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The long-run impact of nuclear waste shipments on the property market: Evidence from a quasi-experiment ☆

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ABSTRACT

We use evidence from a quasi-experiment – the shipping of radioactive spent nuclear fuel by train through South Carolina – to assess whether many years of incident-free transport of nuclear waste no longer negatively affects market valuation of properties along the route. Using Charleston County (SC) property sales data over 13 years we find, to the contrary, that the negative impact of the nuclear waste shipments on property values continues to be felt over the long run. The perception of risk from nuclear waste transport appears to be resilient. We contribute methodologically by comparing well-defined treatment and control groups of properties to estimate the average treatment effect of the nuclear waste shipment program. The results are affirmed in both a pooled cross-section sample, as well as a panel data sample of repeated property sales.

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1. Introduction

Handling highly radioactive waste has proved to be one of the most difficult parts of hazardous materials management. As the United States debates large-scale transport of spent nuclear fuel (SNF) from the 73 storage sites scattered across 33 states to more centralized interim storage sites and permanent deep-geologic repositories versus maintaining the status quo of continued on-site storage at or near reactors,[1] concerns have focused on safety and efficiency of the transport [5], National Research Council, [45]). The Obama administration's decision to withdraw the license application to construct the 77,000-ton capacity Yucca Mountain repository site, reversing the policy of former President Bush, remains controversial. The stalemate leaves in limbo the long-run solution to the current US inventory of 70,000 ton of SNF in existing sites, plus the annual output of more than 2000 ton of SNF annually produced by the country's reactors. Subsequent to its withdrawal of the license application for Yucca Mountain, the Obama administration appointed a blue-ribbon commission to advise the government on a new strategy for managing nuclear waste. In January of 2012 the commission concluded that the US

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[1] Most commercial used nuclear fuel is stored at or near operating reactors. However nine of the 73 storage sites are at shutdown reactors, often referred to as "orphan" storage sites.

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will require interim storage sites and one or more permanent, centralized geologic repositories, and recommended early preparation for transport of used nuclear fuel and high-level radioactive wastes [5].

Of interest in this paper are the economic effects that transporting spent fuel may activate, possibly resulting from beliefs about the risks posed by such transport. Experience with hazards, ranging from chemical wastes at Superfund sites to deposition of lead from smelting plants has demonstrated that property values can be sensitive to proximity to such hazards.[2] But does proximity to the route by which radioactive materials are shipped in highly resilient transport casks also affect property values? If so, by what amount do values diminish, and over what geographic scope? Finally, and most importantly, are these effects permanent or transitory?

This paper supplies answers to these questions using new methods. It is motivated by Gawande and Jenkins-Smith's [17], henceforth GJS, study of shipments of spent fuel through South Carolina in the early years after the shipments began in 1994. At that time, the shipments were beset by enormous controversy and the wide press coverage that followed was rarely positive. Into the first two years of the shipments, GJS found that in populous Charleston County, a home five miles from the shipment route was worth 3% more than a similar home located on the route. This result has been used on both sides of a fierce policy debate over Yucca Mountain.[3]

The shipments continue to this day. There has not been a single negative incident over the fifteen years, and newspaper reports of the shipments are almost negligible. This suggests that individuals' perceptions about the risk of SNF shipments may have been updated over time due to the lack of media coverage and absence of incidents. A large literature on environmental clean-ups argues that clean-ups restore property values in the long run.[4] This literature, while related, is distinct from risk revision. Cleanups entail the removal of a risk, whereas the risk may continue to be inherent in the current context, though individuals may have updated their beliefs about the risk. The time is not only apt for re-investigating the finding using long-term data, but it has critical implications for both research and policy.[5]

This paper uses the same South Carolina SNF shipment setting as Gawande and Jenkins-Smith, and improves on it in three respects. First, we appropriately view the SNF shipment as a natural experiment and use average treatment effect estimators. We use a difference-in-differences strategy to identify and estimate the average treatment effect in the treated population of properties in Charleston, South Carolina. Gawande and Jenkins-Smith [17] suffers methodologically from the same issues that Greenstone and Gallagher [21] critique in earlier studies of the impact of NPL clean-ups, namely that the methods do not control for untreated properties. We remedy this deficiency. Second, the data include property transactions over a much longer duration. We obtained records of all residential property sales in Charleston County between 1992 and 2005 (the GJS paper stopped at 1996). The transactions data permit us to estimate the effects of the spent fuel shipment program on property values over a decade of shipments without incident. Third, we are able to weigh in with panel data, while much of the literature has used pooled cross-sections. Existing studies of the effects of the environment on land and property values has largely used cross-sectional data combined with a heavy reliance on hedonic variables to control for heterogeneity. Even with the controls, doubts may remain about unobserved heterogeneity in the cross-section. Therefore, in addition to the pooled cross-section, we use repeat sales information to create panel data on a number of properties.

The paper proceeds as follows. In Section 2 we describe the foreign spent nuclear fuel shipments that began in 1996. Section 3 describes the difference-in-differences methodology using both pooled cross-section data and panel data. Section 4 explains in detail the construction of our data set. The data are unique in many respects, and add new dimensions to the environmental impact evaluation enterprise. Section 5 presents and analyzes the findings. The main finding is that the prices of properties in the most urban and populous County (Charleston) continue to be influenced negatively by SNF shipments despite the absence of any incidents that might heighten risk perceptions about the shipments. Section 6 provides our discussion and conclusions.

[2] The idea that property values will be affected by the presence of hazardous materials – including incinerators, electricity transmission lines, landfills, and nuclear power plants – has been studied, for example, by Kiel and McClain [33], Kiel [32], McClelland et al. [38], Kohlhase [34], Michaels and Smith [41], and Gamble et al. [16]. These studies use the hedonic pricing logic, viewing proximity to the environment as a characteristic of the property. The earliest efforts involved inference about the marginal value of clean air from housing prices [23,39].

[3] Board of County Commissioners Lincoln County NV [4], Clark County Department of Comprehensive Planning, Nuclear Waste Division [11], Hom et al. [25], Nuclear and Radiation Studies Board [45], O'Connor [46], State of Nevada [52,51], and US Nuclear Regulatory Commission [58].

[4] In a properly functioning market if a disamenity is transitory, it should not have permanent effects on housing prices. Stock [53], Kohlhase [34], and Ketkar [31] find this to be true about properties near cleaned-up hazardous waste sites as do Carroll et al. [7] and Dale et al. [13] in the context of chemical clean-ups. Studies by Nelson [43], Gamble and Downing [15] and Gamble et al. [16] examining incidents near nuclear power plants, specifically the Three Mile Island (TMI) accident, found no decrease in housing prices due to proximity to the TMI plant. However, since nuclear power plants produce jobs and tax revenues, they may offset the possible disamenity effects. Studies of waste sites such as the Frenald plant in Ohio (Feiertag, [60]) and Rocky Flats in Colorado (Hunsperger, [27]) indicate the effects on property values to be similar to those of Superfund sites.

[5] In a white paper, Department of Energy analysts Holm et al. [25, p. 12] write: "The numerous and complex socioeconomic analyses that attempt to quantify stigma damages for various transportation scenarios are based on a single, limited, preliminary study whose authors themselves argue that the issue requires further study. Apart from the GJS study, there appears to be no defensible empirical evidence whatsoever that stigma from transportation even exists. Their finding that there may be a statistically significant effect may be supported by further research, or it may not. What is certain is that repeated and sustained citations to this single isolated study in secondary sources and reports do not validate the findings themselves."

"Much of the research conducted to date has used polling methodologies, as opposed to empirical or real-time data. The GJS study, by contrast, used real estate sales data along with the results of systematic surveys to reach its conclusions. DOE's Appendix I of the FEIS on Yucca Mountain suggests that additional research is needed. If such analysis is undertaken …(t)he research should use actual real estate transaction data for a significant period of time…."

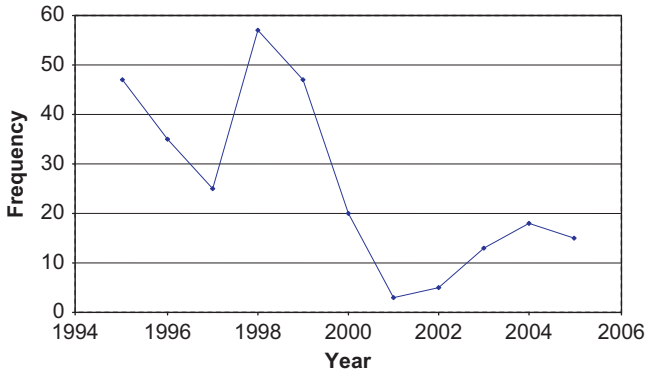

Fig. 1. Monthly reporting on nuclear issues in South Carolina.
Source: Post and Courier.

