicates "or more."
gradeN	Grade of N for housing construction.
condN	Condition N of household.
garage_	AF (attached finished); AU (attached unfinished); DF (detached unfinished); DU (detached unfinished); BA (basement attached); CP (carport); N indicates count of garages.
lmedinc	Natural log of median income in census block group.
white	Share of white population in census block group.
vacant	Share of vacant homes in census block group.
outlier	Outlier indicator.

Table A-3. Findlay, Ohio

	Model A	Model B	Model C	Model D
ld_quarry	-0.0299	-0.0325	-0.0313***	-0.0417***
ld_center	0.0107	0.00132	0.0318***	0.0335**
lsqft	0.386***	0.409***	0.484***	0.482***
lacres	0.0414	0.0864***	0.0666***	0.0586***
basementsh~e	0.215***	0.220***	0.188***	0.183***
onestory	0.0193	0.00819	-0.0019	0.00453
lage	-0.0477**	-0.0555***	-0.105***	-0.103***
remodel10	0.123**	0.0918	0.0647**	0.0868**
airc	0.174***	0.132***	0.109***	0.126***
bedrooms2	0.0109	-0.0757	0.00393	-0.0112
bedrooms3	0.0503	-0.0464	0.0372	0.0186
bedrooms4	0.0825	-0.0259	0.0308	0.0147
bedrooms5m	-0.0455	-0.0956	-0.0124	-0.0486
fullbath2	0.159***	0.149***	0.115***	0.114***
fullbath3	0.280***	0.298***	0.159***	0.157***
fullbath4m	0.246	0.421**	0.336***	0.395***
halfbath1	0.0553***	0.0535***	0.0478***	0.0388***
halfbath2m	0.246***	0.293***	0.120***	0.111***
fireplace1	0.0812***	0.0655**	0.0409***	0.0540***
fireplace2m	0.108**	0.130*	0.0617***	0.0397
gradeB	-0.416***	-0.328**	-0.252***	-0.243***
gradeC	-0.554***	-0.489***	-0.386***	-0.375***
gradeD	-0.655***	-0.557***	-0.482***	-0.484***
condG	0.584**	-0.0595	-0.0667	0.116
condA	0.578**	-0.1	-0.0905*	0.114
condF	0.352	-0.19	-0.129**	0.0185
garage_AF	0.123***	0.0976***	0.0496***	0.0674***
garage_AU	0.0892**	0.0673***	0.0309***	0.0470***
garage_DF	0.0852	0.105	0.0196	0.0256
garage_DU	0.0646	0.0952*	0.0166	0.00765
garage_BA	0.0882	0.314**	-0.0222	-0.00473
garage_CP	-0.119	0.135	-0.0807	-0.109
lmedinc	0.0984*	0.0971**	0.0837***	0.0675***
white	0.302**	0.323**	0.144***	0.208***
vacant	-0.151	-0.141	-0.0632	-0.0834
outlier		-0.776***		
_cons	7.136***	7.908***	7.737***	7.631***
Year Fixed Effects	Yes	Yes	Yes	Yes
N	2,843	2,843	2,843	2,843
R2	0.645	0.723	0.838	