2. Theory

2.1. Background

The United States program to reclaim spent nuclear fuel from overseas reactors seeks to remove from commerce potential access to weapons-grade nuclear materials – both highly enriched uranium and the plutonium byproduct of fission in the reactor. The fuel, originally provided to many nations as part of the Atoms for Peace program, has been owned by the United States.[6] In the 1990s, a campaign to ship accumulated stocks of spent fuel back to the United States was initiated. Initial plans to return the fuel through ports in North Carolina and Contra Costa County, CA, resulted in substantial opposition. The Governor of South Carolina, the state where much of the spent fuel was to be stored, sought unsuccessfully to block the shipments in the courts. South Carolina newspapers and television news provided ample coverage of the dispute, highlighting the route and communicating the dire concerns of some state officials, anti-nuclear activists, and citizens. After a delay of nearly two years following the initial shipment in 1994, foreign spent nuclear fuel (SNF) has been transported at least once a year from the Port of Charleston to the Department of Energy's Savannah River facility in Aiken County, SC. Appendix A (available from the authors) lists the dates of each of the rail shipments between 1996 and 2003.

In contrast to the substantial initial public outcry over the shipments, there has been little negative press over subsequent years. No accidents or incidents have occurred that resulted in release of radiation. Indeed, our review of news articles in the *Charleston Post and Courier* newspaper, summarized in Fig. 1, found no articles claiming that such events had occurred. Did the lack of SNF transport incidents together with declining attention in the news lower the perceived risks from SNF shipments? Specific to nuclear waste, surveys by Slovic et al. [50], and Kunreuther and Easterling [35] have demonstrated that nuclear images of a place lower stated preferences for vacationing and residing there, suggesting long-term stigmatization of properties may occur near nuclear waste storage facilities.

2.2. Theory

A simple model of how risk perception affects property prices is developed by Gayer et al. [18]. Individuals maximize expected utility over two states of the world, U_1 when harm comes to them from exposure to radiation from spent nuclear fuel, and U_2 when they are unexposed and healthy. $U_2 > U_1$ for any given income, and marginal utility of income is greater when healthy. The consumer has income y which is spent on buying a home and a composite good a. Utility in each state is a function of characteristics of the home X, *perceived* risk of harm from exposure to the spent nuclear fuel π, and distance to the SNF route D (which measures the visual disamenity from the SNF shipment). The price of a home P is a function of characteristics X, risk perception π, and distance to the SNF route D. The consumer chooses the arguments in P and a to maximize expected utility subject to the budget constraint:

$$\text{Max EU} = \pi U_1(a,X,D) + (1-\pi)U_2(a,X,D)$$

s.t.

$$y = a + P(\pi,X,D).$$

[6] The objective of the Atoms for Peace program was to provide non-nuclear nations with peaceful means to employ nuclear technologies (usually in the form of research reactors and the reactor fuel) in return for the recipient countries' willingness to forego development of their own nuclear weapons program.

Table 1
Perceived probabilities of FSNF transport accidents and consequences as measured in cross-sectional surveys in 1994, 1995 and 2005.

	1994	1995	2005
Charleston County	1. FSNF train accident? (0=never happen; 10=certain to happen)		
	4.68, sd=0.17	4.77, sd=0.13	5.65, sd=0.13
	2. FSNG canister rupture (if accident)? (0=never happen; 10=certain to happen)		
Charleston County	5.07, sd=0.18	4.66, sd=0.15	5.74, sd=0.14
	3. Expectation of harm to area residents (if accident and canister rupture)? (percent "yes")		
Charleston County	84%, sd=0.03	80%, sd=0.02	91%, sd=0.01

Notes: 1. Sample means and standard deviations (sd).

The main result from this constrained maximization problem [18, p. 441] is the negative impact on home price P of an increase in π[7]:

$$\frac{\partial P}{\partial \pi} < 0.$$

The perceived risk of harm from SNF exposure π may be expressed as the product of three personally assessed conditional probabilities: the probability of harm given that an accident occurs and the canister carrying radioactive spent nuclear fuel ruptures, the probability of a canister rupturing given that an accident occurs, and the probability that an accident occurs:

$$\pi = \text{Prob}(\text{Harm}|\text{Accident and Rupture}) \cdot \text{Prob}(\text{Rupture}|\text{Accident}) \cdot \text{Prob}(\text{Accident}).$$

The change in risk perception $\Delta\pi$ may come about due to new information that changes personal assessments of any of these probabilities. For example, an increase in Prob(Accident), all else constant, will update risk beliefs in the direction of greater risk perception ($\Delta\pi > 0$). Via the comparative static result above, this will lower a home's price.

To ascertain whether a change in perceived risk had indeed occurred, we conducted telephone surveys of residents in 1994 (just prior to the first shipment), 1995 (just after the first shipment), and 2005 (a decade after the first shipments).[8] The survey was designed to measure perceptions of the components of the risks posed by the shipments: Prob(Harm|Accident and Rupture),Prob(Rupture|Accident), Prob(Accident). Table 1 shows the average perception of Charleston County residents of these risk components. The experience with a decade of accident-free SNF transport has not reduced perceived risks among the public along the South Carolina rail route. Indeed, the responses to the questions (using identical wording and very similar question order) suggest that perceived risks increased over the past decade. On average, in 2005 Charleston County residents believe accidents to be more likely, the chance of a canister rupture given an accident to be higher, and the expected harm in the event of an accident and rupture to be greater than a decade before. Since perceived risks are a factor in property values, the survey data suggest a continuing negative effect from being "treated" with exposure to risk from the SNF shipments.

Since the probability components are personally assessed, they are themselves subject to uncertainty, and π is appropriately viewed as a random variable. Riddel and Shaw [48] and Riddel [47] show how the imprecision in risk perception assessment π, denoted σ_π^2, can influence a person's willingness to accept compensation for a negative environmental externality. In particular, a median-preserving increase in σ_π^2 increases the expected willingness to accept [48, p. 346]. Using evidence from a primary survey of South Nevada residents Riddel shows that, of the welfare loss from a hypothetical nuclear waste transportation program, 12.4% is attributable to the uncertainty σ_π^2. The idea that uncertainty about risk perceptions can negatively influence property prices applies naturally in our Bayesian framework. A number of events may have increased uncertainty about risk assessment in recent years, including heightened concerns about nuclear terrorism following the September 11, 2001, terror attacks in the US.

Together, the theory and the survey evidence lead to the hypothesis that the treatment effect from exposure to the SNF shipments will lower property prices in the long run. The remainder of the paper is devoted to testing this hypothesis.

7

$$\frac{\partial P}{\partial \pi} = \frac{U_1 - U_2}{\pi \partial U_1/\partial a + (1-\pi)\partial U_2/\partial a} < 0.$$

If distance directly influences risk perception, $y = a + P(\pi(D), X)$, with $\pi'(D) < 0$, then $\partial P/\partial D > 0$.

8 The 2005 interviews were conducted between October 7 and December 4, 2005. The samples were based on a random digit-dialing frame obtained from Survey Sampling Inc., of Fairfield Connecticut. The surveys lasted an average of 17 minutes, and resulted in a cooperation rate of 57% in 2005, in comparison to cooperation rates (using AAPOR's "COOP2" formula) of 88% in 1994 and 61% 1995 [1]. All three surveys included over 250 Charleston County respondents.

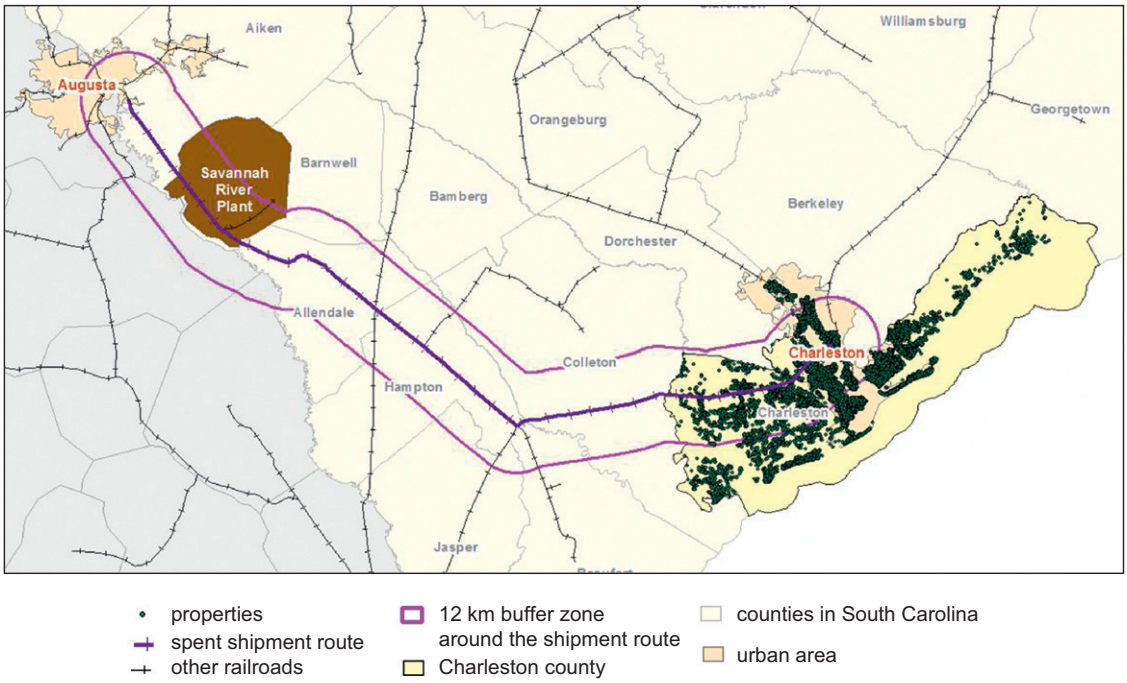

Fig. 2. SNF rail route, non-SNF rail routes, and geographic distribution of the sample of properties.