Sig. Level: * 10% ** 5% *** 1%

Table A-3. Findlay, Ohio

	Model A	Model B	Model C	Model D
ld_quarry	-0.0298	-0.036	-0.00921	-0.0562**
ld_center	-0.0268	-0.0416*	-0.00144	0.011
lsqft	0.345***	0.368***	0.341***	0.361***
lacres	0.0384**	0.0854***	0.0145	0.107***
basementsh~e	0.190***	0.195***	0.200***	0.193***
onestory	0.0216	0.0119	0.0191	0.0111
lage	-0.0189*	-0.0294***	-0.0187*	-0.0265**
remodel10	0.138***	0.108**	0.133***	0.116***
airc	0.156***	0.116***	0.171***	0.101***
bedrooms2	0.00348	-0.0825**	0.0127	-0.0899**
bedrooms3	0.0428	-0.053	0.0526	-0.0602
bedrooms4	0.0679	-0.0399	0.0840*	-0.0506
bedrooms5m	-0.0506	-0.100*	-0.0376	-0.107*
fullbath2	0.134***	0.125***	0.140***	0.118***
fullbath3	0.252***	0.269***	0.254***	0.270***
fullbath4m	0.225***	0.393***	0.246***	0.362***
halfbath1	0.0439***	0.0428***	0.0480***	0.0423***
halfbath2m	0.241***	0.289***	0.239***	0.284***
fireplace1	0.0630***	0.0489***	0.0627***	0.0453***
fireplace2m	0.103***	0.122***	0.107***	0.103***
gradeB	-0.391***	-0.300***	-0.407***	-0.285***
gradeC	-0.505***	-0.437***	-0.527***	-0.422***
gradeD	-0.602***	-0.501***	-0.629***	-0.479***
condG	0.510***	-0.107	0.508***	-0.0987
condA	0.504***	-0.146*	0.491***	-0.123
condF	0.274***	-0.241***	0.260***	-0.209**
garage_AF	0.100***	0.0770***	0.0962***	0.0869***
garage_AU	0.0800***	0.0595***	0.0812***	0.0618***
garage_DF	0.0735	0.0974	0.0796	0.0864
garage_DU	0.0691	0.0976**	0.0716	0.0982***
garage_BA	0.0977	0.317***	0.0871	0.336***
garage_CP	-0.12	0.134*	-0.132	0.137*
lmedinc	0.0343	0.0364	-0.00608	0.111***
white	0.160*	0.176**	0.189**	0.183
vacant	-0.164	-0.153	-0.16	-0.147
outlier		-0.760***		-0.742***
_cons	-2.541**	-1.769*	-1.706***	8.189***
Year Fixed Effects	Yes	Yes	Yes	Yes
lprice	0.912***	0.907***	0.880***	
e.lprice	0.941***	0.953***		3.012***
var(e.lprice)	0.105***	0.0818***	0.107***	0.0814***
N	2,843	2,843	2,843	2,843

Sig. Level: * 10% ** 5% *** 1%

Table A-5. Delaware, Ohio

	Model I	Model J	Model K	Model L
ld_quarry	-0.0194	-0.0222	0.0106	0.00898
ld_center	0.0661**	0.0489	0.0629***	0.0702***
lsqft	0.557***	0.596***	0.529***	0.535***
lacres	0.0758***	0.0805***	0.0895***	0.0754***
onestory	0.0775**	0.0860**	0.0765***	0.0853***
lage	-0.0358**	-0.0314*	-0.0481***	-0.0422***
remodel10	0.0439***	0.0508***	0.0602***	0.0405***
airc	0.0437	0.0191	-0.0221**	0.016
fullbase	0.149***	0.150***	0.145***	0.151***
partbase	0.118***	0.113***	0.129***	0.136***
bedrooms2	0.0283	-0.260***	0.156**	0.251***
bedrooms3	0.140**	-0.183**	0.192***	0.315***
bedrooms4	0.117**	-0.215**	0.174**	0.300***
bedrooms5m	0.0981*	-0.186**	0.0941	0.234***
fullbath2	0.0361	0.0406	0.0715***	0.0665***
fullbath3	0.144**	0.144**	0.157***	0.153***
fullbath4m	0.190**	0.212**	0.186***	0.165***
halfbath1	0.0297	0.0297	0.00161	0.00818
halfbath2m	0.217***	0.261***	0.133***	0.157***
fireplace1	0.0346*	0.0330*	0.0348***	0.0324***
fireplace2	0.157**	0.166**	0.0703***	0.0731*
fireplace3m	0.396***	0.513***	0.301***	0.341***
lmedinc	0.101*	0.112*	0.0703***	0.0780***
white	0.0902	-0.0233	0.0952*	0.0558
vacant	0.0482	0.0143	-0.185**	-0.309***
garage1	0.0983**	0.0728**	0.0287**	0.0569***
garage2	0.109**	0.0869**	0.0445***	0.0687***
garage3	0.108**	0.123***	0.131***	0.152***
garage4m	0.195***	0.233***	0.146***	0.148***
outlier		-0.378***		
_cons	6.272***	6.356***	6.978***	6.652***
Year Fixed Effects	Yes	Yes	Yes	Yes
N	2,439	2,439	2,439	2,439
R2	0.705	0.736	0.881	

Sig. Level: * 10% ** 5% *** 1%

Table A-6. Delaware, Ohio

	Model I	Model J	Model K	Model L
ld_quarry	-0.0778*	-0.0810**	-0.0246	-0.0337
ld_center	0.0879***	0.0383*	0.0139	0.0716***
lsqft	0.555***	0.582***	0.522***	0.551***
lacres	0.0669***	0.0730***	0.0696***	0.0677***
onestory	0.0633***	0.0745***	0.0705***	0.0653***
lage	-0.0294***	-0.0246***	-0.0278***	-0.0287***
remodel10	0.0408**	0.0478***	0.0398**	0.0417**
airc	0.0415**	0.0163	0.0493**	0.0423**
fullbase	0.139***	0.133***	0.133***	0.137***
partbase	0.109***	0.0992***	0.106***	0.108***
bedrooms2	0.0514	-0.248**	0.0651	0.0492
bedrooms3	0.176	-0.162	0.185	0.175
bedrooms4	0.156	-0.192	0.161	0.151
bedrooms5m	0.148	-0.15	0.141	0.141
fullbath2	0.0312	0.0416**	0.0387**	0.0340*
fullbath3	0.134***	0.134***	0.133***	0.141***
fullbath4m	0.198***	0.225***	0.190***	0.199***
halfbath1	0.0265	0.0311**	0.0291*	0.0267
halfbath2m	0.202***	0.252***	0.208***	0.203***
fireplace1	0.0291**	0.0286**	0.0328***	0.0308**
fireplace2	0.152***	0.161***	0.160***	0.154***
fireplace3m	0.390***	0.515***	0.398***	0.389***
lmedinc	0.125***	0.120***	0.0589**	0.103***
white	0.0953	0.0323	0.222**	0.105
vacant	0.0685	0.077	0.122	0.0323
garage1	0.0920***	0.0743***	0.104***	0.0928***
garage2	0.0958***	0.0804***	0.112***	0.0974***
garage3	0.126***	0.143***	0.124***	0.128***
garage4m	0.217***	0.247***	0.215***	0.221***
outlier		-0.405***		
_cons	9.345***	7.987***	3.256***	6.264***
Year Fixed Effects	Yes	Yes	Yes	Yes
lprice	-0.271***	-0.133	0.293***	
e.lprice	0.903***	0.915***		0.582***
var(e.lprice)	0.0652***	0.0573***	0.0660***	0.0660***
N	2,439	2,439	2,439	2,439