3. Data

Our data consist of the population of properties that were sold at least once during the period 1992–2005 in Charleston, South Carolina. Fig. 2 maps the South Carolina counties through which the SNF rail route runs. The SNF route is indicated by the dark line through Charleston–Colleton–Hampton–Allendale, through the Savannah River Plant, and ending in Aiken. It is enclosed by a 12 km "buffer zone", which separates the treatment and control groups of properties. Other non-SNF rail lines are also shown in Fig. 2. Each of the approximately 80,000 property sales is indicated by a dot on the map.[9] Data on sale price and date of sale were obtained from REIS, a firm that specializes in the collection and reporting of property values and transactions in South Carolina. It is the only database of its kind for the state of South Carolina. Only properties with sale price above $25,000 but less than $500,000 were considered for this study. Thus, the average treatment effect we estimate is of greatest relevance for a population of urban properties within this range of values.

Charleston County, where the Port of Charleston is located, is densely populated and 88% urban. It is the third-most populous (330,000) among the 51 South Carolina counties, and accounts for 12% of the state's GDP. The treatment group T and control group C of properties are entirely located within Charleston County. Properties within a 12-km distance from the SNF route comprise the treatment group, while properties 12 km or more from the SNF route comprise the control group. The 12-km cutoff is determined by searching over properties in distance-bands around the SNF route. The search is described in detail below. The treatment and control group together comprise the full sample of 79,560 properties. A subset of this control group that is proximate to another rail route over which no shipments were planned or occurred, may be used to control for the "placebo" effect of simply being near a rail route. The treatment group plus this sub-sample of the control group comprise the "Near Rail Routes" sample of 58,674 properties.

The distance of each property in the sample from the SNF route (DistanceSNF) is calculated as the nearest distance from the center of the property to the route. Coordinates obtained from the GIS based on the address of the property were used to calculate this distance. Housing characteristics in the REIS database include built-up square foot area (Square Feet) and the year it was built (Year Built). REIS also provided coordinates of amenities including parks, schools, bays, landmark buildings, churches, hospitals, the cape, streams and islands, which were used to compute the closest distance of each property from these amenities.[10]

[9] We also have property sales data for the four rural South Carolina counties Aiken, Berkeley, Dorchester and Orangeburg. Our focus in this paper is on urban and densely populated Charleston County. While not reported, the treatment effect estimates for these other counties is available from the authors. Perhaps not surprisingly, since proximity to a rail route is an amenity in rural areas as it reduces costs of transporting agricultural products, we find different effects for Charleston versus the rural counties.

[10] The distances were computed using Haversine's formula for spherical distances.

Census-block demographic and income data obtained from the 1990 United States Census were mapped to each property based on its address and zip code. These variables include the percent of the population in the census block who are White (% White), Black (% Black), and Hispanic (% Hispanic), and the median household income in the census block (HH Income). In sum, we have as complete a data set as possible on sale price, property characteristics, external amenities, and census block characteristics with which to investigate the effect of SNF shipments on property sale prices.

Table 2 provides descriptive statistics for the Charleston County pooled cross-section. Of the 79,650 residential properties in the full sample, 48% belong to the treatment group and 52% to the control group. 10% of the transactions in the sample preceded the shipments ($DT0$) and 90% were recorded in the shipments regime. We will distinguish the program's short-term impact (8/1994–12/1997) from its long-term impact (1/1998–2005). 21% of the sample is from the short-term regime ($DT1$) while 71% is from the long-term regime ($DT2$). The average building in the sample was 1893 square feet and was built in 1971. The distance of properties from the SNF route had a mean of 11.63 km and standard deviation equal to 6.79 km. The average distance of treated properties from the SNF route was 6.052 km.

Our panel data are constructed as three separate data sets, one comprising 46,537 properties that were sold at least twice, another comprising 17,870 properties that were sold at least thrice, and a third comprising 4926 properties that were sold at least four times during the 1990–2005 period. Appendix Table A1 provides descriptive statistics for the panels. The statistics indicate considerable within-variation in the price data.

4. Methodology

4.1. Pooled cross-section

The SNF shipment program provides a natural experiment for assessing the impact of nuclear waste shipments on residential property prices. Residential properties in Charleston, South Carolina potentially impacted by the shipments, or "treated" to the risk of exposure, are the units of analysis. We use difference-in-differences (DID) to identify and estimate the average treatment effect on this population of treated properties (ATT).[11]

The difference in differences compares the effect of SNF shipments on properties perceived to be exposed to the risk of contamination (the treated group) versus properties that were not perceived to be exposed to the risk (the control group). Specifically, the pre-shipment to post-shipment change in the selling price of properties for the treated group is compared to the pre-shipment to post-shipment change in the selling price of properties for the control group. The post-shipment phase is broken down into a two periods to enable us to contrast the short-term versus the long-term impact of the shipments. Specifically, using a pooled cross-section of property prices, we estimate parameters of the econometric model

$$\ln(\mathrm{P}_{it}) = \gamma T_i + \tau^S (DT1_t \times T_i) + \tau^L (DT2_t \times T_i) + \beta' X_i + \text{year fixed effects} + e_{it}, \tag{1}$$

where P_{it} is the selling price of property i at in year t. The assignment to treatment group indicator $T_i = 1$ if property i is within 12 km of the SNF route, that is, perceived to be exposed to risk from the SNF shipments. Properties beyond 12 km of the shipment route are assigned to the control group. The property bands model described below is used to determine the 12 km cutoff. $DT1_t$ and $DT2_t$ are short run and long run indicators: $DT1_t = 1$ if the observation records a sale after the first SNF shipment in 8/94–12/97; $DT2_t = 1$ if the observation records a sale during 1/98–12/05.[12] The coefficient γ measures the average time-invariant difference between properties perceived to be exposed to risk versus properties that were not so perceived. The difference-in-differences estimators are the coefficients on the interaction terms: τ^S measures the short-run average treatment effect of the shipments in the 3-year period following the inception of shipments. τ^L measures the long-run average treatment effect of the SNF shipments.

4.1.1. Assumptions

Three assumptions are needed for the error term e_{it} to be independent of assignment to treatment T_i, so that the DID estimators τ^S and τ^L are identified.

4.1.1.1. Functional form. The first assumption concerns stability of functional form across treated and control units. Hedonic variables X_i described in the data section measure property-specific attributes, census block characteristics and proximity to amenities, all of which have been emphasized in the literature (e.g. [9]). The use of hedonic models in which the parameters β measure the marginal valuations of each characteristic (linearly) is standard in the large literature on property valuation. This is relevant for our estimation strategy, since DID relies on strong assumptions about stability of functional form. Specifically, the large literature on hedonics supports our assumption that β is the same for treated and

[11] Rubin's [49] potential outcomes framework motivates this analytical framework (see [28]). If the property-specific treatment effect is constant across every property, then DID estimates the Charleston county population average treatment effect (ATE). However, if the treatment effect is heterogeneous then DID estimates the average treatment effect on the treated properties (ATT). The treatment effect is heterogeneous in a specific and measurable way, as we show below.

[12] Their own effects are absorbed into the year fixed effects.

untreated properties, and is not a source of bias.[13] The log-linear specification solves the problem of skewness in the housing price, which would otherwise make the errors non-normal.[14]

4.1.1.2. Common trends. The second assumption is that in the absence of the SNF shipments, properties in both the treatment and control groups would have common trends. This assumption would be violated if, for example, the shipment route was chosen endogenously, deliberately on the basis of trends that distinguished the treatment properties from the control properties. We believe the assignment of properties to treatment from the SNF program was done independently of their value. Two reasons for this view are, first, the choice of the South Carolina SNF rail route was highly constrained by requirements associated with distance, track quality, and traffic density (DOE [57]) and second, only existing routes were utilized. No new routes were constructed. If interest groups representing high-values homes, for example, had been able to use their influence to move the route away from their homes, then assignment to treatment would not be exogenous. Or if a new route were built at a safe distance from the city of Charleston by policymakers in response to strong public opinion, the assignment to treatment of homes built around this new route would be endogenous. Neither of these occurred. The transportation corridor was chosen from routes that had existed for decades, imposing a random shock on properties along the chosen route. Quite simply, properties near the SNF route became exposed to risk, while properties located outside its range of influence were much less exposed or unexposed. In the empirical section we attempt to falsify this assumption by testing the equality of trends using pre-shipment data.

4.1.1.3. SUTVA. The third assumption needed for the error term e_{it} to be independent of assignment to treatment is the stable unit treatment value assumption (SUTVA) that the treatment has no externalities. That is, treatment of a property has no repercussions on the values of other properties. This assumption is likely to be violated because of strong spatial correlation inherent in neighboring property values. In a neighborhood, the market prices similar properties similarly. Realtors often advise sellers to set the price according to the best "comp" or comparable house in the neighborhood.

We consider two options. The first option is to ignore the externality and use (1) to estimate the treatment effect. If the price of a treated home is depressed because the comps are all selling for less, but the comps sold for less due to the treatment, then one should not control for the price of comps in the analysis. Since we are interested in the total derivative of the SNF treatment on home value, this eliminates "intermediate outcomes" such as the effect on comps. Netting out the effect on the comps underestimates the treatment effect on a home, since, in this view, the effect on the comps should be attributed to the home.

The second option is to control for the neighborhood externality directly by including a spatially lagged regressor. We do so by including the variable COMP10, constructed as

$$\mathrm{COMP10}_i = \sum_{j=1}^{10} \left[\frac{\frac{1}{d_{ij}}}{\sum_{j=1}^{10} \frac{1}{d_{ij}}} \right] P_j,$$

where P_j's are prices of homes closest to home i, each d_{ij} kilometers from it. To avoid endogeneity, the P_j's are taken from property sales that occurred between six and twelve months prior to the sale date of property i. COMP10 limits the comps to 10 previously sold properties neighboring property i. Adding COMP10 to (1) results in the model

$$\ln(\mathrm{P}_{it}) = \gamma T_i + \tau^S (DT1_t \times T_i) + \tau^L (DT2_t \times T_i) + \phi \ln(\mathrm{COMP10}_{it}) + \beta' X_i + \text{year fixed effects} + e_{it}. \tag{2}$$

A reason for including COMP10 is econometric. Ignoring comps induces spatial correlations in the errors, leading to inefficient estimates of the DID and other parameters [2]. We find that including COMP10 greatly reduces spatial correlation in the errors.

Another reason for including COMP10 is that it may ameliorate the impact of the SUTVA violation. There is a possible positive externality on the price of control units, due to their lack of treatment and consequent greater demand. Thus, DID is an upper bound on the cost to homeowners in the treated units, but does reflect the total effect on the relative price of treated versus control units. COMP10 then captures some of the effect of the treatment on the decrease in price of the treated units and increase in price of control units. COMP10 also captures unobserved neighborhood attributes of individual units that may be correlated with treatment status. Even though COMP10 may not fully internalize the externality, including COMP10 may nevertheless alleviate the problem. We find a substantial difference between DIDs from the model without comps versus the model with comps, and report both, leaving the choice for the reader to make.[15]

[13] For example, X may change in response to the treatment if only smaller properties were built in the region along the route exposed to risk from the SNF shipments. Results available from the author show that there was no statistical difference in property characteristics between the treatment and control groups.

[14] Estimating the same models with a Box–Cox transformation yields results that are close to those reported here.

[15] If it is possible to satisfy no externalities across clusters defined by comps, then a neighborhood-level SUTVA, or NL-SUTVA assumption is valid [59]. However, spillovers do traverse comps-levels and even across the treatment and control groups since diminished demand for homes in the treatment group may increase demand in the control group. Still, it is worth considering the following possibility in future research. NL-SUTVA requires that there be no treatment externalities between homes in different comp groups, that is, the effect of the SNF shipments in one comp cluster does not affect the outcome in another comp cluster. Suppose any externality from the treatment, reflected in values of the comps, is confined to the treated group, and there are no cross-group spillovers (this may be tested). Then, since NL-SUTVA is satisfied, Eq. (2) may be used in a manner similar to

4.1.2. Heterogeneity

A key source of heterogeneity in the treatment effect, recognized in the theory section, and also in the GJS study, is that perceived risk from exposure decreases as distance from the SNF route increases. Two extensions of (2) are used to take this into account. In the first extension, we assign properties within three parallel 4 km distance bands, each band successively further from the SNF route:

$$\ln(\mathrm{P}_{it}) = \gamma T_i + \sum_{j=1}^{3} \tau_j^S (DT1_t \times T_{ij}) + \sum_{j=1}^{3} \tau_j^L (DT2_t \times T_{ij}) + \phi \ln(\mathrm{COMP10}_{it}) + \beta' X_i + \text{year fixed effects} + e_{it}. \tag{3}$$

where assignment of each property i to a band is indicated by the three dummy variables T_{ij}, $j = 1, \ldots, 3$. We expect the DIDs to follow the order $\tau_1 > \tau_2 > \tau_3$ (for both SR and LR treatment effects) since properties located further from the shipment route become less exposed to perceived risk. We use this model to search for a credible distance cutoff for defining the unexposed control group of properties. To start the search we define the treatment group indicator $T_i = 1$ if property i is within 18 km of the SNF route.[16]

In the second extension, rather than estimating constant DIDs within different bands we estimate it as a continuous function of distance from the SNF route:

$$\begin{aligned}\ln(\mathrm{P}_{it}) = {} & \gamma T_i + \tau^S (DT1_t \times T_i) + \tau^L (DT2_t \times T_i) + \tau_D^S (\mathrm{DistanceSNF}_i \times DT1_t \times T_i) + \tau_D^L (\mathrm{DistanceSNF}_i \times DT2_t \times T_i) \\ & + \phi \ln(\mathrm{COMP10}_{it}) + \beta' X_i + \text{year fixed effects} + e_{it}.\end{aligned} \tag{4}$$

The DID for property i is computed as $\tau + (\tau_D \times \mathrm{DistanceSNF}_i)$, where the constant treatment effect τ is adjusted for the ameliorating effect of distance from the SNF route. From a modeling perspective, (4) captures distance from the shipment route as an essential source of heterogeneity. Since the property-specific treatment effect is not constant across every property, the DID estimates the average treatment effect on treated properties (ATT) in the Charleston county population. Specifically, the DID estimates the additional change over time in property values for the treated relative to the controls. From a policy perspective, the distance effect is critical in assessing damage valuations for individual properties.

4.2. Panel data

The availability of repeat sales data is uncommon because several years of data must be available before we can obtain a mix of properties that have been sold two, three, four, or more times. We have that luxury, and are able to estimate panel models with property-fixed effects. The panel DID model of short- and long-run ATTs is specified as

$$\begin{aligned}\ln(\mathrm{P}_{it}) = {} & \tau^S (DT1_t \times T_i) + \tau^L (DT2_t \times T_i) + \tau_D^S (\mathrm{DistanceSNF}_i \times DT1_t \times T_i) + \tau_D^L (\mathrm{DistanceSNF}_i \times DT2_t \times T_i) \\ & + \phi \ln(\mathrm{COMP10}_{it}) + \text{year fixed effects} + u_i + \epsilon_{it}.\end{aligned} \tag{5}$$

In (5) u_i are property fixed effects. Time-invariant regressors like property attributes, distance to amenities, and neighborhood characteristics are absorbed into the property fixed effects.[17] COMP10 is time-varying and controls for spatial errors. Bertrand et al. [3] caution about underreporting standard errors, since in panels with long durations of treatment, autocorrelation of treatment with the outcome is likely. We note that since individual properties sell at random points during the period of the sample, the autocorrelation problem in our case is not severe. Regardless, we follow their suggestion of using White's robust standard errors, which accounts for clustering on fixed effects, for computing t-values [3, fn 29].

5. Results

5.1. Pooled cross-section

5.1.1. Distance bands of properties

OLS estimates from the pooled cross-section of parameters in the distance bands model (3) are reported in Table 3. The effect of the spatial control variable COMP10 is measured extremely precisely. As expected, it is a good predictor of the change in sale prices. In the first model, for example, a 10% increase in the price of the closest 10 properties sold is associated with a 4.62% increase in the value of a home in that neighborhood. The spatial variable accomplishes its other task, namely reducing spatial correlation. While it is not possible to compute spatial statistics such as Moran's I and Getty's

(*footnote continued*)
VanderWeele's [59] two-level model for estimating neighborhood effects. In the two-level model properties are treated in clusters of comps (i.e. "neighborhood"), enabling estimation of *comps-level* ATTs.

[16] The plausibility of 18 km as a cutoff choice is based on these considerations. If a "safe" distance such as 25 km is chosen as a cutoff to determine the boundary between treated and control properties, then 99% of the Charleston properties fall in the treated group. On the other hand, a shorter cutoff, say at 5 km, may include a sizable set of properties the control group that are actually perceived to be exposed to risk from the SNF. The DID coefficient τ would then understate the actual treatment effect.