Sig. Level: * 10% ** 5% *** 1%

Table A-7. Lima, Ohio

	ModeQ	Model R	Model S	Model T
ld_quarry	0.0185	-0.0254	-0.110**	-0.0178
ld_center	0.0854	0.081	0.0738	0.0822
lsqft	0.490***	0.439***	0.537***	0.469***
lacres	0.136**	0.124**	0.0539	0.0931**
basementshare	0.262**	0.317**	0.292**	0.294
onestory	0.00474	0.0125	0.123***	0.0622
lage	-0.290***	-0.269***	-0.294***	-0.267***
remodel10	0.0369	0.0134	0.126**	0.0521
airc	0.0383	0.0843**	0.185***	0.124***
fullbase	0.00846	-0.0221	-0.0231	-0.0262
bedrooms2	0.0905	0.256	-0.000842	0.0675
bedrooms3	0.128	0.282	-0.0157	0.0549
bedrooms4	-0.0346	0.0509	-0.0484	-0.00189
bedrooms5m	0.388	0.169	0.15	0.268*
fullbath2	0.022	0.0201	0.0736*	0.0611
fullbath3	-0.148	0.268	-0.0671	-0.136
fullbath4m	0.362	0.503	-0.0121	0.44
halfbath1	0.0109	0.0289	0.0863**	0.0623*
halfbath2m	-0.303**	-0.741**	-0.126	-0.286
fireplace1	0.0494	0.0535	0.0937**	0.0438
fireplace2m	0.0548	0.0399	0.104	0.0627
gradeB	-0.0611	0.656	-0.733**	-0.29
gradeC	-0.378	0.438	-1.033***	-0.58
gradeD	-0.655	0.141	-1.343***	-0.898**
garage1	0.0153	0.0115	0.0552	0.0584*
garage2	0.0512	-0.00986	0.0112	0.0174
garage3	0.258*	0.0308	0.106	0.116
lmedinc	0.185*	0.247**	0.365***	0.240***
white	-0.097	-0.0152	0.0495	0.0301
vacant	-0.347	-0.446*	-0.389**	-0.375*
outlier		1.203***		
_cons	7.132***	5.773***	5.339***	6.657***
Year Fixed Effects	Yes	Yes	Yes	Yes
N	1,169	1,169	1,169	1,169
R2	0.333	0.432	0.591	
Sig. Level: * 10% ** 5% *** 1%				

Table A-8. Lima, Ohio				
	Model U	Model V	Model W	Model X
ld_quarry	-0.0654	-0.116	-0.0728	-0.0109
ld_center	0.147*	0.158**	0.101	0.182**
lsqft	0.477***	0.424***	0.475***	0.484***
lacres	0.141***	0.128***	0.138***	0.142***
basementsharee	0.253	0.315*	0.26	0.245
onestory	-0.00787	-0.00536	0.00659	-0.0185
lage	-0.278***	-0.253***	-0.284***	-0.275***
remodel10	0.0176	-0.00967	0.0164	0.0221
airc	0.0174	0.0587	0.0253	0.017
fullbase	0.0219	-0.00563	0.0194	0.0195
bedrooms2	0.101	0.27	0.0998	0.101
bedrooms3	0.154	0.311*	0.153	0.149
bedrooms4	0.00679	0.0949	0.000812	0.00597
bedrooms5m	0.407	0.194	0.402	0.401
fullbath2	0.00796	0.00387	0.0166	0.00293
fullbath3	-0.159	0.261	-0.145	-0.173
fullbath4m	0.454	0.599	0.463	0.415
halfbath1	0.000382	0.0165	0.00212	0.00102
halfbath2m	-0.309	-0.752***	-0.315	-0.303
fireplace1	0.0408	0.0411	0.0396	0.0488
fireplace2m	0.0432	0.0249	0.0482	0.0452
gradeB	-0.0228	0.693*	-0.0338	-0.027
gradeC	-0.318	0.5	-0.333	-0.33
gradeD	-0.551	0.252	-0.57	-0.569
garage1	0.0114	0.00475	0.0193	0.00653
garage2	0.0508	-0.00981	0.0521	0.0486
garage3	0.241	0.0132	0.251	0.229
lmedinc	0.123*	0.183***	0.119*	0.148**
white	-0.103	-0.00632	-0.129	-0.0813
vacant	-0.242	-0.343	-0.228	-0.287
outlier		1.211***		
_cons	3.384	1.947	2.293*	7.409***
Year Fixed Effects	Yes	Yes	Yes	Yes
lprice	0.401**	0.407**	0.512***	
e.lprice	0.326	0.396*		0.585***
var(e.lpri~)	0.371***	0.324***	0.372***	0.373***
N	1,169	1,169	1,169	1,169
Sig. Level: * 10% ** 5% *** 1%				