[17] In theory, improvements to properties may change their characteristics, and building new amenities can introduce time-variation. However, in our sample too few properties expanded or contracted in terms of square footage, and the stock of amenities remained constant.

Table 2
Descriptive statistics for pooled cross-section sample.

Variable	Description	Mean	sd
Ln(Sale Price)	Log of $ sale price	11.765	0.685
Ln(Comp10)	Log of average price of closest 10 properties sold in the past year	11.783	0.587
*DT*0	1 if date of sale *is prior* to onset of SNF shipment (8/1994), else 0	0.10	0.31
*DT*1	Short run: 1 if sale after onset of shipments, but before 1997.	0.22	0.42
*DT*2	Long run (post-1997): 1-*DT*0–*DT*1	0.67	0.47
T	1 if in treatment group (< 12 km. from SNF route), 0 otherwise	0.48	0.50
C	1 if in control group (≥ 12 km. from SNF route), 0 otherwise	0.52	0.50
*T*0	Potential treatment group in the Pre-Shipment period = T × *DT*0	0.04	0.20
*T*1	Assignment to treatment in the short run = *T* × *DT*1	0.10	0.30
*T*2	Assignment to treatment in the long run = *T* × *DT*2	0.34	0.47
DistanceSNF	Distance to spent nuclear shipment (SNF) rail route (km)	11.63	6.79
DistanceSNF × *T*	DistanceSNF × *T* (km)	2.894	4.075
DistanceSNF × *T*1	DistanceSNF × *T* × *DT*1 (km)	0.605	2.211
DistanceSNF × *T*2	DistanceSNF × *T* × *DT*2 (km)	2.029	3.659
DistanceNon-SNF	Shortest distance to rail route other than the SNF rail route (km)	7.578	5.024
DistanceNon-SNF × *T*	DistanceNon-SNF × *T* (km)	4.621	5.858
DistanceNon-SNF × *T*1	DistanceNon-SNF × *T* × *DT*1 (km)	0.911	3.122
DistanceNon-SNF × *T*2	DistanceNon-SNF × *T* × *DT*2 (km)	3.313	5.427
Square Feet	Square footage, 1000 sq. ft.	1.893	0.759
Year Built	Year Built (scaled by 1000)	1.971	0.127
HH Income	Median annual household income in census block ($ mn.)	0.054	0.019
% White	Fraction of population in the census block that is white	0.808	0.255
% Black	Fraction of population in the census block that is black	0.165	0.249
% Hispanic	Fraction of population in the census block that is Hispanic	0.015	0.035
Bay	Shortest distance to the bay ('000 km)	0.009	0.007
Building	Shortest distance to major building ('000 km)	0.007	0.004
Park	Shortest distance to a park ('000 km)	0.006	0.004
Island	Shortest distance to an island ('000 km)	0.004	0.003
Stream	Shortest distance to a stream ('000 km)	0.002	0.001
Cape	Shortest distance to the cape ('000 km)	0.005	0.004
School	Shortest distance to a school ('000 km)	0.002	0.002
Church	Shortest distance to a church ('000 km)	0.002	0.002
Hospital	Shortest distance to a hospital ('000 km)	0.009	0.008

Note: 1. Sample of 79,650 residential properties sold at least once in Charleston County (SC) during 1992–2005.
2. DistanceNon-SNF variables based on "Near Rail Route" sample of 58,674 properties.

C in such a large sample, we computed them in sub-samples and found the presence of the spatial variable greatly reduced, even if it did not eliminate, spatial correlation.

Before turning to ATT estimates, it is worth noting the importance of the hedonic variables. They are very precisely estimated and have coefficients in the direction we expect. Larger square footage, for example, increases property value. Census-block characteristic measures have the expected signs on their coefficients. Higher income is associated with higher prices in that census-block. In line with a number of other studies, the greater the proportion of the census-block population that is African American or Hispanic, the lower is the property sale price. In the first model, for example, in census blocks where the percentage of black and Hispanic population is 10 percentage points higher, property price are 5.5% and 4.9% lower, respectively. The many statistically significant coefficients on the proximity-to-amenity variables indicate their usefulness as controls. Finally, year fixed-effects capture Charleston-wide annual changes in property price trends. *DT*1 and *DT*2 are absorbed into the year dummies and do not appear explicitly.

We turn to the ATTs in each property band. In the 4 km band around the SNF route, the short-run difference-in-differences (vis-a-vis the control properties beyond 18 km from the SNF route) τ^S is estimated to be -0.062. It is statistically significant at the 1% level. The long-run ATT τ^L is estimated to be -0.133, also statistically significant at 1%. ATTs for properties in the [0,4) and [4,8) km bands are larger than in the furthest band. There are two distinct reasons for this pattern. First, the further are treated properties from the SNF route the lower is the perception of risk exposure to SNF shipments. Second, the further are treated properties from the SNF route the closer they are to the control group of properties, making the difference-in-differences smaller.

Since the long-run ATT τ^L dies out in the [8, 12) km band, we choose 12 km to define the boundary between properties assigned by the SNF natural experiment to treatment and control groups. The specific cutoff used to assign treatment and control properties in Table 3 is not important for this result: it is robust to the choice of either 15 km, 18 km or 22 km In all cases, the long-run ATT disappears beyond 12 km. Finally, we note that the long-run ATT is larger than the short-run ATT. The *z*-statistic at the bottom of the table tests this hypothesis, and rejects equality of the two ATTs (except of course in the last column where both the long- and the short-run ATTs approach zero). The result that the long-run ATT significantly exceeds the short-run ATT is robust across the variety of models we estimate.

Table 3
Average treatment effect on the treated (ATT), in bands of properties. Pooled cross-section data: OLS.

		Treatment: bands around SNF route		
Variable type	Variable/Coefficient	[0, 4) km	[4, 8) km	[8, 12) km
Spatial	Ln(Comp10)	0.462***	0.464***	0.506***
		[0.009]	[0.010]	[0.008]
ATT	τ^S	−0.062***	−0.035	0.006
		[0.020]	[0.024]	[0.022]
	τ^L	−0.133***	−0.076***	−0.013
		[0.020]	[0.022]	[0.022]
	T	0.086***	0.104***	0.035
		[0.022]	[0.024]	[0.023]
Property	Square Feet	0.093***	0.102***	0.096***
		[0.005]	[0.006]	[0.006]
	Year Built	−0.098***	−0.108***	−0.138***
		[0.024]	[0.025]	[0.023]
	HH Income	4.097***	3.326***	0.44
		[0.280]	[0.399]	[0.306]
Census block	% White	−0.251***	0.102	0.026
		[0.083]	[0.099]	[0.095]
	% Black	−0.553***	−0.146	−0.303***
		[0.083]	[0.100]	[0.095]
	% Hispanic	−0.490***	0.076	−0.341***
		[0.104]	[0.114]	[0.115]
Amenities	Bay	1.804	−5.299***	−4.675***
		[1.266]	[1.371]	[1.095]
	Building	−0.43	−3.912***	−4.171***
		[1.182]	[1.306]	[1.220]
	Park	3.648**	0.371	−0.292
		[1.482]	[1.521]	[1.363]
	Island	−4.605**	−1.882	4.591*
		[2.171]	[2.550]	[2.657]
	Stream	−6.079	−15.43***	−0.904
		[3.999]	[4.570]	[4.104]
	Cape	3.284**	−0.788	−3.944*
		[1.519]	[1.595]	[2.013]
	School	10.13***	12.46***	21.66***
		[2.905]	[3.321]	[3.423]
	Church	22.47***	13.69***	4.527*
		[2.785]	[2.965]	[2.628]
	Hospital	−4.656***	−2.498***	−3.719***
		[0.837]	[0.915]	[0.882]
	Year-FE	Yes	Yes	Yes
N		27,340	20,914	27,639
Adj. R^2		0.472	0.432	0.397
# Regressors		32	32	32
z-stat. for Ho: $\tau^L = \tau^S$		4.418***	2.319***	1.183

Notes: 1. Robust standard errors. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.
2. Treated properties within the distance band (above) around the SNF route; control properties lie > 18 km from the route.
3. "S" indicates short-run post-shipment period 9/94–12/97; "L" indicates long-run period 1/98–12/05.

5.1.2. Core ATT results

Table 4 presents our core ATT results from models (2) and (4). They demonstrate robustness of the results to (i) the full sample as well as the "Near Rail Routes" sample, and (ii) the model with and without the spatial control. Consider estimates with the spatial control COMP10 using the full sample of 79,650 property sales in the first column. The short-run average treatment effect of the SNF shipments is estimated to have been a 4.1% reduction in property values, while the long-run ATT of the shipments τ^L is twice this magnitude, or 8.0%. The difference between the short- and long-run ATTs is statistically significant at 1%. The long-run 8% decrease is a nontrivial reductions in property values: by these estimates, the SNF program lowers the price of a $150,000 property located within 12 km of the shipment route by $12,000 over the long run. For the hundreds of thousands of homes in Charleston County alone, the total property loss may run into billions of dollars.

As shown in the distance-band models, properties further from the route should have ATTs close to zero as the influence of the shipments diminishes, while those closer to the route experience the greatest diminution in prices. The second column produces precise, per kilometer estimates, of this distance effect. While the short run distance effect τ_D^S was statistically insignificant (which differs from the GJS finding of a statistically significant short-term effect of similar magnitude), the long-run effect τ_D^L is precisely estimated. The ATT for property i is estimated to be $(-0.117 + 0.006 \times \text{DistanceSNF}_i)$. Thus, our estimate is that a property 1 km from the route changed −11.1% in value on

Table 4
Core results: ATT w and w/o distance effects dependent variable: Ln(Sale Price).

	With spatial control				*Without spatial control*			
	Full sample		*Near Rail Routes*		*Full sample*		*Near Rail Routes*	
Ln(Comp10)	0.512***	0.506***	0.479***	0 477***				
	[0.006]	[0.006]	[0.007]	[0.007]				
τ^S	−0.041***	−0.055***	−0.027	−0.040*	−0.092***	−0.132***	−0.056***	−0.093***
	[0.012]	[0.018]	[0.018]	[0.022]	[0.013]	[0.019]	[0.019]	[0.022]
τ^L	−0.080***	−0.117***	−0.071***	−0.109***	−0.213***	−0.270***	−0.179***	−0.241***
	[0.012]	[0.017]	[0.017]	[0.020]	[0.012]	[0.017]	[0.017]	[0.020]
T	0.066***	0.040**	−0.044**	−0.041*	0.196***	0.099***	−0.028	−0.040*
	[0.0116]	[0.017]	[0.018]	[0.022]	[0.012]	[0.017]	[0.019]	[0.022]
τ_D^S		0.003		0.002		0.007***		0.006**
		[0.003]		[0.002]		[0.003]		[0.003]
τ_D^L		0.006***		0.006***		0.010***		0.010***
		[0.002]		[0.002]		[0.002]		[0.002]
$T \times D$		0.003		0.0002		0.012***		0.003
		[0.002]		[0.002]		[0.002]		[0.002]
τ_D^S (non-SNF route)			−0.003	−0.003			−0.004*	−0.003
			[0.002]	[0.002]			[0.002]	[0.002]
τ_D^L (non-SNF route)			−0.002	−0.002			0.001	0.002
			[0.002]	[0.002]			[0.002]	[0.002]
$T \times D$ (non-SNFroute)			0.015***	0.012***			0.031***	0.024***
			[0.002]	[0.002]			[0.002]	[0.002]
N	79,650	79,650	58,674	58,674	79,698	79,698	58,706	58,706
Adj. R^2	0.445	0.445	0.486	0.486	0.359	0.363	0.418	0.419
# Regressors	32	35	35	38	31	34	34	37
$ATT^{LR}-ATT^{SR}$	−0.039***	−0.039***	−0.044***	−0.045***	−0.121***	−0.117***	−0.123***	−0.122***
Non-SNF ($\tau_D^L-\tau_D^S$)			0.001	0.001			0.005***	0.005***

Notes: 1. See Notes to Table 3.
2. Models include but do not report property, census block, and amenity characteristics + year FE.
3. ATT^{SR} and ATT^{LRare} the short- and long-run ATTs, respectively. In models w/o SNF route distance effects, they are simply τ^S and τ^L, respectively. In the distance effect models, they are evaluated at the mean distance of treated properties from the SNF route.

account of the SNF program, while a property 10 km from the route diminished −5.7%. At the mean distance for treated properties of 6.052 km, the diminution in property value is the same as the ATT in the first model, or −8.0%. The (homogeneous) ATT is therefore interpreted as the treatment effect on a property located at the "average" distance from the route among treated properties.

The "Near Rail Routes" sample has the same treatment group as the full sample, but includes only the subset of control group properties that are less than 12 km away from a non-SNF rail route. The control group therefore also picks up the disamenity (the negative placebo effect) of being near a rail route per se. The third column indicates that the ATT continues to be both statistically and economically significant: the long-run ATT of the SNF program is −7.1%. Thus, the program's long-run impact is robust to placebo control. The fourth column shows that this sample produces almost the same distance-from-the-SNF-route effect and the impact of the program on each property that was found using the full sample. This sample also informs us whether the distance effects observed with respect to the SNF route are also observed for the non-SNF route. The estimates on the non-SNF route τ_D^S and τ_D^L are both statistically no different from zero. Unlike the post-shipment distance effect from the SNF route, the distance effect from the non-SNF route remained unchanged from that which existed before the shipments started.

The models with COMP10 included do not suffer from spatial correlation in the data, and provide our preferred estimates for the ATTs. However, as we have mentioned, controlling for COMP10 may absorb some of the "true" treatment effect. Owners may argue that their home price is depressed because the comps are all selling for less, and that the comps sold for less due to the treatment. The correct ATT then requires dropping the price of comps in the analysis. The last four columns mirror the first four columns, but without the spatial control COMP10. The magnitudes of the ATT estimates without the comps are sharply higher than the ATTs with the spatial control. The long run ATT of the SNF program is estimated to be −21.3% in the full sample and −17.9% in the "Near Rail Routes" sample, depressing prices by two to three times as much as the diminution estimated by the comps models. On the other hand, omitting COMP10 produces spatial correlation in the error term. Perhaps the real value of reporting the (possibly biased) estimates without the comps is to indicate that the true ATT is probably higher than in the model with the comps, but lower than without.

In sum, the pooled cross-section evidence overwhelmingly rejects the null hypothesis of no treatment effect from the SNF shipments over the long run. The negative quantitative impact of the SNF shipments is striking, especially for

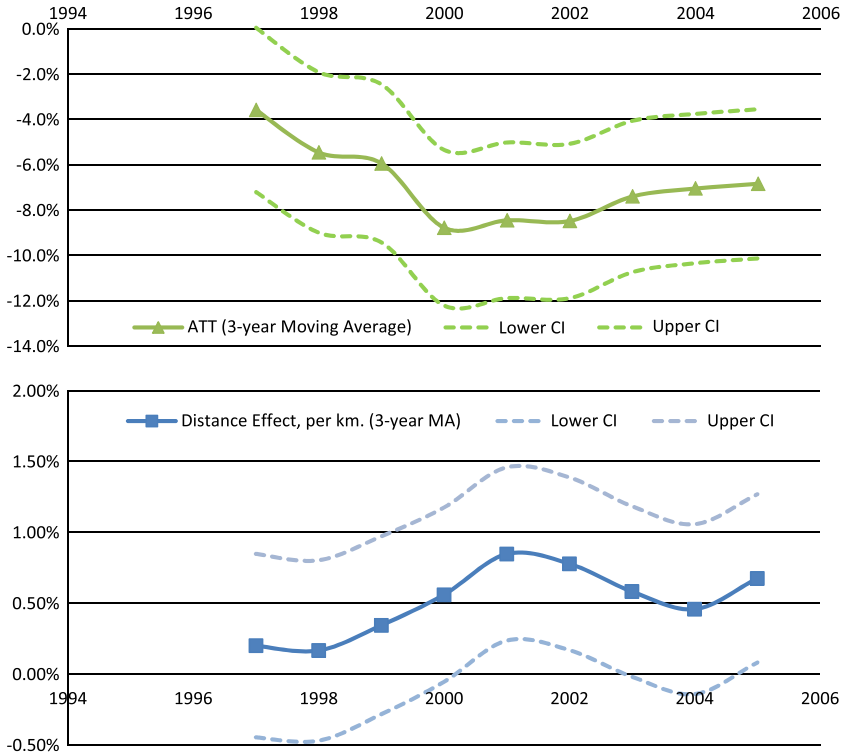

Fig. 3. Annual average treatment effects (ATT) and two-standard deviation confidence intervals: 3-year (sample-weighted) moving average. Top panel: average treatment effect for treated properties (% of sale price). Bottom panel: distance effect in ATT: % increase in sale price of treated properties per km away from SNF route.

properties closer to the SNF route. Regardless of the sample or specification to which one subscribes, the estimated impact on property prices is nontrivial.

5.1.3. ATT evolution

How did the ATTs evolve over time, and have they reached a steady state? Whether the ATT has converged after more than ten years of experience with the SNF shipments is an important policy question, and also an essential ingredient into any valuation exercise. We answer this question by interacting T with the full set of year dummies from 1995 to 2005 to see how the treatment effect varies over time. In Fig. 3 the result is plotted as a three-year moving average of the coefficients on the interactions with the year dummies, along with their two-standard deviation confidence intervals.[18] The top panel indicates that the ATT dipped from -3.6% in 1997 to almost -9% in 2000. Since 2003 it appears to have settled at around -7%.

The bottom panel of Fig. 3 traces the evolution of the distance effect, expressed here per kilometer a property is located from the shipment route. The graph indicates three phases: an increasing price premium on locating away from the route peaking at 0.85% per km in 2001, a decrease in that premium bottoming out at 0.46% per km in 2004 and an increase in 2005. The long-run effect seems to be converging to around 0.6% per km, similar to our core Table 3 result. The smaller annual samples lead to less precise estimates of the distance effect than the full-sample estimates in Table 3—the confidence intervals include zero for more than half the years. Still, the results appear to describe learning in the property market about risk perceptions from the SNF shipments over this period. A possible conclusion about the periods for which the confidence intervals included zero is that learning about the distance premium was itself imprecise. We note that the annual distance effects estimated in models without the spatial control COMP10 are all statistically significantly greater than zero, and approximately twice the magnitude of the effects reported in Fig. 3. Those results are available from the authors.

5.1.4. Falsification test

A key assumption needed for the difference-in-differences method to identify the treatment effect is that the treatment and control groups both have common time trends in the absence of treatment. We use a falsification test to affirm that this is indeed true. Since we have multiple years of data prior to the start of the SNF shipments, we can estimate model (2)

[18] These are sample-weighted averages, where the DID for year t is weighted by the number of properties in the sample in year t. The confidence interval are similarly constructed.

Table 5
Identification: falsification test with pre-shipment data dependent variable: Ln(Sale Price).

	W/spatial	*W/o spatial*
Ln(Comp10)	0.422***	
	[0.0173]	
$d^{\text{"PRE"}}$	−0.033	−0.041
	[0.040]	[0.040]
T	−0.059	0.097***
	[0.038]	[0.037]
$d^{\text{"POST"}} \times T$	0.137***	0.034
	[0.036]	[0.035]
Square Feet	0.171***	0.216***
	[0.011]	[0.011]
Year Built	−0.877**	−0.863*
	[0.445]	[0.479]
HH Income	2.048***	5.046***
	[0.528]	[0.541]
% White	0.227	0.277*
	[0.159]	[0.161]
% Black	−0.128	−0.222
	[0.162]	[0.164]
% Hispanic	−0.206	−0.149
	[0.168]	[0.178]
Amenities	Yes	Yes
Year-FE	Yes	Yes
N	7867	7915
Adj. R^2	0.293	0.225
# regressors	21	20

Note: 1. OLS, robust errors. See Notes 1 and 2 to Table 3.
2. Pre-shipment sample: from 1992 through 8/1994. $d^{\text{"POST"}}=1$ if property sold after 1/1993.
3. Treated properties ($T=1$) within 12 km, of the SNF route; 41% "treated" and 59% "control".

using only data before the start of the shipments (8/1994), with 1/1993 as a "placebo" treatment cutoff. If the assumption about common trends is valid, there should be no significant treatment effect using only this data (see e.g. [36]).

Table 5 reports results from the falsification test. In the model without spatial controls the ATT is statistically not significant, suggesting no important differences in the time trends of control and to-be-treated properties prior to knowledge of the SNF shipments. The model with comps shows a statistically significant ATT but in the *opposite* direction to our core ATT results. If there were differences in the time trends of control and to-be-treated properties prior to the shipments, then the shipments reversed these trends. It is possible that the difference in the ATT estimates in the models with and without comps is due to this difference in pre-treatment trends. Subsequent reporting of our results are from the model with comps. We note that in every case the models without comps produce the same contrast as we have seen in Tables 4 and 5.

5.1.5. ATTs for quantiles

Are ATTs different for properties in different price ranges? We investigate this source of ATT heterogeneity using quantile regressions, and report the results in Table 6. For brevity, results with the shorter sample are omitted here and available from the authors. The short run ATTs are statistically insignificant except for properties priced in the third quartile. The long-run ATTs are statistically significant, and large. At the mean distance of treated properties, the ATT of the SNF program is an expected loss of 10.2% over the long run for properties at the 25th quartile, of 5.0% for properties at the median, and of 3.1% for properties at the third quartile. Higher-priced properties appear to be a bit more resilient, but not by much. A 3.1% price decline for properties priced above $300,000 is a significant reduction in value.

5.2. Panel data

Data on repeated sales of properties are not easy to find. Even in the rare instance that they are available, the absence of identifying information about the property such as address or cross-streets-plus-zip-codes makes them less useful. Hence the tradition in the literature assessing the impact of environmental disamenities is to use a (pooled, if possible) cross-section of properties and available hedonic variables as controls, as we do above. However, even an extended list of controls cannot fully account for the heterogeneity in the cross-section. A feature that distinguishes this from other studies is that we have available detailed identifying information on the properties. We use that to construct three panel data sets: one consisting of properties that were sold at least twice during the 1992–2005 period (sample size=46,632 with 19,940 distinct units); another consisting of properties that were sold at least thrice (N=17,877 with 5523 units); and a third consisting of properties that were sold at least four times during this period (N=4926 with 1191 units). The panels

Table 6
Robustness: quantile regressions dependent variable: Ln(Sale Price).

	Quantiles		
	0.25	0.5	0.75
Ln(Comp10)	0.633***	0.597***	0.473***
	[0.007]	[0.004]	[0.004]
τ^S	−0.047	−0.027	−0.049***
	[0.030]	[0.017]	[0.017]
τ^L	−0.155***	−0.079***	−0.054***
	[0.026]	[0.016]	[0.016]
T	0.085***	0.012	−0.051***
	[0.026]	[0.016]	[0.015]
τ_D^S	0.004	−0.0001	0.001
	[0.004]	[0.002]	[0.002]
τ_D^L	0.009***	0.005**	0.004*
	[0.003]	[0.002]	[0.002]
$T \times D$	−0.006*	0.004**	0.012***
	[0.003]	[0.002]	[0.002]
N	79,650	79,650	79,650
# Regressors	35	35	35
Pseudo R^2	0.292	0.362	0.383
ATT^{SR} at mean DistSNF	−0.021	−0.028***	−0.043***
ATT^{LR} at mean DistSNF	−0.102***	−0.050***	−0.032***
$ATT^{LR} - ATT^{SR}$	−0.081***	−0.022***	0.011**

Notes: 1. ***, **, * indicate statistical significance at 1%, 5%, and 10%.
2. Models include but do not report property, census block, and amenity characteristics + year FE.

Table 7
ATT from panel data sets full sample. Dependent variable: Ln(Sale Price).

	# Repeated sales ≥ 3					
	≥ 2		≥ 3		≥ 4	
Ln(Comp10)	0.464***	0.460***	0.487***	0.483***	0.525***	0.522***
	[0.012]	[0.012]	[0.018]	[0.018]	[0.034]	[0.034]
τ^S	−0.092***	−0.127***	−0.0094***	−0.139***	−0.077*	−0.11
	[0.0168]	[0.026]	[0.025]	[0.039]	[0.044]	[0.074]
τ^L	−0.187***	−0.289***	−0.174***	−0.288***	−0.166***	−0.263***
	[0.016]	[0.023]	[0.023]	[0.035]	[0.043]	[0.070]
τ_D^S		0.006*		0.007		0.005
		[0.003]		[0.005]		[0.008]
τ_D^L		0.016***		0.018***		0.014*
		[0.003]		[0.004]		[0.008]
N	46,632	46,537	17,877	17,870	4926	4926
# Homes	19,940	19,889	5523	5520	1191	1191
Max # sales	6	6	6	6	6	6
Within R^2	0.470	0.471	0.520	0.521	0.565	0.565
% var due to FE	0.492	0.490	0.453	0.451	0.404	0.401
$ATT^{LR} - ATT^{SR}$	−0.095***	−0.096***	−0.086***	−0.081***	−0.089***	−0.088***

Notes: 1. OLS with property-fixed effects and year dummies.
2. Robust standard errors. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.
3. Treated properties are < 12 km from SNF route; control properties ≥ 12 km.
"S" indicates short-run post-shipment period 9/94–12/97; "L" indicates long-run period 1/98–12/05.
4. See Note 3 to Table 4 regarding SR and LR ATTS.

overcome concerns about time-invariant effects not captured by observed hedonic variables. The pooled model removes variables that do not vary over time or across properties within the treatment or control groups. The panel model removes time invariant attributes, regardless of whether these attributes differ within the treatment or control groups. For example, if building grade is time invariant, correlated with T, but varies across properties even conditional on T, then this is an unobservable that is removed in the panel model but not the pooled cross-section model.

Property fixed effects estimates of the ATT from both samples are presented in Table 7. The long-run estimates of the negative impact of the SNF shipments are larger than their pooled cross-sectional counterparts in Table 4. In the first column the long-run ATT is estimated to be −18.7%, twice the short-term effect here, and more than twice the long-run

ATT (of -8%) from the pooled data. The distance effect τ_D^L is also more than double that from the pooled data, indicating a stronger influence of the shipments on homes proximate to the route. The total effect on home i is estimated to be $(-0.289+0.016 \times \text{DistanceSNF}_i)$. A home located at the mean treatment distance (of 6.233 km) from the route has a long-term treatment effect equal to that in the first column, or -18.7%.

A possible reason for why the panel ATTs differ markedly from the pooled ATTs is omitted variables bias in the pooled data. Property-fixed effects in the panel data control for *all* variables that are time-invariant, while the set of hedonic variables in the pooled cross-section only capture time-invariant influences that are measurable. In particular, in (2) if an omitted time-invariant regressor has a theoretically positive (negative) coefficient, and is positively (negatively) correlated with the assignment to long-run treatment variable $DT2_t \times T_i$, then the absolute size of the coefficient τ^L is diminished. Examples of omitted property-specific variables include number of bedrooms or bathrooms, swimming pool, condition of the building, and building grade. If building grade, for example, is time invariant, correlated with T, but varies across properties even conditional on T, then this is an unobservable that is removed in the panel model but not the pooled cross-section model. Specifically, suppose treated properties are of higher grade than control properties. Since this omitted variable is positively correlated with T, the absolute value of the OLS estimate of τ^L is attenuated in the pooled cross-section.

A second reason is that the panel data includes only those properties that have been sold more than once. If the propensity to re-sell increased after the inception of the SNF shipments, then it provides a new explanation for how the shipments negatively influenced prices for the treated properties. Suppose the distribution of risk aversion among owners is heterogeneous, but the distributions are the same in the treatment and control groups. Exposure to the risk from the SNF shipments induces especially risk-averse owners of treated properties to sell at whatever price they can get, even if this means taking a loss on the property in order to move to a safer location. Owners in the pre-shipment era or owners of control properties in the post-shipment era, on the other hand, do not perceive the same risk and do not need to sell their property on unfavorable terms. Since the onset of the SNF shipments makes this channel of influence salient, the causal mechanism is clearly identified. Perceived risk from the shipment reduces the bargaining power of sellers assigned to treatment but leaves unaltered the bargaining power of other potential sellers. Therefore, the sample consisting of repeat sales produces a larger negative average treatment effect than a sample in which a predominance of single-sale homes mutes this mechanism. The predominance of single-sale properties in the pooled cross-section is evident in the much smaller samples in Table 7 in which they are dropped, as compared with Table 4.

This finds support in Riddel and Shaw's [48] survey of Southern Nevada residents about their perceived mortality risk and willingness to accept the risks related to nuclear waste transportation. Riddel [47] reports that willingness to accept risk varied significantly across population characteristics. Women perceived more risk than men, higher education was correlated with lower risk perception, and older persons perceived greater risk. The pooled cross-section does not include information about the gender and age of the homeowner, and their relation to risk perception. To the extent these characteristics are time-invariant, the DIDs from the panel reflect the disparate attitudes.

The results from the three panel samples produce remarkably similar inferences about the magnitudes of the short- and long-run ATTs. The long-run ATTs are greater by about 8–10 percentage points. As a further robustness check we estimate the models using the "near Rail Routes" panel samples. They produces ATTs similar in magnitude to those reported in Table 7, showing the results are driven by the proximity to the shipment route, not a non-shipment rail route. Finally, the panel allow us to take account of autocorrelation in repeat-sale prices. An AR(1) model of (5) produces estimates of the AR(1) coefficient of over 0.55, which indicate that dynamics may be important.[19] The long-run ATTs from the AR(1) models are estimated to be between -6% and -15.8%.

6. Conclusion

Modern industrial societies produce and manage many types of hazardous materials that may impose risks on those who live near their storage sites and transport routes. While the benefits from industrial and commercial activities that generate hazardous materials may be of sufficient social value to justify those perceived risks, important equity concerns are raised when those perceived risks are involuntary and the potential losses are geographically concentrated. In such cases, fixed values in property may come to reflect lower market valuation attributable to proximity to the hazardous materials. From a property rights perspective, if the imposition of such a cost was verified, then it could be perceived as a "taking" by those who experience the reduced property values. The policy implications of studies that weigh in on this issue are of major consequence.

This paper quantifies the cost of transporting radioactive spent nuclear fuel (SNF), based on property sales data from Charleston, South Carolina over the 1992–2005 period. The SNF shipments began in 1994 and are ongoing. The impact on housing values in the early years of these shipments was studied by Gawande and Jenkins-Smith [17], GJS. We reconsider the evidence in that study. First, the GJS study estimates only the distance gradient – the effect of the distance from the SNF route on the price of a property – but not the absolute effect of the shipment program on the property price, or the treatment effect. We are able to estimate the average treatment effect of the SNF shipment program using appropriate program evaluation methods [22]. Second, the treatment effect measured by GJS ignored trends in prices of comparable properties that were

[19] Due to the differencing, properties that sold twice are dropped, reducing the effective sample considerably.

unaffected by the SNF shipments. We use difference-in-differences comparing affected properties with a carefully chosen control group. Third, we bring to bear both pooled cross-sectional data as well as panel data evidence.

In populous Charleston County we find evidence of a reduction in property prices due to the SNF shipments. Both the pooled cross-section and the panel provide compelling evidence of a negative average treatment effect in properties that experienced heightened risk perception from the SNF shipments program. This treatment effect is long-lived even in the absence of any accident involving the SNF shipments. For properties located within 18 km from the SNF route, the pooled cross-sectional data indicates average treatment effects of between 2.5% and 5% declines in long run property price due to the SNF shipment program. There is strong distance-heterogeneity, so that properties located further from the route are less affected by the shipments. Our estimates may be used to obtain precise estimates of the ATT for specific properties.

Our finding implies that policymakers should evaluate how to mitigate that effect and, when it can be clearly demonstrated, consider compensation for those who bear these costs. The estimate of the total property loss due to the shipments is likely to run into billions of dollars in urban Charleston County. As the nation debates how to store its nuclear waste, at Yucca Mountain or elsewhere, substantial concerns about damages are sure to be raised. Because the policy implications of the findings are enormous, quantitative assessments of environmental impacts need to be carefully developed. Our study contributes methodologically to that end.

We note some limitations applicable to our findings. The effects identified in this study apply to Charleston County, but did not appear to affect other counties on the rail route (GJS [17]). While we can speculate that offsetting amenities may be responsible for these differences, it is possible that effects of SNF transport are not uniform. Some regions may experience negative property price effects, while others may not. We leave this an open question for further research.

Finally, from the point of view of policy, it is not surprising that programs (such as the SNF return program) that generate clear and substantial benefits to society also impose localized costs. In such cases, considerations of both justice and practicality dictate a need to understand the effects and find appropriate policies to address them. Effective policy design thus seems to require a willingness to carefully evaluate and then respond to inadvertent transfers of wealth that result from otherwise sound programs. What policies might the government use to address such concerns? The default might be to argue that under eminent domain, the government need not pay anything. It is not certain that the courts would uphold this claim [25,19,10,54]. Moreover, opposition to transport policies would almost certainly find expression; for example, the state of California has explicitly forbidden a similar transport through that state into Nevada. Therefore, it is not only practical for the government to find a solution before a possible incident triggers claims, but ex ante policy is very likely to make it less onerous for the government and taxpayers. A range of mechanisms from mitigation through insurance and compensation [37,30] in order to address this problem are important areas of further research. In our view, the time for consideration of such policies is before rather than after the large-scale transport of SNF commences within the US. The recent call by President Obama's Blue Ribbon Commission to undertake "Prompt efforts to prepare for eventual large-scale transport of spent fuel and high-level wastes to consolidated storage facilities…" [5]: vii makes this an opportune time to do so.

Appendix A

See Table A1.

Table A1
Descriptive statistics for panel data sample.

	> 2 sales			≥ sales			> 4 sales		
	mean	sd	within-sd	mean	sd	within-sd	mean	sd	within-sd
Ln(Sale Price)	11.806	0.672	0.431	11.833	0.658	0.476	11.834	0.662	0.510
Ln(Comp10)	11.830	0.577	0.325	11.853	0.561	0.365	11.866	0.570	0.393
*DT*0	0.095	0.294	0.224	0.098	0.298	0.251	0.111	0.314	0.280
*DT*1	0.216	0.412	0.312	0.223	0.417	0.352	0.228	0.420	0.378
*DT*2	0.688	0.463	0.340	0.678	0.467	0.390	0.661	0.473	0.421
T	0.456	0.498	0	0.439	0.496	0	0.398	0.489	0
C	0.544	0.498	0	0.560	0.496	0	0.601	0.489	0
*T*0	0.039	0.193	0.143	0.038	0.157	0.234	0.038	0.189	0.162
*T*1	0.092	0.290	0.205	0.092	0.290	0.227	0.088	0.284	0.236
*T*2	0.324	0.469	0.227	0.308	0.461	0.252	0.272	0.445	0.259
DistanceSNF	11.854	6.576	0	11.947	6.285	0	12.300	5.686	0
DistanceNon-SNF	10.990	7.557	0	10.971	7.237	0	10.863	6.876	0
N	46,537			17,870			4926		

Note: 1. Charleston County (SC) residential properties sold between 1992 and 2005.
2. *N* is the sample size.
3. See Table 1 for definitions of variables and their units.

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Attachment J
Exhibit 4011-000018-CWF
Columbia Waterfront LLC